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Car accidents, smartphone adoption and 3G coverage[2]

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ABSTRACT

This paper examines the relationship between smartphone use by drivers and traffic accidents in California between 2001 and 2013. In order to estimate smartphone use, we first show that widespread adoption of modern smartphones began in 2009 after the release of the iPhone 3G and T-Mobile G1. This information is combined with annual 3G coverage maps that are constructed from cellular tower information in a machine learning framework. In a difference-in-differences framework, we estimate the combined effect of smartphone adoption and 3G coverage along quarter-mile road segments. Controlling for census tract population density, road and year fixed effects, Poisson regression results show that there is a statistically significant increase in the traffic accident rate along a road segment when smartphone use becomes possible. Our preferred specification suggests smartphones caused accident rates to increase by 2.9 percent, resulting in 3500 additional accidents per year in California. Event study results rule out the possibility that our smartphone treatment is capturing a trend in the accident rate. The results are robust to a variety of specifications and consistent with individual-level studies showing that cell phone use leads to lower driving quality. The findings also provide guidance for policies aimed at reducing cell phone related accidents and distracted driving.

1. Introduction

According to the National Safety Council (NSC), cell phone use was involved in 26 percent of all motor vehicle crashes in 2014 (Council, 2014). Consistent with the NSC estimate, laboratory and simulation studies show that when drivers use a cell phone, driving quality decreases and the probability of a traffic accident increases.[1] Wilson and Stimpson (2010) estimate that individuals who text while driving are 23 times more likely to have an accident than a non-distracted driver. Concerns about cell phone use while driving have led to the enactment of cell phone and texting bans in many states (Legislatures, 2020). Additionally, a variety of agencies are involved in public awareness campaigns aimed at eliminating

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[1] See Redelmeier and Tibshirani (1997), Abdel-Aty (2003), Strayer et al. (2003), Törnros and Bolling (2005), Caird et al. (2008) and Caird et al. (2014) for evidence from individual-level studies, laboratories and simulations showing that the quality of driving worsens when drivers use a cell phone.

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distracted driving, including the National Highway Traffic Safety Administration, AAA Insurance and the cellular coverage provider, AT&T.[2]

Although there is evidence that cell phones reduce the quality of driving, data limitations have made it difficult for researchers to directly investigate how cell phone use is related to the accident rate in an area. To explore the potential effects of cell phone use, many previous studies examine the consequences of enacting state-level cell phone or texting bans. These studies provide insight about the effectiveness of bans, but the bans may not be an accurate proxy for changes in cell phone use. Abouk and Adams (2013) find a temporary reduction in fatal accidents immediately after a texting ban is enacted, but accident rates return to pre-ban levels soon after. The temporary response by drivers to texting bans observed by Abouk and Adams (2013) may explain why bans appear to reduce traffic fatalities in some settings,[3] but not others.[4]

This paper explores the relationship between cell phone use by drivers and traffic accident rates by examining the increase in smartphone usage beginning in the late-2000s. To estimate smartphone use while driving, two sources of variation are leveraged: the presence of 3G coverage along a quarter-mile stretch of road and the widespread adoption of modern smartphones beginning in 2009.

The existence of 3G coverage along a quarter-mile stretch of road is estimated by combining reliable cellular coverage maps from recent years and historical cellular tower information in a machine learning framework. The dataset we create merges estimates of 3G coverage along road segments in California with accident data for each year between 2001 and 2013. A concern with using 3G coverage as the sole proxy for smartphone use is that 3G coverage pre-dates smartphone adoption in many areas. Although 3G coverage was available in the early-2000s, modern, 3G-compatible touchscreen smartphones did not become widely used until 2009. As a result, we set 2009 as the year of smartphone adoption and do not allow 3G coverage to effect accident rates until that year.

Our initial results from fixed-effects Poisson regressions show that there is a statistically significant increase in the accident rate along a road segment once smartphone usage becomes available. At least two notable findings are observed in event study results. First, there is not a significant change in the accident rate prior to a road being treated with our measure of smartphone usage, reducing concerns that trends in the accident rate are biasing the estimated effect of smartphone use. Second, when we set the adoption of smartphones to occur earlier than 2009, the potential effect of 3G coverage on accident rates is delayed. When the adoption of smartphones is assumed to occur in 2010, there is an increase in the accident rate that precedes estimated smartphone use. The event study results suggest smartphone use by drivers began in 2009 and after that time, accident rates increase significantly when gaining 3G coverage.

Without further details about the cause of accidents, we are unable to determine the exact mechanism driving our results. However, a plausible story emerges from our analysis linking 3G coverage, the growth of smartphones and accident rates. When 3G coverage first became available in the mid-2000s, the functionality of cell phones did not immediately change, and accident rates and early 3G coverage are unrelated. Following the release of the 3G-compatible iPhone and Android smartphones in late-2008, there was an increase in mobile broadband subscriptions, text messaging and accessing of the internet while driving (Anderson, 2011). After restricting the first year of smartphone adoption to be 2009, we find a significant increase in the accident rate in areas where 3G is available. Our results suggest that 3G coverage alone does not appear to be responsible for traffic accidents, but the combination of 3G coverage and smartphone adoption is associated with an increase in the accident rate.

Our analysis differs from previous work by focusing specifically on the potential impact of smartphone usage while driving. Related work by Bhargava and Pathania (2013) proxy for cell phone use by drivers using the 9pm cutoff associated with the “free nights and weekends” plans in the mid-2000s. They do not find any change in state-level accident rates after 9pm, however, the time period of their study stopped before the introduction of modern smartphones. Taken together, our current study and the work by Bhargava and Pathania (2013) suggest that the potential distraction caused by the advanced functions of a smartphone can lead to an observably higher accident rate, but talking on a cell phone while driving does not. This is consistent with Klauer et al. (2014) who find that the odds of a crash increase significantly more when using the internet and texting while driving, compared to talking on a cell phone.[5]

The current paper is also relevant to policy makers. We find that smartphone use increases accident rates in spite of limited evidence in previous research that cell phone bans reduce accident rates. The ineffectiveness of cell phone bans may be due to the design of the bans, the penalties associated with being caught or unawareness by drivers as to what the cell phone laws are. Regardless of the source, policy makers would be well-served to find ways to reduce cell phone-related accidents. Blincoe et al. (2015) estimate that the economic cost of the 24 million vehicles involved in crashes in 2010 is $242 billion, or $784 for each person in the United States that year. The estimated social costs of cell phone use do not appear to align with the current fine of $20 for a cell phone infraction in California (McCurley, 2019).[6]

[2] See https://www.nhtsa.gov/campaign/distracted-driving, https://www.aaa.com/dontdrivedistracted and https://www.itcanwait.com.

[3] See Kolko (2009), Nikolaev et al. (2010), Sampaio (2014) and Rocco and Sampaio (2016)

[4] See Kolko (2009), Burger et al. (2014), McCartt et al. (2014) and Liu et al. (2019).

[5] Researchers also find that cell phone overuse and addiction cand lead to depression, relationship issues, anxiety, eye strain, “text neck” and male infertility (Deepinder et al., 2007; Babadi-Akashe et al., 2014; Andreassen, 2015; Lee et al., 2015; Rosenfield, 2016). Cell phone use may reduce grades in science courses (Douglas et al., 2012) and productivity at work (Thornton et al., 2014). Palsson (2017) shows that when a hospital becomes part of AT&T’s 3G network, injuries for young children increase and the results are possibly driven by parents being distracted by their smartphone.

[6] Assessments are added to this fine, which add up to $150, but the official base fine is $20.

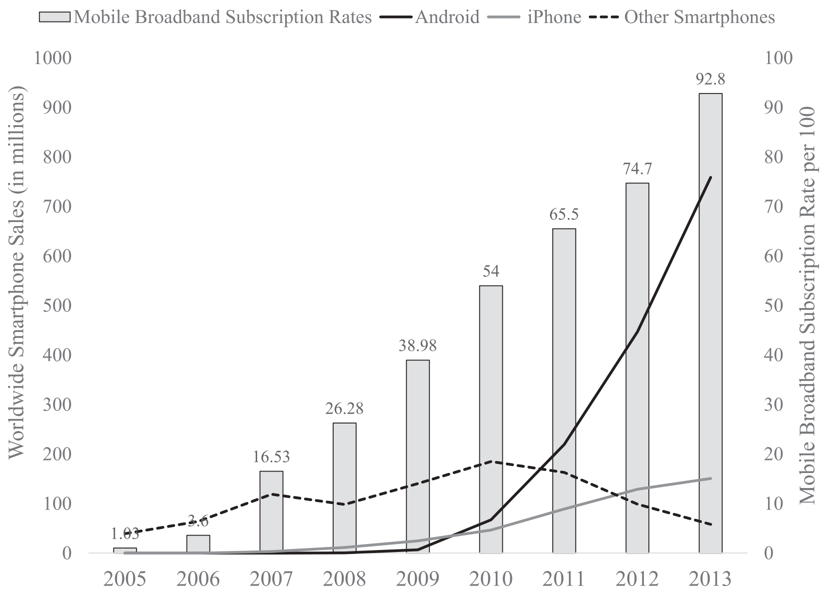


Fig. 1. Worldwide Smartphone Sales and Mobile Broadband Subscription Rate Growth. *Notes:* Mobile broadband subscription rates are from Union (2020). Smartphone sales are from Cozza et al. (2014).

2. Background

Prior to the rollout of 3G coverage in the early 2000s, 2G coverage existed throughout much of the United States and cellular subscription rates had reached more than 38 per 100 (Union, 2020).[7] It was possible for 2G network users to reach download speeds of 120 kilobytes per second, however this speed was difficult for users to obtain.[8] When 3G coverage became available, users could reach speeds of 2000 kilobytes per second, but early 3G devices had limited capabilities. Verizon first offered 3G service in 2002, but the two devices capable of accessing the 3G network had to be connected to a computer or have a PC card (CNN, 2002). Shortly after Verizon began offering 3G service, existing 2G phones ("flip phones") were augmented to take advantage of 3G coverage (Wearden, 2011).

The second-half of the 2000s saw the release of a new generation of 3G-compatible phones ("smartphones") that were designed with the higher speeds offered by 3G coverage in mind. In June 2008, the iPhone 3G was released and more iPhones were bought in the third quarter of 2008 (4.7 million) than the previous three quarters combined (4.5 million). The first Android smartphone was released in September 2008 (T-Mobile G1) and became the leading operating system in the smartphone market by 2011 (Cozza et al., 2014).

Figure 1 reports the worldwide sales of smartphones by operating system since 2005, with Android smartphones depicted with a solid black line, iPhones in solid gray and other smartphones (Windows, Blackberry, etc.) represented by the dashed line (Cozza et al., 2014). The bars in Fig. 1 show that mobile broadband subscription rates mirrored the growth in smartphone sales. The mobile broadband subscription rate was only 1.03 per 100 in 2005. After the release of the T-Mobile G1 and iPhone 3G in 2008, mobile broadband subscription rates increased from 26.28 per 100 in 2008 to 54 per 100 by 2010 (Union, 2020). Our empirical analysis estimates the consequences of smartphone usage and Fig. 1 suggests that widespread usage began around 2009 following the release of newly-designed, modern smartphones.

The new design of smartphones in the latter-half of the 2000s brought about new uses for phones beyond traditional talking. The solid black line in Fig. 2 shows the number of minutes spent talking on mobile phones increased from 1.5 trillion minutes in 2005 to 2.1 trillion minutes in 2007 but stabilized between 2008 and 2013. The number of text messages sent annually (CTIA, 2020), depicted by the gray line in Fig. 2, shows limited growth in the number of messages sent between 2005 and 2007. Between 2008 and 2010, the number of text messages sent annually more than doubled from 1.01 trillion to 2.05 trillion and peaked at 2.3 trillion in 2011.

The reduction in text messages after 2011 coincided with the introduction of Apple's iMessage in October 2011. Detailed data on the number of iMessage's sent are not available, but Apple reported that users had sent 300 billion iMessages by October 2012 (Epstein, 2012) and 200,000 iMessages per second were being sent by 2016 (Leswing, 2016). As time talking on the phone stabilized and text messaging decreased, mobile wireless data increased substantially as seen in the dashed line in

[7] In 1983, the first 1G cell phone was launched. Ameritech's 2-pound DynaTAC 8000× costs $3995 and could be used for 35 min before needing ten hours of charging (NBC, 2005).

[8] See Ghosh et al. (2010) and Sauter (2013) for more information on the history and technology of cellular networks.

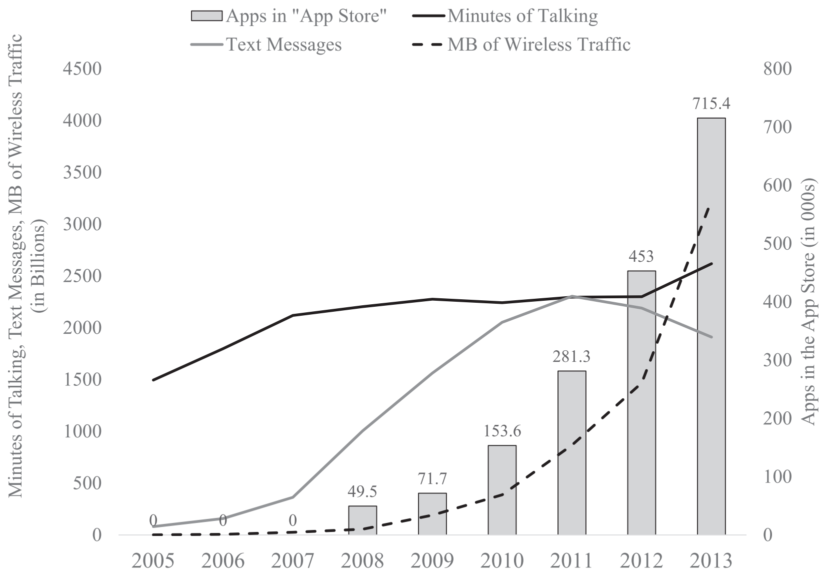


Fig. 2. Mobile Phone Talking, Texting and Data Usage. *Notes:* Number of Apps in the App Store is from PocketGamer (2020). Data on amount of cell phone talking and texting are from CTIA (2020). Wireless traffic data are from CTIA (2016).

Fig. 2 (CTIA, 2016). The growth in data usage coincided with the market for "apps", applications designed to take advantage of smartphone functionality. The bars in Fig. 2 shows the number of apps available in Apple's "App Store" annually. After opening in 2008, the App Store had nearly 500,000 apps available for download by 2012 (PocketGamer, 2020).

In order to study the relationship between smartphone use and accident rates, we combine the timing of widespread smartphone adoption and the rollout of 3G coverage to create our variable of interest. Because 3G coverage pre-dates the growth in mobile broadband use, it is not reasonable to expect drivers to change their behavior when gaining 3G coverage if they do not have a device that can utilize faster broadband speeds. Figures 1 and 2 suggest that the release of the iPhone 3G and T-Mobile G1 in late-2008 align with a noticeable rise in mobile broadband use beginning in 2009. When estimating the potential effect of smartphone use on traffic accidents, we constrain smartphone use to begin in 2009. Additionally, we estimate 3G coverage annually along road-segments and do not allow smartphone use to occur in areas where 3G coverage is unavailable. In the next section, we describe how the 3G coverage estimates are constructed and merged with individual accident data to create a panel of road segment-year observations.

3. Data

3.1. Accident rate data

Our main dependent variable is the number of accidents on a road segment or postmile in a year.[9] There are 63,733 postmiles along California highways The average distance between postmiles is 0.25 miles, although the distance can be larger in rural areas.[10] We only include postmiles that are in existence over the entire time period, so we do not account for road construction or destruction.[11]

Accident data is available continuously in California between 2001 and 2013 from the California Highway Patrol (CHP) Statewide Integrated Traffic Records System. The CHP reports the location of a collision based on the county, route number and exact postmile. The data report whether the cause of the accident is inattention or involves alcohol, but these characteristics are not reliable, as the definitions appear to change over time and detailed recording differs across police jurisdictions.

If traffic data along road segments was widely available, it would be possible to create an accident rate variable using the traffic volume. However, accurate annual traffic counts are only reported for six percent of our data (3365 road segments) by the California Department of Transportation (CalTrans). Because traffic data are scarce, we substitute it with population density data from the United States Census. Population density data are compiled by merging postmiles to 2010 census tract boundaries. We then attach population data from the 2000 Decennial Census converted to 2010 census tract boundaries using the National Change Database from Geolytics. The population data from the 2000 Decennial Census is assigned as

[9] The terms "road segment" and "postmile" are used interchangeably.

[10] Only 5% of the postmile observations represent road segments greater than one mile and only 1% are greater than 2.25 miles.

[11] For more information about postmiles, see https://postmile.dot.ca.gov/.

population in each census tract in 2001. We then attach population data from the 2013 American Community Survey five-year estimates to the data to serve as the population in 2013. We interpolate population for the years 2002 through 2012 and calculate population density by dividing each year's population by the census tract land area in miles.

3.2. Estimating 3G coverage

Our goal is to estimate how smartphone use by drivers affects car accidents, but smartphone adoption occurred across all locations at the same time. In order to construct an experimental framework to answer this question, we estimate which road segments already had 3G coverage at the time of smartphone adoption. Because smartphone capabilities are more useful with 3G coverage, we propose that the effect of smartphone adoption will be stronger on road segments that have gained 3G coverage, relative to those without 3G coverage. Therefore, we must develop reliable estimates of annual 3G coverage along a road segment.

Starting in December 2014, the Federal Communications Commission (FCC) began publishing detailed 3G coverage maps, but information on 3G coverage is not available before then. The time period from 2001 to 2013 is a crucial period of adoption, and failing to include data from this period could significantly bias our results. We therefore use machine learning to estimate annual 3G coverage for each postmile using the annual growth in cellular towers. The FCC publishes information on the location, elevation, year of construction and height of all antenna structures (towers) that are over 200 feet tall through the Antenna Structure Registration (ASR) system.[12] In addition to the information specific to cellular towers, we also create variables that capture geographic characteristics surrounding postmiles, such as the standard deviation of elevation within a 20 mile radius, which could affect the likelihood that a cellular tower effectively provides 3G coverage.

To estimate annual 3G coverage we first merge tower information to each road segment from 2001 to 2013 and 2016 using ArcGIS. The 2016 data are used because it provides us with recent, accurate information about 3G coverage from the FCC. We also assume that no road segments had 3G coverage prior to 2005 since around one percent of the population had mobile broadband service in 2005. The results are not sensitive to assuming 3G coverage began in earlier years. This assumption provides us with accurate 3G coverage information before 2005 (no 3G coverage) and in 2016 (FCC data). Using a machine learning random forest model, we estimate the influence that cellular tower characteristics have on the probability of 3G coverage along postmiles in the years we have accurate 3G coverage data. The results are then used to predict 3G coverage between 2005 and 2013.

Detailed information about the machine learning process is found in the appendix, but it is relevant to note that the random forest model is estimated using 1000 decision trees. We further partition our estimation dataset (2001 to 2004 and 2016) into a training set (N_{train} = 254,912, 80% of the observations) and a test set (N_{test} = 63,728, 20% of the observations). This allows us to perform model diagnostics on the test data, which was not used to fit the model and functions as a better approximation of out-of-sample performance.

Similar to a binary dependent variable model, the results of the machine learning process provide estimated probabilities of 3G coverage for each road segment for every year between 2005 and 2013. Unlike a binary dependent variable model, a random forest model does not estimate a single coefficient for each variable used to predict 3G coverage. Instead, Fig. 3 reports the relative importance of each tower characteristic used to predict coverage. The variable importance plot shows that the year that the nearest tower is constructed is the most important characteristic in estimating 3G coverage and is assigned a value of 100. The standard deviation of the elevation interacted with the number of towers within 20 miles of a road segment is assigned a value of approximately 40, suggesting the year the nearest tower is constructed is 2.5 times as important as the interaction term. Some variables, such as distance to the nearest tower, are not important relative to other tower characteristics.

For ease of interpretation, we transform the estimated probability of 3G coverage into a binary indicator such that any road segment with a 3G coverage probability greater than or equal to C is defined as having coverage,

$$\hat{y}_i = \begin{cases} 1, & \text{if} \quad p_i \geq C \\ 0, & \text{if} \quad p_i < C. \end{cases}$$

There are notable tradeoffs from using more or less stringent cutoffs, C, to define an area as having 3G coverage. If we define an area as having 3G coverage when the probability of coverage is a relatively lax threshold of 0.20, we increase the probability that a road segment is defined as having 3G coverage when it does not exist (false positive). Setting the cutoff to be a high value, such as 0.80, would limit concerns about false positives. However, using such a high threshold would almost guarantee that we do not assign coverage to many areas that do have coverage (false negative).

Recognizing the errors that come from defining a threshold, we use the natural cutoff of 0.50 in our preferred specifications, but examine other cutoffs in our results. With this cutoff, the random forest model yields an accuracy rate of 99.27% in our test data and is larger than the accuracy rate when using a logit model to predict 3G coverage (66.1%).[13]

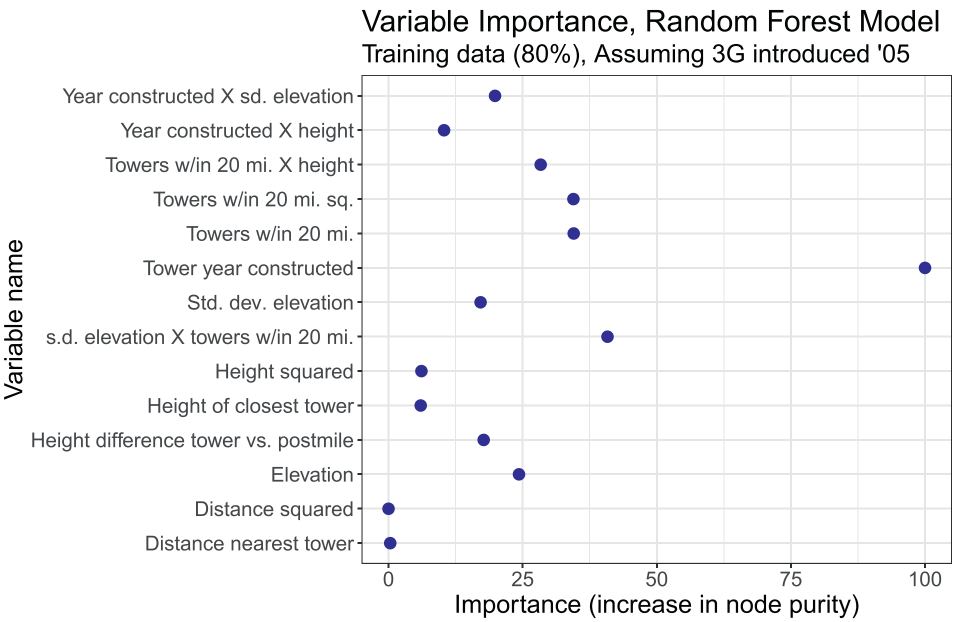


Fig. 3. Random forest model variable importance plot. *Notes:* Variable importance plots are constructed according to Breiman (2001). The importance of variable *j* is calculated by taking each decision tree in which the variable appears and re-calculating the out-of-bag error. Importance is calculated by averaging over all of the decision trees the difference in out-of-bag error with and without this permutation. Scores are normalized by dividing by the importance score of the variable with the highest importance scores, thus the variable importance scores measure contribution relative to the highest variable.

Using the 0.50 threshold, Fig. 4 reports estimates of 3G coverage along road segments in 2005, 2008, 2010 and 2013 in California, with white dots representing areas without 3G coverage and black dots representing areas with 3G coverage. The figure shows that 3G coverage was available along 10% of road segments in 2005, 66% in 2010 and 90% in 2013. According to our estimates, 3G coverage first became available in the MSAs surrounding Los Angeles and the Bay Area. Later, coverage was gained throughout the suburbs and Central Valley before moving into the more rural parts of the state in 2013. The growth in 3G coverage is consistent with the increase in mobile broadband subscriptions, smartphones and wireless data usage reported in Figs. 1 and 2 above.[14]

Our final dataset consists of postmile-year observations in California, between 2001 and 2013. For each observation, we have the number of accidents that took place in the calendar year, estimates for when the postmile gained 3G coverage and the annual population density in the surrounding census tract. We will estimate the effects of smartphone adoption in postmiles that have gained 3G coverage, assuming that the first possible year of adoption is 2009.

3.3. Summarizing accident rates and 3G coverage

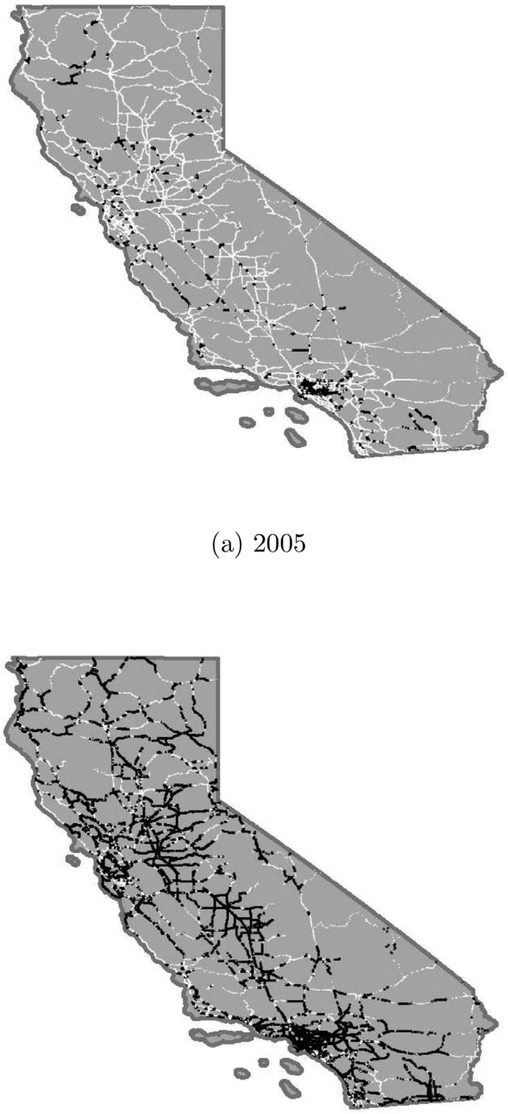
Before fully exploiting the granular data, Fig. 5 reports the annual accident rate (accidents per 1000 of census tract population density per square mile) based on when a postmile gains 3G coverage using the 0.50 cutoff. Postmiles that are estimated to have gained 3G coverage between 2005 and 2007 (early coverage) are represented by the solid black line. Along postmiles that gained coverage between 2008 and 2010 (middle coverage, dashed black line) and after 2010 (late coverage, gray line) are also shown. The fraction of postmiles with 3G coverage each year is depicted with gray bars.

The accident rates along all road segments are slightly increasing from 2001 through 2004, after which they begin to decrease. There is a noticeable increase in the accident rate along road segments with early 3G coverage between 2009 and 2010 and then the downward trend continues. The accident rate among middle coverage postmiles increases slightly between 2009 and 2010 and there is no change in the accident rate for late adopting postmiles in those years.

[12] All towers over 200 feet are required to be registered with the ASR system, but 98% of the 110,855 towers built after 1990 in the ASR are below 200 feet and the average tower height is 70 feet.

[13] This accuracy rate is also calculated using a 0.50 threshold. Despite the relatively poor fit from using a logit or LPM to estimate 3G coverage, the predictions yield similar findings as the machine learning estimates.

[14] It would be ideal to compare our estimates of 3G coverage in a year between 2005 and 2013 to an accurate coverage map provided by the FCC during that time. Historical 3G coverage maps are available from cached websites of cellular providers, but the maps were made for marketing purposes and are not reliable. In 2009, AT&T sued Verizon over misleading coverage maps (Hamblen, 2009).



(a) 2005 (b) 2008 (c) 2010 (d) 2013

Fig. 4. Predicted 3G Coverage (black) and No Coverage (white) by Year using the 0.50 Prediction Threshold. *Notes:* Maps were created using data on predicted 3G coverage, which were generated by a random forest model. The predicted value is continuous between zero and one. For the purpose of these maps, a postmile is defined as having coverage if the predicted value is greater than 0.50.

There are several potential explanations for the elevated accident rate along early adopting road segments after 2009. With regards to smartphones, 2009 was a point of inflection for both Android and iPhone sales worldwide, as seen above in Fig. 1. Data usage, text messaging and the availability of apps all grew substantially starting in 2009 and the primary use of a smartphone transitioned from talking to other functionalities. It is possible that in early coverage areas, the initial effects of 3G coverage were limited, due to the low subscription rates and limited cell phone capabilities. If by 2009, smartphone use among drivers was possible in highly-populated areas, but less likely along more rural road segments, we would expect to see the relative increase in the accident rate in the early coverage areas that we observe in Fig. 5. Because Fig. 5 reports aggregate statistics, the comparison of accident rates over time is limited. To better understand how accident rates change in response to smartphone adoption, paired with 3G coverage, the next section explores the relationship in a fixed-effects regression framework.

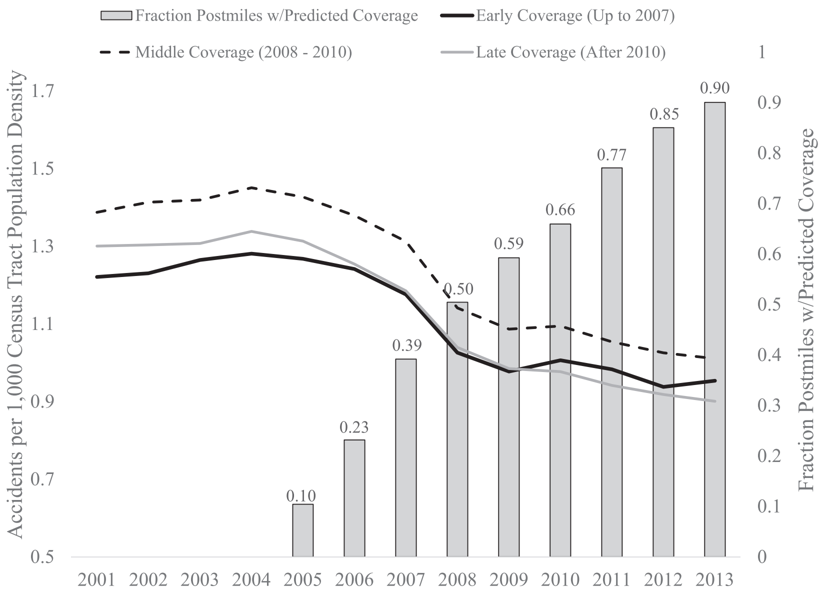


Fig. 5. Annual Accident Rate by Year of Predicted Coverage. *Notes:* Predicted coverage is defined as when the predicted coverage variable from the random forest algorithm crosses the 0.50 threshold. The number of accidents is from the California Highway Patrol Statewide Integrated Traffic Records System. Postmiles are assigned annual population density by spatially merging them to census tract boundaries. Accident rates are reported for the subsamples of postmiles based on when they are predicted to have gained 3G coverage.

4. Empirical analysis

4.1. Empirical specifications

The distribution of car accidents is skewed heavily to the right with 41 percent of postmile-year observations having no accidents and 92 percent reporting fewer than 10 accidents. Because of the nature of car accident data, we propose a Poisson fixed-effects model to examine the relationship between smartphone adoption and car accidents. Assuming that the conditional mean assumption holds, the estimates are equivalent to clustering standard errors at the postmile level (Cameron and Trivedi, 2005; Gourieroux et al., 1984).

The exposure variable is the population density of the census tract in which each postmile is located for a given year, so it enters the specification with its coefficient constrained to equal one.[15] The resulting Poisson difference-in-differences specification is the following:

$$\begin{aligned} E[Accident_{ict}|\cdot] = {} & \exp(\alpha_1 I(p_{ict} \geq C) + \alpha_2 I(p_{ict} \geq C) \times I(t \geq T) \\ & + \ln(PopDensity_{it}) + \kappa_{ic} \times \lambda_t + \gamma_i + \tau_t + \upsilon_{it}). \end{aligned} \tag{1}$$

The variable $Accident_{it}$ represents the number of accidents that occur at postmile i, located in county c, in year t. In the first term of the specification, predicted 3G coverage values from the random forest model above, p_{ict}, are converted to a binary variable that is equal to one when the probability of coverage is above cutoff C. The postmiles that have gained 3G coverage by the time of smartphone adoption serve as the treatment group in our difference-in-differences analysis. The year of smartphone adoption is notated in the specification as T and the interaction term associated with α_2 measures the effect of smartphone adoption on the accident rate near postmiles that have gained 3G coverage, relative to postmiles that have not gained 3G coverage.[16] The evidence above suggests that widespread smartphone adoption began in 2009, but we also present results setting the year of adoption to 2008 and 2010.

Other variables in specification (1) include $PopDensity_{it}$, which is the annual census tract population density for the postmile. The term $\kappa_{ic} * \lambda_t$ is a linear county-specific trend for each county c, γ_i is a postmile fixed effect and τ_t is a time fixed effect. While the regression does not have a large number of controls, the analysis is able to control for changes in population density surrounding postmiles, reducing concerns that the results are capturing a change in traffic volume. Postmile fixed effects control for time-invariant road segment characteristics associated with traffic accidents, further strengthening our identification strategy.[17]

[15] If the coefficient is not constrained to one, the estimated coefficient of interest is not meaningfully altered.

[16] The percentage change in the accident rate is equal to $e^{\alpha_2} - 1$.

[17] Note that in panel Poisson regressions, the postmiles that do not have an accident in any of the years in the data are automatically dropped from the regression. This results in fewer observations in the regressions than the entire sample of postmiles.

Table 1
Difference-in-Differences Results by Adoption Year and Coverage Threshold.

	Adoption Year (T)		
	2008	2009	2010
Continuous Predicted Coverage (p)	−0.0051	−0.0054	−0.0051
	(0.0067)	(0.0063)	(0.0062)
× I(t≥T)	0.031***	0.045***	0.067***
	(0.010)	(0.011)	(0.013)
I(p≥0.40)	−0.0038	−0.0046	−0.0057
	(0.0048)	(0.0044)	(0.0042)
× I(t≥T)	0.015**	0.025***	0.044***
	(0.0076)	(0.0083)	(0.0095)
I(p≥0.50)	−0.0065	−0.0086*	−0.0089**
	(0.0049)	(0.0044)	(0.0043)
× I(t≥T)	0.017**	0.029***	0.044***
	(0.0071)	(0.0076)	(0.0086)
I(p≥0.60)	−0.0077	−0.0083*	−0.0083*
	(0.0050)	(0.0045)	(0.0043)
× I(t≥T)	0.022***	0.030***	0.043***
	(0.0071)	(0.0074)	(0.0083)

***<0.01, **<0.05, *<0.10. Each set of two coefficients and their standard errors are from a separate regression under the predicted coverage threshold and adoption year assumptions. The dependent variable in every regression is annual number of accidents at a postmile. The predicted coverage is a variable between zero and one that indicates the probability of 3G coverage. The adoption year is the year in which it is assumed that drivers on postmiles with 3G coverage begin using smartphones. Every regression includes 53,223 postmiles over 13 years, resulting in 691,899 observations. Year and postmile fixed effects are included in every regression, as well as a county-specific linear trend. A postmile's annual census tract population density is the exposure variable in every regression.

Specification (1) is unable to show the dynamic change in accident rates before and after smartphone adoption in postmiles with 3G coverage. To examine the annual changes in accident rates, we construct an event study specification with a five-year lead and three-year lag.[18] The omitted category is the year before smartphone adoption in a postmile that has gained 3G coverage. The general equation is:

$$E[Accident_{ict}|\cdot] = \exp\left(\sum_{k=-5+}^{-2} \theta_k S_{ict+k} + \sum_{j=0}^{3+} \theta_j S_{ict+j} + \ln(PopDensity_{ict}) + \kappa_{ic} \times \lambda_t + \gamma_i + \tau_t + \upsilon_{it}\right). \tag{2}$$

The term S_{ict} captures the first year in which a postmile is defined to have 3G coverage after smartphones have been adopted. In other words, S_{ict} equals one in the year that the term $I(p_{ict} \geq C) * I(t \geq T)$ equals one for the first time and is otherwise equal to zero.

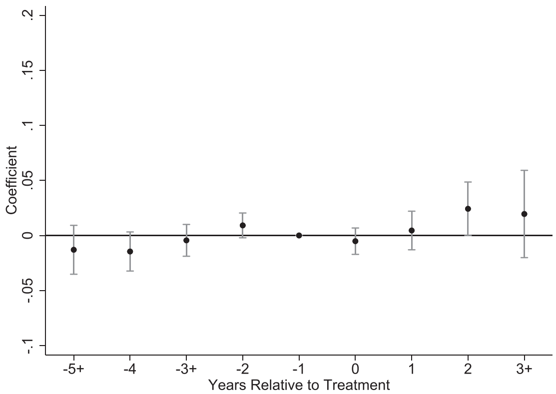
The identifying assumption in our analysis is that unobserved characteristics that influence the accident rate in a postmile are not systematically related to the introduction of 3G coverage and smartphone adoption. Without a controlled experiment, we are not able to verify the exogeneity of 3G coverage, but can address some of the assumptions that our identification strategy hinges on. The unit of observation is only a 0.25-mile stretch of road and our empirical specification is able to examine the same small road segment immediately before-and-after gaining 3G coverage and smartphone adoption. The granularity of the data allows us to use postmile fixed effects and capture many characteristics of a road segment that could be related to both traffic accidents and 3G coverage and cannot be controlled for when data are aggregated to the county or state level. Controlling for the changes to population density surrounding a road segment reduces concerns that our results are driven by changes in traffic volume.

4.2. Results

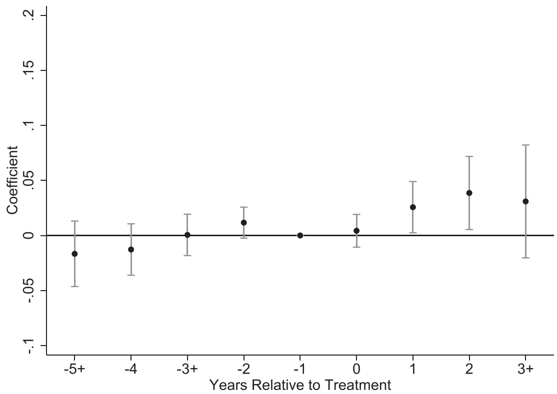
Table 1 shows results from specification (1). We report two coefficients from 12 different regression iterations that differ based on the year of assumed smartphone adoption, 2008, 2009 or 2010, and measure of 3G coverage. The first row of coefficients uses the continuous measure of predicted coverage to estimate 3G coverage, so the first coefficient can be interpreted as the effect on the accident rate when the predicted coverage measure increases from zero to one. Regardless of the assumed year of smartphone adoption, this coefficient is not statistically significant. In column (1), the first year of smartphone adoption is set to 2008 and the coefficient on the interaction term is equal to 0.031 and statistically significant. The coefficient suggests that when the predicted coverage threshold increases from zero to one after smartphone adoption, the average accident rate increases by 3.1 percent on average, relative to postmiles with predicted coverage equal to zero. The coefficient increases to 0.045 and 0.067 when the adoption year is assumed to be 2009 or 2010, respectively.

The remaining coefficients in Table 1 report regression results when the predicted coverage variable is transformed into a binary variable that is equal to one after the estimated coverage crosses over a threshold of 0.40, 0.50 or 0.60. Across

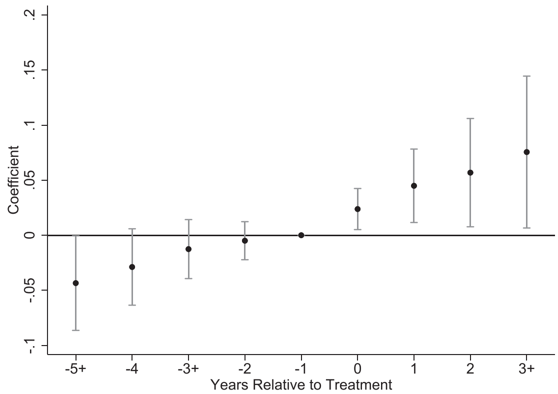
[18] The leads and lags are unbalanced because there are fewer years of data available after smartphone adoption.



(a) Smartphone Adoption in 2008



(b) Smartphone Adoption in 2009



(c) Smartphone Adoption in 2010

Fig. 6. Event Studies by Adoption Year. *Notes:* Dependent variable is annual number of accidents at a postmile. The omitted category is the year before smartphone adoption. The confidence intervals shown are at the 95 percent level. A postmile is defined as having coverage when the predicted coverage variable is greater than 0.50 and the year is greater than or equal to the year that smartphone adoption takes place. Year and postmile fixed effects are included in every regression, as well as a county-specific linear trend. Annual census tract population is the exposure variable and county-specific linear trends are included in every regression. The sample in each regression includes 49,000 postmile observations from 2001 to 2013, resulting in 637,000 total observations.

all three thresholds and for every assumed adoption year, the coefficient associated with passing the coverage threshold is negative. This indicates that gaining 3G coverage may have been associated with a slight decrease in accident rates before smartphone adoption, which is consistent with the general decreasing trend in the accident rate seen above in Fig. 5. The interaction term coefficients indicate that smartphone adoption near postmiles that have gained 3G coverage is associated with an increased accident rate. Across different adoption years, the point estimates change in their level of significance and magnitude, however, the general conclusions drawn from Table 1 are unchanged when assuming smartphone adoption occurred in 2008, 2009 or 2010.

Figure 6 provides a graphical representation of estimates derived from the event study regression described by specification (2). The omitted category is the year before a postmile is treated with both 3G coverage and smartphone adoption. The number of observations are fewer in these regressions, relative to those presented in Table 1 because only postmiles that eventually cross the 0.50 threshold are included. Panel (a) assumes that smartphone adoption occurs in 2008. The accident rate is similar between the control and treatment group until two years after treatment, when it increases slightly and is marginally statistically significant. The delayed effect we observe in panel (a) is suggestive of widespread smartphone adoption occurring after 2008.

Panel (b) assumes smartphone adoption in 2009. This figure is similar to 2008, but there is a more pronounced increase in the accident rate one year after treatment. The difference persists over time, although the statistical strength of the coefficient diminishes in the last year of the sample. In panel (c), we set smartphone adoption to take place in 2010. Although there is an immediate increase in the accident rate when assuming smartphone use begins in 2010, the effect appears to be

Table 2
Robustness Checks.

	Coefficient	
	3G Coverage	3G × 2009 Adoption
Baseline Result	−0.0086*	0.029***
	(0.0044)	(0.0076)
Panel A: Traffic, Trends, Controls & Standard Errors		
Remove Exposure Variable	−0.0091**	0.021***
	(0.0043)	(0.0070)
Postmiles with Full Traffic Data (N=3365)	−0.014	0.057**
	(0.014)	(0.023)
Remove Linear County-Specific Trend	−0.0081*	0.054***
	(0.0044)	(0.0078)
Include County Controls	−0.0025	0.023***
	(0.0045)	(0.0077)
Bootstrapped Standard Errors	−0.0086	0.029***
	(0.0052)	(0.0082)
Panel B: Non-RF 3G Predictions		
Logit 3G Prediction (Threshold=0.35)	0.0234**	0.0407*
	(0.00914)	(0.0213)
LPM 3G Prediction (Threshold=0.35)	0.0270***	0.0397*
	(0.00967)	(0.0239)
Panel C: Falsification Test		
Gain Coverage in Random Year	0.00049	−0.00023
	(0.00548)	(0.00834)

*** <0.01, ** <0.05, * <0.10. Each row of coefficients and standard errors are from a different regression. The dependent variable in every regression is annual number of accidents at a postmile. A postmile gains 3G coverage when the predicted 3G coverage variable crosses the 0.50 threshold. All of the regressions, except those using the subsample of postmiles that report traffic every year, include 53,223 postmiles over 13 years, resulting in 691,899 observations. County control variables include the fraction of the population that is over 65 years old, the natural log of population and the natural log of GDP per capita. The logit and LPM predictions are calculated where every tower characteristic enters the first stage linearly. Year and postmile fixed effects are included in every regression.

part of an upward trend in the accident rate prior to treatment. A possible explanation for the pre-trend in panel (c) is that smartphone adoption may have occurred before 2010.

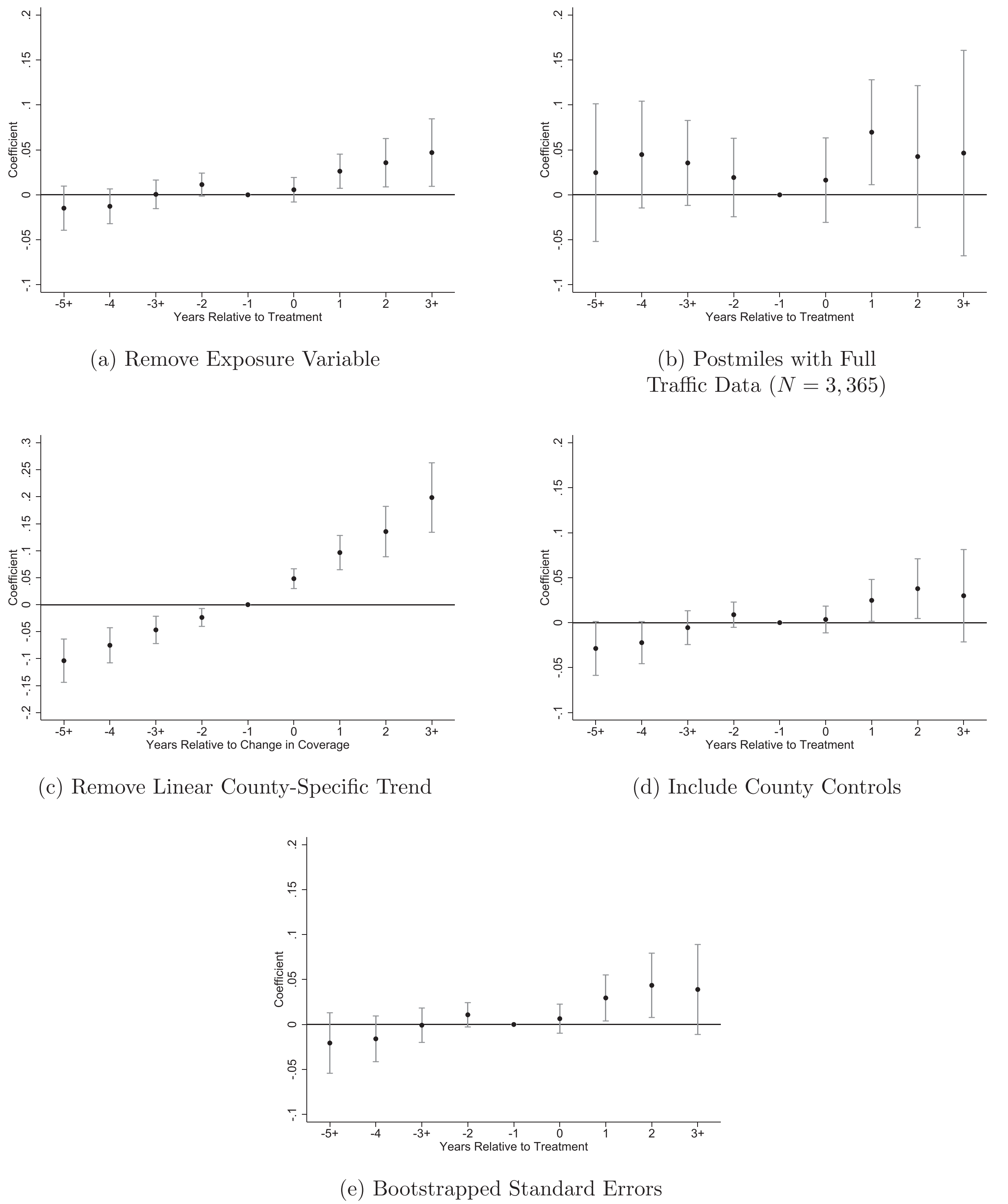
It is not possible to rule out that other events took place around 2009 that caused an increase in the accident rate in areas with 3G coverage, relative to areas without 3G coverage. However, the results are consistent with a story where 3G coverage is gained starting in the early to mid-2000s, but was not accompanied by widespread adoption of devices that fully utilized 3G capabilities. Even if early adopting drivers did have 3G service, the 3G-compatible cell phones that were available had similar functionality as 2G cell phones, so it is unlikely their driving behavior changed because of 3G coverage. After smartphones designed with high-speed internet access in mind became available in late-2008 and widespread throughout 2009, areas with 3G coverage experienced an increase in the accident rate. Again, we cannot eliminate all concerns that our treatment variable is not biased by an event that influences the accident rate, but we have aligned our measurement of 3G coverage and smartphone usage with average national statistics measuring growth in the mobile broadband and smartphone industry. In the next section, robustness checks are presented and provide further evidence showing that smartphone adoption influenced accident rates in areas with 3G coverage.

4.3. Robustness checks

We present evidence of robust findings based on the difference-in-differences framework outlined in specification (1) in Table 2. The first row of the table provides the baseline estimates that were calculated using the 0.50 cutoff for 3G coverage and the assumption of 2009 smartphone adoption. These two characteristics are the same throughout the entire table unless otherwise noted.[19] The coefficient in the first column of Table 2 reports the coefficient on 3G coverage and the second column reports the interaction term between 3G coverage and smartphone adoption. All of the specifications in Table 2 are presented in tandem with their associated event study, which are found in Figs. 7 and 8.

Panel A of Table 2 alters the specification by changing the exposure variable, removing the linear county-specific trend, adding additional control variables and bootstrapping the standard errors. The first row of Panel A provides coefficients from a specification with no exposure variable. The effect on the interaction term is smaller in magnitude but not meaningfully altered. The associated event study in Fig. 7(a) indicates that removing the exposure variable does not change the implications of the baseline event study results. The second row of Panel A in Table 2 includes only postmiles in which CalTrans

[19] Although the most striking increase in accident rates occurs in 2010, we present robustness checks that assume smartphone adoption in 2009 because of the upward trend shown in Fig. 6(c). We provide replications of the robustness table (Table A.3) and figures (Figs. A.2 and A.3) in the Appendix that assume smartphone adoption in 2010.



(a) Remove Exposure Variable

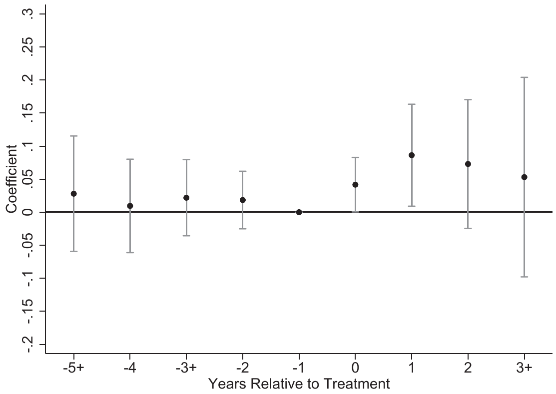
(b) Postmiles with Full Traffic Data ($N = 3,365$)

(c) Remove Linear County-Specific Trend

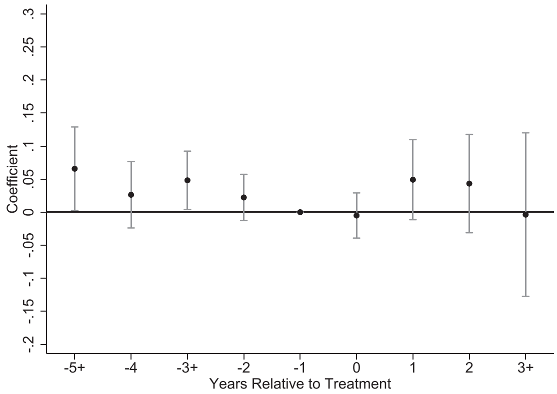
(d) Include County Controls

(e) Bootstrapped Standard Errors

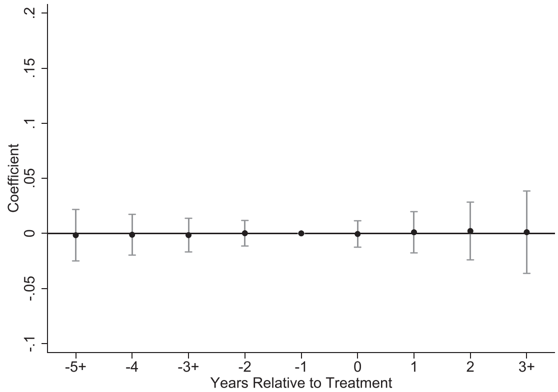
Fig. 7. Robustness Event Studies Related to Traffic Exposure and Control Variables. *Notes:* Dependent variable is annual number of accidents at a postmile. The omitted year is the year before treatment, which is defined as a postmile having 3G coverage and the year being after smartphones are adopted. The coverage threshold for specification is 0.50 and the assumed year of smartphone adoption is 2009. Average annual daily traffic is the exposure variable in figure (b) and census tract population is the exposure variable in figures (c) and (d). County linear trends are included in all but figure (c). Except for figure (b), the sample includes 49,000 postmile observations from 2001 to 2013, resulting in 637,000 total observations. Year and postmile fixed effects are included in every regression.



(a) 3G Prediction Using Logit
($N = 42,424$)



(b) 3G Prediction Using LPM
($N = 43,641$)



(c) Falsification Test
3G Assigned in Random Year

Fig. 8. Additional Robustness Event Studies. *Notes:* Dependent variable is annual number of accidents at a postmile. The omitted year is the year before treatment, which is defined as a postmile having 3G coverage and the year being after smartphones are adopted. The assumed year of smartphone adoption is 2009. *N* represents the number of postmiles in the regression sample. The falsification test coefficients are derived from the average of 50 simulations. Year and postmile fixed effects are included in every regression, as well as a county-specific linear trend. The exposure variable is annual census tract population density in every regression.

reports the average annual daily traffic (AADT) for every year in the sample. The AADT is included as the exposure variable in this regression and the interaction coefficient is larger in magnitude but not meaningfully different from the baseline. The associated event study in Fig. 7(b) shows that the smaller sample results in less precision of the annual estimates, but the general pattern is unchanged from the baseline results.

The third row of Panel A of Table 2 reports estimates after removing the linear county-specific trend from the specification and the associated event study in Fig. 7(c) shows a strong upward trend in accidents among treated postmiles before smartphone adoption. This indicates that it is important to account for this trend and that the effects we estimate in the baseline regressions are deviations from this upward trend. In the fourth row, we include the annual fraction of the population that is aged over 65 years from the US Census and the annual GDP per capita at the county level from the Bureau of Economic Analysis. The estimates in Table 2 and the corresponding event study in Fig. 7(d) support the baseline results. In the last row of Panel A standard errors are bootstrapped with 50 replications and the statistical significance of the coefficients is unchanged. In summary, our results are robust to all of the changes made to the specification in Panel A.

Panel B of Table 2 provides regression estimates that show how sensitive our results are to different measures of 3G coverage. Our baseline results use a random forest algorithm to calculate a probability of 3G coverage. The first row of Panel B provides estimates where 3G coverage is predicted using a logit model in which all of the tower characteristics enter the model linearly. Only 29,703 of the 53,223 postmiles cross the 0.50 logit threshold, as compared to 49,000 postmiles crossing the random forest 0.50 threshold. To make the logit results more comparable to the baseline results, we reduce the logit

Table 3
Difference-in-Differences Decomposition.

	Comparison Groups		
	Early 3G vs. Never 3G	Late 3G vs. Never 3G	Early 3G vs. Late 3G
I(p≥0.50)	−0.011**		−0.0084*
	(0.0052)		(0.0045)
× I(t≥2009)	0.078***	0.025**	0.025***
	(0.014)	(0.012)	(0.0083)
Early 3G Postmiles (≤2009)	32,458	-	32,458
Late 3G Postmiles (>2009)	-	16,542	16,542
Never Postmiles 3G	4223	4223	-
Total Postmiles	36,681	20,765	49,000

***<0.01, **<0.05, *<0.10. The dependent variable in every regression is annual number of accidents at a postmile. Each column represents estimates from a separate regression using a different comparison within the sample. The variable p the predicted 3G coverage and the variable t is the year a postmile-year observation. The 3G coverage threshold is equal to 0.50 and the assumed year of smartphone adoption is 2009. A postmile's annual census tract population density is the exposure variable in every regression. Year and postmile fixed effects are included in every regression, as well as a county-specific linear trend.

threshold to 0.35. This increases the number of postmiles crossing the threshold to 42,424. We do a similar adjustment for the regressions that use a 3G coverage prediction derived from a linear probability model (LPM).[20]

The results using the logit and LPM 3G predictions in the first two rows of Panel B are slightly different from the baseline but still suggest that smartphone adoption increases accident rates. The coefficient on 3G coverage is positive and statistically significant and the interaction term is similar in magnitude to the baseline, but only significant at the 10 percent level. The event studies in Fig. 8(a) and (b) suggest a similar pattern as the baseline. There is no obvious upward trend before treatment, but an increase in the accident rate after treatment.

In Panel C of Table 2, we present a falsification test of our results. Postmiles are randomly assigned 3G coverage over a uniform distribution between 2004.5 and 2013.5 and we define treatment to occur with smartphone adoption in 2009. This exercise is performed 50 times and the results indicate no relationship between car accidents and the placebo 3G coverage. The event study results in Fig. 8(c) confirm the null finding.

In the results presented in Tables 1 and 2, the timing of treatment varies across postmiles in a unique way. No postmile can be treated until after the assumed year of smartphone adoption. However, some postmiles gain 3G coverage before that year, some gain 3G coverage after that year and others never gain 3G coverage. The effects we have estimated so far are derived from a combination of the comparisons between these groups but it is not clear which comparison is driving the effects. Goodman-Bacon (2021) characterizes a method to decompose the effects using least squares regression, but we provide Poisson estimates akin to that decomposition in Table 3.

Table 3 reports results from three regressions that provide three different comparisons (the 3G coverage threshold is set at 0.50 and smartphone adoption is assumed to begin in 2009). The first column compares early 3G adopters versus the never adopters. Early adopters are defined as having adopted 3G coverage on or before 2009. This comparison yields a relatively large, positive and statistically significant effect equal to 0.078. The second column of Table 3 presents the comparison between late 3G adopters and never adopters. The third column compares the early 3G adopters to the late 3G adopters. The estimates in both of these columns is one third the size of the coefficient in the first column, but still statistically significant at conventional levels.[21]

The results in Table 3 suggest that the largest effects are derived from the comparison between the early 3G adopters and the never adopters. This comparison could be considered less desirable because of underlying differences between early 3G adopting postmiles and postmiles that never gain 3G coverage. The point estimates from the two other comparisons, both equal to 0.025, are closer to our average estimated effect of 0.029 in Table 1. The similarity suggests that our estimate is likely driven by comparisons between postmiles that are similar to each other before treatment.

It is impossible to rule out all bias in our estimates. However, the findings above suggest that the distraction caused by smartphone adoption can lead to an increase in the accident rate when 3G coverage is available. Our results are consistent with stylized facts about the growth in mobile broadband adoption and sales of newly designed smartphones in the late-2000s. The findings are also supported by the individual-level studies that show drivers are more distracted and exhibit poor driving quality when using a cell phone (Abdel-Aty, 2003; Strayer et al., 2003; Törnros and Bolling, 2005; Caird et al., 2008; 2014).

[20] Using the 0.50 threshold of 3G predictions from logit and linear probability models yields difference-in-difference estimates that are similar to the baseline, but the effects in the event studies are much less pronounced.

[21] Note that only one coefficient is reported in the second column because the two variables are collinear for the later adopting postmiles.

5. Discussion and conclusion

Research shows that individual driving behavior is impaired when a driver is using a phone, but data limitations have made it difficult for researchers to find a link between cell phone use and traffic accident rates. The majority of previous studies do not find a strong relationship between cell phones and accident rates, but our analysis differs considerably from those studies. Arguably the most important difference lies in our measurement of smartphone use. Previous papers using laws to proxy for changes in cell phone use rely to some extent on self-enforcement. Cell phone use by drivers may lead to more traffic accidents, but if a cellular ban does not lead to a persistent change in driver behavior, a change in accidents is difficult to observe.

Our analysis shows that smartphone use is associated with a persistent increase in traffic accidents. The point estimate in our preferred specification suggests that the accident rate in a postmile increased by approximately 2.9 percent with the adoption of smartphones. The statewide average annual number of accidents on road segments with 3G coverage from 2009 to 2013 was 124,000. Our estimates suggest smartphone adoption accounted for approximately 3500 of those accidents each year.

The magnitude of our results can be compared to Adams et al. (2012), who find that fatal accidents involving 16 to 20 year olds increase 5 to 10 percent when there is a 10 percent increase in the minimum wage. Carpenter and Dobkin (2009) show that accident rates increase when individuals become legally allowed to drink at the age of 21. Faccio and McConnell (2018) find that Pokémon Go was responsible for 134 crashes, in Tippecanoe County in the 5-month time period after the game became popular. Being legally allowed to drink alcohol and addictive mobile games are strongly related to traffic accidents, but the effects found in these studies are temporary. Cell phone use grew throughout the 2000s and continues to grow today (Deloitte, 2017).

A limitation of our study is that we cannot observe what drivers are doing when they enter an area with 3G coverage starting in 2009, and are unable to provide more insight into the exact mechanism causing the increase in accidents. However, we show that the distinct increase in the accident rate around the time of smartphone adoption is concentrated to areas where 3G coverage enhances the use of smartphones. Even though drivers throughout many areas of California could send text messages before 3G coverage was available, 3G coverage made newly developed “apps” easier and faster to use. These apps, combined with touch screens that may lead to additional distraction, are a plausible explanation for an increase in the accident rate.

Despite not being able to identify a specific mechanism, the findings speak directly to policy makers. Cell phone laws in California have been shown to be ineffective (Burger et al., 2014) and the fine for a cell phone infraction in the state is only \$20 before assessments (McCurley, 2019). With a cost estimate of a car accident without injuries equal to \$4600, our estimates suggest smartphone use leads to an additional annual cost of approximately \$16 million after 2009 (Council, 2019).[22] It is not unreasonable to assume that strengthening both the enforcement and penalties associated with cell phone use while driving may decrease the accident rate and can lead to substantial savings.

An alternative policy approach would be to require advanced car safety features such as blind spot monitoring, lane drift alerts and collision avoidance systems. Effective in May, 2018, back-up cameras are required on all new vehicles less than 10,000 pounds (Bomey, 2018) and requiring additional safety features on new cars could mitigate the distraction caused by drivers using cell phones. It is not clear whether these advanced safety features will result in a decrease in the accident rate, but exploring this relationship is a potential avenue for future research.

Declaration of Competing Interest

None.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2022.01.033.

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[22] In Appendix Fig. A.4 we provide weak evidence that the effect we find is driven by less severe accidents, so we use this conservative cost estimate, which is in 2019 dollars.

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