

# Car Accidents and 3G Coverage: New Evidence Using Cell Phone Tower Construction

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## ABSTRACT

We examine the relationship between the growth of 3G cellular coverage and traffic accidents in California between 2001 and 2013. Using machine learning techniques to predict historical 3G coverage, we find that car accident rates increase after 3G coverage is introduced, controlling for traffic volume and road fixed effects. The accidents most responsive to 3G coverage are non-severe crashes that take place in highly trafficked areas. Accidents caused by drivers over 65 do not change in response to 3G coverage. In contrast to previous research examining cell phone laws, we find a positive relationship between accidents and cell phone use.

**Keywords:** cellular phone coverage, car accidents, machine learning, random forest

**JEL Codes:** R41, C52, O33

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# I. Introduction

Between 2000 and 2015, the number of mobile cellular subscriptions in the United States increased from 109 million to 382 million (International Telecommunications Union, 2017). The rise in mobile phones corresponds with an increase in cell phone functionality. In addition to being able to make a phone call, hand-held cellular devices are able to text message, browse the internet, video chat and analyze data anywhere there is an adequate wireless connection.<sup>1</sup> A potential consequence of the increased use of wireless devices is that users may become distracted by their phone while engaging in common activities, such as driving.

The potential costs of using a cell phone while driving has caught the attention of public health advocates, cellular providers, policy makers and researchers. The National Highway Traffic Safety Administration (NHTSA) frequently promotes distracted driving awareness campaigns<sup>2</sup> and AT&T has released controversial advertisements depicting fatal car crashes caused by cell phone use as part of their "It Can Wait" campaign.<sup>3</sup> There is strong public support for cellular bans while driving, with support for texting bans ranging from 86 to 98 percent.<sup>4</sup> All but two states have enacted a cellular phone ban for drivers (National Conference of State Legislatures, 2018) and the state-level bans are often used to proxy for cell phone use by drivers. Research relating cellular bans to traffic accidents are sensitive to the geographical setting, time period and severity of accidents being analyzed.<sup>5</sup> The inconclusive relationship between aggregate cell phone use and accident rates are in contrast to individual-level research, which finds that cell phone use reduces the quality of driving.<sup>6</sup>

In this paper, we predict 3G coverage along all road segments in California from 2001 to 2013 and examine how the frequency of accidents changes before and after 3G coverage

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<sup>1</sup>Wireless 3G coverage is reportedly available on the summit of Mt. Everest (Oberhaus, 2016).

<sup>2</sup>The NHTSA has turned to Twitter in order to personally tell drivers to stay off their phone (Matyszczyk, 2016)

<sup>3</sup><https://www.itcanwait.com/videos>

<sup>4</sup>These numbers come from polls conducted by the New York Times (Connelly, 2009), the American Automobile Association (American Automobile Association, 2013) and the Insurance Institute for Highway Safety (Williams et al., 2011).

<sup>5</sup>Hahn and Prieger (2006), Kolko (2009), Abouk and Adams (2013), Nikolaev et al. (2010), Sampaio (2014) and Burger et al. (2014) all examine the relationship between cell phone laws and accident rates.

<sup>6</sup>See Redelmeier and Tibshirani (1997), Abdel-Aty (2003), Strayer et al. (2003) and Törnros and Bolling (2005) for evidence showing that cell phones reduce the quality of driving and increase the likelihood of a crash.

becomes available. Poisson fixed-effect regression results show that car accident rates increase significantly by 1.1 percent when a road segment gains 3G coverage. In event-study analyses, there is no change in accident rates prior to a road gaining 3G coverage, but a significant and persistent increase in accidents after an area gains 3G coverage. The types of accidents most responsive to 3G coverage are those that do not involve bodily harm, those that take place in high traffic areas, and those where the driver at fault is younger than 65 years old. While the magnitude of our results are smaller than related research studying the determinants of fatal accidents, we find that 3G coverage is responsible for approximately 3,305 accidents per year in California.<sup>7</sup>

In order to carry out our empirical analysis, we construct a novel dataset that estimates annual 3G coverage for a quarter-mile stretch of road (road segment). Each road segment in California is assigned 3G coverage in 2016 using data from the Federal Communications Commission (FCC). Because accurate coverage data is not available prior to 2016, information on licensed antenna towers are linked to road segments in 2016. Machine learning techniques are used to determine which attributes of towers best predict 3G coverage, considering that 3G coverage was not available until the mid-2000s. Tower information is available annually and the machine learning results are applied to road segments between 2001 and 2013, the time period in which 3G cellular towers were built. The resulting dataset consists of the annual number of reported traffic accidents along a road segment in California, annual traffic counts for each road segment and an estimate of whether 3G coverage is available.

The reliability of our results hinge on a number of assumptions. The first assumption is that the predicted coverage variable we create accurately measures the growth in 3G coverage. It is not possible to confirm the existence of 3G coverage before 2015, but we have evidence that our coverage estimates are accurate. The machine learning results are created using a random sample of 80% of data. The remaining 20% of the data is used as test data and our results accurately predict coverage in over 98.5% of road segments in the test data. Additionally,

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<sup>7</sup>The fatal accident rate increases by 15 percent after an individual turns 21 (Carpenter and Dobkin, 2009) and the accident rate in Tippecanoe County, Indiana increased by 47 percent in the months following the introduction of Pokémon Go (Faccio and McConnell, 2018). Adams et al. (2012) find that a 10 percent increase in the minimum wage is associated with a 5 to 10 percent increase in fatal accidents involving 16-20 year olds.

predicted growth in the fraction of road segments covered by 3G are strongly correlated with the growth in mobile broadband subscriptions over the time period of our analysis.

Another assumption we make is that the construction of new towers explains the growth in 3G coverage, but tower construction is not related to unobservable characteristics that increase accidents. Our empirical analysis controls for the annual average daily traffic (AADT) along a road segment, mitigating concerns that the results are biased by an increase in overall traffic. We are reasonably confident that the increase in accidents we observe along a road segment when 3G coverage is introduced is caused by drivers changing their cell phone related behavior.

The existing data is not able to identify what drivers may be doing on their phone when they enter a road segment that has 3G coverage. In areas that already had basic cellular coverage prior to gaining 3G coverage, our results are measuring the effect of moving from a 2G to 3G network. The primary difference between 2G and 3G coverage is that data can be transferred hundreds of times faster on a 3G network allowing users to quickly access data from the internet and use web-based applications (Qualcomm, 2014). If texting behavior does not change when drivers enter an area with 3G coverage, the results suggest that checking email and using phone applications while driving increase the likelihood of an accident.

It is also possible that the positive relationship between car accidents and 3G coverage is caused by an increase in text messaging. Although texting was available throughout much of California prior to 2001, the growth in text messaging coincided with the proliferation of 3G coverage and an increase in the functionality of cellular devices.<sup>8</sup> If drivers with 3G compatible phones are more likely to operate their phone when they have 3G coverage, and the phone is used primarily for texting, it is possible that text messaging is the primary cause of the increase in traffic accidents when 3G coverage becomes available. Because we do not know what exactly drivers are doing on their phones when they get in an accident, our results capture the overall impact of drivers becoming distracted as they enter an area with 3G coverage.

One contribution of our paper is that we are able to better inform policy makers about the

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<sup>8</sup>In December, 2000, there were 14.4 million text messages sent in the US. By December, 2011, there were 193.1 billion text messages sent. These numbers are generated by the Cellular Telecommunications Industry Association (CTIA) and the Wayback Machine (<https://archive.org/web/>). The CTIA's Wireless Quick Facts ([www.ctia.org/consumer\\_info/service/index.cfm/AID/10323](http://www.ctia.org/consumer_info/service/index.cfm/AID/10323)) from April 20, 2010 and April 22, 2012 yield the monthly texts sent in the United States.



consequences of using a cell phone while driving. We improve upon many related studies that use state-level data and fatal accidents to estimate the relationship between cell phones and accidents. We analyze accidents along a one-quarter mile stretch of road and road segment fixed-effects capture time-invariant unobserved determinants of accidents, such as the inherent dangers along a road. These unobservable factors cannot be captured when data are aggregated to the county, state or national level. A policy implication of our paper is that existing cell phone laws do not appear to be effective, but developing laws that substantially alter how drivers use their cell phone may lead to a reduction in car accidents.

In addition to providing new and important insight into a relevant policy discussion, the current paper adds to the growing use of machine learning in economics (Athey, 2017; Mullainathan and Spiess, 2017).<sup>9</sup> Cicala (2017) builds random forest models to non-parametrically estimate operating rules for counterfactual electricity markets, which are then embedded in a difference-in-difference framework. Bajari et al. (2015) use machine learning based ensemble methods to estimate consumer demand, showing machine learning methods often outperform the standard demand estimation methods. Other researchers have used machine learning for predicting relevant information when surveys may be too expensive or of insufficient spatial or temporal resolution.<sup>10</sup> The novel application here is embedding a machine learning prediction into a causal model.

In the next section, we review the growth of mobile and broadband coverage. Section 3 introduces the data and develops coverage maps using machine learning techniques. Empirical results are presented in section 4. We discuss the implications of our findings in section 5 before concluding in section 6.

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<sup>9</sup>The range of applications has led some researchers to suggest that machine learning methods should be taught as part of core empirical methods in graduate programs (Hersh and Harding, 2018).

<sup>10</sup>Glaeser et al. (2017) use data on changes in businesses and restaurants on the website Yelp to forecast change in establishments and restaurants at small geographies in official data. Engstrom et al. (2017) and Babenko et al. (2017) generate poverty headcount rates for Sri Lanka and Mexico respectively, using machine learning models developed on features derived from high resolution satellite images.

## II. Background

The first commercial mobile phone service in the United States was developed in 1983 by AT&T Bell Labs. Ten antenna towers ranging from 150- to 550-feet high covered 2,100 square miles around Chicago. This early analog system technology was costly, used sparingly and eventually replaced by a digital, second generation (2G) wireless system in the early 1990s. The 2G mobile system allowed for better voice quality, more efficient use of frequency bandwidths and improved security as simple encryption became possible. The 2G networks facilitated the creation of the Short Messaging Service (SMS), also known as text messaging and initially transferred data at a speed of around 10 kilobytes per second. Improvements in the structure of 2G networks and the quality of antenna towers increased the maximum downloading speed to 120 kilobytes by the late-1990s, but this speed was difficult for the typical user to obtain. By the early 2000s, technology for 3G networks had been developed, although the adoption of 3G coverage did not begin until the mid-2000s.<sup>11</sup> Devices on 3G networks could initially download data at a rate of 144 kilobytes per second when driving and 2000 kilobytes per second in a building environment. By 2005, 3G coverage data speeds were over 500 kilobytes per second for the average user.<sup>12</sup>

Improving wireless download speeds spurred growth in related industries. When Ameritech launched the first 1G network phone in 1983, the 2-pound DynaTAC 8000x retailed at \$3,995 and could be used for 35 minutes before needing ten hours of charging (NBC, 2005). The growth in 2G networks led to the creation of smaller mobile phones that had longer battery lives and improved functionality. Browsing the internet on a 2G network was possible, but limited as a result of the slow data transmission speed.<sup>13</sup>

The growth of the faster 3G networks led to further improvements in the functionality of phones. When 3G service in the United States was first introduced by Verizon in 2002, two devices were capable of accessing the 3G network as long as the device was connected to a computer or had a PC card (CNN, 2002). In June 2007, Apple released the first iPhone (Apple,

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<sup>11</sup>Prior to 2005, less than one percent of the United States population had a mobile broadband subscription, which increased to 52 percent by 2010 (TekCarta, 2018).

<sup>12</sup>See Ghosh et al. (2010) and Sauter (2013) for more information on the history and technology of cellular networks.

<sup>13</sup>By the end of the 1990s, mobile phones in Europe were being used to purchase goods from vending machines (Peña-López et al., 1999) and Japan released full internet service on mobile phones in 1999 (Ishii, 2004).

2007). The processing power of the 4.8-ounce first generation iPhone was faster than the 1980s supercomputer CRAY-1 and comparable to laptops in the year 2000 (Experts Exchange, 2018). The HTC Dream, with its QWERTY keyboard, was launched in 2008 and became the first smartphone to use Google’s Android operating system (T-Mobile, 2008).

The influence of modern smartphones on individual lifestyles and behaviors is hard to understate. Increased smartphone functionality gave rise to a market of smartphone applications. By 2009, over 1 billion “apps” had been downloaded in Apple’s “App Store” (Dormehl, 2018) and by 2012, both the Google Play and the App Store had over 500,000 unique apps available for download (Dogtiev, 2018). Smartphones are now used for many activities, including watching TV, getting directions, trading stocks and video calls. In 2017, Deloitte found that 89 percent of individuals check their phone within an hour of waking up and 81 percent look at their phone less than an hour before going to bed (Deloitte, 2017). Teens are estimated to spend nine hours per day on social media (Common Sense Media, 2015) and approximately 20% of adults are estimated to own a smartphone but do not have landline broadband internet at home (Pew Research Center, 2018).

Cell phone use is often compared to substance abuse and gambling disorders (DeSola Gutiérrez et al., 2016) and cell phone addiction has been linked to depression, relationship issues and anxiety (Babadi-Akashe et al., 2014; Andreassen, 2015). Smartphone overuse can lead to physical problems such as eye strain, “text neck” and male infertility (Rosenfield, 2016; Lee et al., 2015; Deepinder et al., 2007). Researchers have found a negative correlation between cell phone use and grades in science courses (Douglas et al., 2012) and productivity at work (Thornton et al., 2014). Nasar and Troyer (2013) show that mobile phone related injuries among pedestrians that resulted in emergency room visits increased significantly between 2004 and 2010. Palsson (2017) makes a significant stride in measuring high-speed wireless coverage in the United States and shows that when a hospital becomes part of AT&T’s 3G network, injuries for young children increase and the results are arguably driven by parents being distracted.

Considering that parents are less attentive to their children as a result of 3G coverage, it is reasonable to believe that drivers would also be less attentive when using their cell phone. Redelmeier and Tibshirani (1997) examine cell phone records from 700 accidents and find that

the likelihood of a car crash increases significantly when a driver uses a cell phone. Studies from driving simulations find that drivers on cell phones have reduced peripheral detection (Törnros and Bolling, 2005), increased braking time (Strayer et al., 2003) and are more likely to be involved in a crash (Abdel-Aty, 2003). Reviews of laboratory and simulator studies by Caird et al. (2008) and Caird et al. (2014) suggest that texting while driving leads to increased reaction time, more collisions and worse lane positioning.

Despite the evidence that cell phone use reduces the effectiveness of individual drivers, there is less evidence showing that cell phone use increases the overall accident rate. The lack of evidence can be partially attributed to the difficulty in obtaining data that reports traffic accidents and cell phone use accurately over a relevant period of time. Many studies use the adoption of cell phone and texting bans to proxy for changes in the use of cell phones, but the results of the studies vary based on the empirical approach used and time period examined (Nikolaev et al., 2010; Sampaio, 2014; Burger et al., 2014; Abouk and Adams, 2013; Kolko, 2009; Hahn and Prieger, 2006). Cheng (2015) does show that bans are associated with reductions in cell phone use at specific intersections, but it is possible that drivers respond to cell phone bans by increasing their use of a hands-free cellular device (Carpenter and Nguyen, 2015). Bhargava and Pathania (2013) exploit discontinuities in the "free nights and weekends" cellular plans from the mid-2000s and show that reducing the marginal cost of cellular calls at 9pm is not associated with a change in the rate of car accidents at the state level.

A recent survey of 3 million individuals over 3 months by Zendrive found that drivers use their phones on 88 percent of trips and are on their phone 3.5 minutes per hour of driving (Zendrive.com, 2018).<sup>14</sup> Although many drivers use their cell phone, and cell phone use is related to poorer driving, researchers have been unable to consistently show that cell phone use leads to an increase in the overall accident rate. The current paper improves upon existing research by using a unique dataset and a new identification strategy to explore if gaining access to 3G cellular coverage increases the rate of traffic accidents. Our analysis provides important insight into the the relationship between cell phone use and traffic accidents that has been hard

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<sup>14</sup>This estimate is comparable to Hahn and Prieger (2006) who construct a survey and find that between October, 2001 and September, 2002, 73 percent of drivers used a cell phone while driving.

to observe in previous research.

### III. Data Description and Predicting 3G Coverage

The first step in the construction of our data is defining a unit of observation. California defines their highways with a postmile system. A postmile value reports the mileage along a route, within a county. The postmile value starts at zero whenever a route crosses over a county border or when it originates.

In the analysis below, the postmiles of interest represent the road segment east or north until the next postmile on the route. This is done because postmile values increase to the east and north. Imagine a route runs west to east, the start of the route is postmile zero, one mile east is postmile one and two miles east is postmile two. The first road segment is defined between postmile zero (which lies on the west side of the road segment) and postmile one. The second road segment is defined between postmile one and postmile two. The same process occurs when the route runs from south to north.

California reports two different postmiles for each location on a highway, one for each direction. We combine these two points into a single postmile observation, which yields a total of 63,733 postmiles along California highways. The average distance between postmiles is approximately 0.25 miles, although the distance can be larger in rural areas. However, only 5% of the postmile observations represent road segments greater than one mile and only 1% are greater than 2.25 miles. Each postmile can be thought of as representing a road segment along a California highway. The postmile definitions do not change from year-to-year, so we use them as our unit of observation.<sup>15</sup>

#### A. 3G Coverage Data

The Federal Communications Commission’s (FCC) Mobile Deployment Form 477 shapefiles provide information on mobile broadband coverage, by provider, on December 31, 2014 and

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<sup>15</sup>We only include postmiles that are in existence over the entire time period, so we do not account for road construction or destruction. For more information about postmiles, see <https://postmile.dot.ca.gov/>

December 31, 2015. Because the coverage maps are so similar between the two years, we focus on the shapefile that was published on December 31, 2015, but refer to it as the broadband coverage in 2016. The 477 files define and report broadband coverage in categories based on speed.<sup>16</sup> We build our coverage data using the shapefiles for coverage defined as 3G or faster. The data only includes the coverage maps for the four largest mobile service providers, measured by market share in 2016 (in parentheses): Verizon (34.9%), AT&T (32.3%), T-Mobile (16.8%) and Sprint (14.4%).<sup>17</sup>

Using ArcMap, software for Geographical Information System (GIS) analysis, we overlay the 3G coverage maps with the postmiles. Then we define a postmile as having 3G coverage in 2016 if the postmile intersects with the shapefile from the FCC. If the shapefile overlaps with the postmile (a point on the map), the entire road segment the postmile represents is assumed to have 3G coverage. This assumption is not strong, given the average distance between postmiles is only 0.25 miles. We define 61,074 out of the 63,733 postmiles as having 3G coverage in 2016, or 97%.

While the FCC shapefiles are useful for establishing coverage in 2016, official 3G coverage information is not available between 2001 and 2013, the years in which detailed accident data are available in California. Because this is also the time period in which 3G coverage was expanding, we devise a strategy to predict coverage during that time period. We merge cellular tower information to each road segment for 2001 to 2013 and 2016 (the year that 3G coverage information is available from the FCC). It is reasonable to assume that no road segments had 3G coverage prior to 2005 since less than one percent of the population had mobile broadband service before 2005.<sup>18</sup> With accurate 3G information before 2005 and in 2016, we predict the influence that time-varying cellular towers have on the probability of 3G coverage. The results are then used to predict 3G coverage between 2005 to 2013.

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<sup>16</sup>The codes for 2G coverage are 85 and 86. The codes for 3G coverage are 80 and 82. The codes for 4G coverage are 81 and 84. The code for 4G LTE coverage is 83.

<sup>17</sup>Market share statistics are from <https://www.androidheadlines.com/2016/11/top-7-us-wireless-carriers-q3-2016.html/>.

<sup>18</sup>The results are not sensitive to assuming 3G coverage began in earlier years.

## B. Cellular Tower Data

The FCC requires all antenna structures over 200 feet high (towers) to be registered through the Antenna Structure Registration (ASR) system and information on tower location, elevation, year of construction and height is available publicly. Even though all structures over 200 feet high are required to be registered, roughly half of the towers in the registry are less than 200 feet.

The location of towers are geocoded using Geographical Information System (GIS) software and are laid on the map consisting of California postmiles. We restrict the sample of towers to those that were built after 1990, as older towers are less likely to be used for cellular coverage. In 2001, there were 3,101 existing towers within California’s borders, which increased to 6,255 towers in 2013. In 2016, there were 6,556 towers. We create variables that measure the spatial relationship between postmiles and towers, based on information at the beginning of each year. Table I reports those statistics.

The first variable we create is the number of towers that exist within a 20-mile radius of each postmile. The range of coverage from a tower is unknown and varies. A tower’s range depends on the type of cell tower built, the strength of the transmitter, the relative height, the surrounding landscape and the number of users in the area. In densely populated areas, such as business parks and campuses, picocell towers are common and have a range of 250 yards (Harris, 2011). Macrocell towers in rural areas can provide coverage more than 20 miles away (Heimerl et al., 2013). Based on estimates of maximum tower ranges, we determine that a 20-mile radius is a sufficiently large range to capture the relevant towers for each postmile. The average number of towers within a 20-mile radius in 2001 was 82.4 and increased to 170.4 in 2013.

The remaining variables we create are based on the attributes of the tower that is closest to the postmile in a given year. The average distance of the closest tower decreased from 3.66 miles in 2001 to 2.60 miles in 2016; the average year of construction for the closest tower increased from 1996.1 to 2001.4 between 2001 and 2016; and the average elevation of the top of the nearest towers decreased from 455.9 to 445.7 between 2001 and 2016. The shortening

Table I: Relationship between Postmiles and Towers: Descriptive Statistics

Year	Towers Within 20 Miles	Attributes of Tower Nearest to Postmile		
		Distance	Construction Year	Max Tower Elevation
2001	82.4	3.66	1996.2	455.9
2002	92.1	3.42	1996.8	452.4
2003	97.3	3.21	1997.1	449.7
2004	103.2	3.11	1997.5	447.4
2005	111.9	3.03	1997.9	447.0
2006	122.1	2.98	1998.2	446.7
2007	131.9	2.86	1998.7	448.8
2008	138.2	2.82	1999.0	447.5
2009	144.3	2.78	1999.3	449.4
2010	149.3	2.77	1999.5	448.3
2011	158.5	2.72	2000.0	446.5
2012	165.6	2.68	2000.4	448.8
2013	170.4	2.65	2000.7	445.6
2016	179.0	2.60	2001.4	445.7

Describes 63,733 postmiles in California. Distance is reported in miles. Elevation is reported in feet. The average elevation of the postmiles is 498.3 feet and the standard deviation of the elevation within 20 miles is 36.3 feet.

of towers over time is consistent with an increase in demand for "stealth towers" by citizens. Stealth towers are built to look like the surrounding area (Wikle, 2002). Assuming that new and closer towers are indicative of an area gaining 3G coverage, the tower data is consistent with the expansion of 3G coverage throughout California over this time period.

### C. Predicting 3G Coverage with Machine Learning

Using information on whether a postmile has 3G coverage in 2016, and assuming that 3G coverage was not available before 2005, we use machine learning methods to predict whether a postmile has 3G coverage during the years 2001 to 2013, during which we only observe detailed cellular tower characteristics and not 3G coverage. Specifically we fit a random forest model (Breiman, 2001) to predict 3G coverage based on characteristics of cellular towers close to the postmile.

We estimate a model using data from 2001 to 2004 and 2016 to predict if postmile  $i$  has 3G coverage  $y_i$  where



$$y_i = \begin{cases} 1 & \text{if postmile has 3G coverage} \\ 0 & \text{if postmile does not have 3G coverage} \end{cases}$$

The desired output is a model of conditional probability  $p_i \equiv Pr(y_i = 1|\mathbf{X})$  where  $\mathbf{X}$  is a vector of characteristics about cellular towers located near the postmile. Table II shows the full list of variables available to model 3G coverage. These include the number of towers within 20 miles of the postmile, the distance to the nearest cellular tower, elevation and standard deviation of elevation of the areas near postmiles, year of construction of the closest tower, among others. In total we use fourteen continuous variables to model the probability a postmile has 3G coverage.

The standard approach is to fit a parametric logistic regression of  $y_i$  on  $\mathbf{X}$ . There are several reasons why this approach is inadvisable for this prediction task. The relationship between  $y_i$  and  $\mathbf{X}$  may be sufficiently non-linear such that we cannot assume to know the functional form mapping the two. Indeed, estimating a logit of  $y_i$  results in a very poor fit of the data. Without assuming the functional form of  $y_i$  we estimate a model of the form

$$p_i = (Y = 1|\mathbf{X}) = f(\mathbf{X}) + \epsilon$$

where  $f(\mathbf{X})$  is estimated using a random forest. Random forests are a popular method for classification and regression prediction that produce reliable out-of-sample prediction. A random forest model is an ensemble method, meaning it combines many different models, each of which is a simple decision tree. Decision trees partition the target data (postmile 3G coverage) by finding a variable (e.g. height of tower) and a proposed split of that variable (e.g. less than 30 feet) that best partitions the target into groups that reduce within-group variance.<sup>19</sup> A series of variable selection and splits are performed until some stopping criterion is reached.

Random forests are comprised of many of these decision trees, however there is a catch

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<sup>19</sup>Classification problems such as this amounts to separating postmiles into those that have and don't have 3G coverage.

Table II: Summary statistics, 3G coverage estimation data

	mean	sd	min	max
<b>Panel A: Summary statistics, data used to estimate postmile 3G coverage, 2001-05; 2016</b>				
Towers within 20 mi. of postmile	111	138	0	843
Towers within 20 mi. squared	31,279	76,678	0	710,649
Distance to nearest tower from postmile	3.2	4.3	.0018	46
Distance to nearest tower squared	29	86	3.2e-06	2,130
Std. dev. of elevation of land within 20 mi.	36	11	7.2	64
Elevation at centroid of postmile	498	514	-21	2,665
Year of construction of nearest tower	1,998	4.4	1,990	2,015
Height in feet of nearest tower	30	22	0	584
Height squared	1,405	3,773	0	340,706
Height above sea-level of nearest tower minus height	-48	275	-1,373	1,850
Std. dev. elevation X Towers in 20 mi.	1102698	2987691	0	2.9e+07
Year of construction X height nearest tower	60,518	44,099	0	1176156
Year of construction X std. dev elevation	2888102	1709135	103,996	8222200
Towers within 20 miles X height nearest	2,906	4,767	0	158,246
Observations	318640			
<b>Panel B: Summary statistics, data used to predict 3G coverage, 2006 - 2013</b>				
Towers within 20 mi. of postmile	132	160	0	843
Towers within 20 mi. squared	42,846	90,502	0	710,649
Distance to nearest tower from postmile	2.9	4	.0018	46
Distance to nearest tower squared	25	76	3.2e-06	2,130
Std. dev. of elevation of land within 20 mi.	36	11	7.2	64
Elevation at centroid of postmile	498	514	-21	2,665
Year of construction of nearest tower	1,999	4.7	1,990	2,015
Height in feet of nearest tower	30	22	0	584
Height squared	1,369	3,027	0	340,706
Height above sea-level of nearest tower minus height	-50	271	-1,373	1,850
Std. dev. elevation X Towers in 20 mi.	1521921	3519389	0	2.9e+07
Year of construction X height nearest tower	60,134	43,046	0	1176156
Year of construction X std. dev elevation	2889420	1710047	103,996	8222200
Towers within 20 miles X height nearest	3,435	5,535	0	158,246
Observations	892237			

in estimating each regression tree. Each time a decision tree is estimated, we bootstrap a subsample of data on which we estimate (also known as train) the decision tree. Further, at each decision node (or variable split), we sample which variables the decision tree can use to partition the response data. This may seem as if we are needlessly handicapping the model by reducing the variables the model can choose. However, in practice this approach works well for fully exploring the parameter space and preventing overfitting, or fitting noise rather than signal. Prediction in a random forest is performed by combining (or ensembling) all of the decision trees. The resulting  $p_i$  for any postmile  $i$  is the fraction of decision trees that predict the postmile with characteristics  $\mathbf{X}_i$  have 3G coverage.

Our random forest model is estimated using 1,000 decision trees. We further partition our estimation dataset into a training and test set, of sizes 80% ( $N_{train} = 254,912$ ) and 20% ( $N_{test} = 63,728$ ) of the full estimation dataset respectively.<sup>20</sup> Our model is estimated against the training set and model diagnostics are performed on the test data, which was not used to fit the model and thus functions as a better approximation of out-of-sample performance. The remaining parameter to select is how many variables to randomly sample at each decision split. Appendix figure 9 shows cross-validation model accuracy across a number of values of the parameter. We achieve best cross-validated accuracy by randomly sampling five variables at every decision split.

A remaining assumption to make is the date of 3G cellular introduction. We set 3G coverage to be equal to zero from 2001 to 2004, giving 2005 as the first date of introduction of 3G service. This assumption best matches rates of mobile broadband in the US (TekCarta, 2018), which show broadband subscriptions per 100 persons in 2004 of 0.41. In 2005 the US achieved 1.03 mobile broadband subscriptions per 100 persons.<sup>21</sup>

The Receiver Operating Characteristic (ROC) plot from using the fitted random forest model to predict 3G coverage for observations in the test set is shown in figure 11. The ROC plot shows an exceptional model fit, with an Area Under Curve (AUC) of 0.9966. This is an

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<sup>20</sup>Summary statistics for the estimation and prediction stages are shown in table II. Summary statistics for the observations used for prediction are shown in panel B of the same table.

<sup>21</sup>Appendix figure 10 shows model diagnostics varying the assumption of 3G introduction from 2003, 2004, and 2005. Prediction performance is comparable across models varying this date of introduction.

impressive result given that these are diagnostics from predicted observations into the test set, which were not used to estimate the random forest model. The prediction task is all the more challenging given that the majority of postmiles have 3G coverage in 2016, and none had 3G coverage between 2001 and 2004.

### Threats to identification embedded in the prediction model

One threat to identification is that the random forest model learns and predicts characteristics that increase the probability of traffic accidents that are correlated with changes in predicted 3G coverage but are not related to 3G coverage itself. An example is that changes in predicted 3G coverage may be correlated with road disrepair, which may increase the likelihood of traffic accidents in absence of 3G coverage.

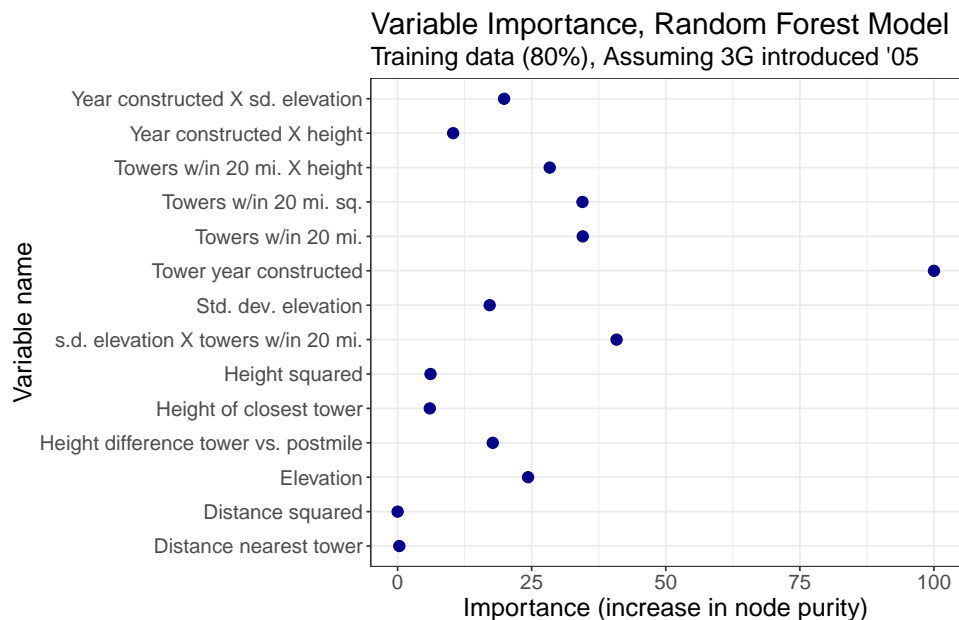


Figure 1: Random forest model variable importance plot

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.

One is naturally tempted to ask the random forest model how it calculates its predictions. While inference with these models is cumbersome, we can infer which variables are most useful

for the estimation by constructing a variable importance plot, as shown in figure 1, according to the method described by (Breiman, 2001). The variable importance plot shows that the year of construction of the closest tower is the most important variable used to predict 3G coverage, over three times as important as the next variable. Other important predictor variables are elevation, number of cellular towers and the standard deviation of elevation near the postmile. The random forest appears to have "learned" that postmiles located close to few, old cellular towers, and near rocky terrain, do not have 3G coverage. We have no reason to believe why any of these are correlated with unobservables that positively impact the probability of traffic accidents, thus we are reasonably certain the prediction model is measuring changes in 3G coverage and not unobservables that are correlated with 3G coverage.

### **From continuous probabilities to binary 3G coverage prediction**

To generate a binary prediction from the continuous probabilities of postmile 3G coverage  $p_i$ , we must define some threshold  $c$  such that

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

This is to say that we must make a threshold decision such that postmiles with probabilities below this cutoff will be classified as not having 3G coverage, and those above this threshold will be classified as having 3G coverage. The ROC curve, which presents the true and false positives from any threshold, presents guidelines for that decision process.

The consequence of various thresholds in terms of type I and type II error rates is shown in table III. Our preferred threshold cutoff value is 0.8. At this cutoff, we have a high level of accuracy (98.63%) and the correlation between the annual fraction of postmiles above the 0.8 threshold and the observed mobile broadband subscription rate TekCarta (2018) is 0.9729 (shown in figure 3). We experiment with a variety of threshold values between 0 and 1 and nearly all cutoffs between 0.5 and 0.99 do not qualitatively impact the results.

Predicted 3G coverage over time in California, using 0.8 as the threshold to define coverage,

Table III: Binary prediction accuracy varying cutoff threshold

Prediction Threshold	Accuracy	False negative rate (type 1 error)	False positive rate (type II error)	Correlation Coefficient
1	88.42%	60.52%	0.00%	0.9852
0.9	97.78%	11.43%	0.04%	0.9671
0.8	98.63%	6.89%	0.07%	0.9729
0.7	99.02%	5.55%	0.09%	0.9728
0.6	99.16%	3.78%	0.14%	0.9682
0.5	99.27%	3.01%	0.19%	0.9590
0.4	99.29%	2.52%	0.28%	0.9433
0.3	99.22%	2.13%	0.46%	0.9204
0.2	99.22%	1.78%	0.81%	0.8865
0.1	98.23%	1.51%	1.83%	0.8306

is seen in figure 2. The maps denote the postmiles without 3G coverage as white dots and postmiles with predicted coverage above 0.8 as black dots. Maps for the years 2005, 2007, 2009, 2011, 2013 and 2016 are reported. The growth in our estimates of 3G coverage occurs in a predictable way. Panel (a) of figure 2 shows very few postmiles with 3G coverage in 2005. This is consistent with the broadband subscription rate of 1% in 2005. By 2007, many postmiles in the urban areas of California have 3G coverage, according to our definition. The fraction of postmiles with 3G coverage in both urban and rural areas increased in 2009 and 2011. A relatively small fraction of rural postmiles were without coverage in 2013 and by 2016, approximately 97% of postmiles had 3G coverage, which is consistent with the mobile broadband subscription rate growth in figure 3.

It would be ideal to compare our estimates of 3G coverage in a year between 2006 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 not reliable.<sup>22</sup>

It is possible to apply the random forest 3G coverage predictions to another state that has less coverage than California. This is a computationally intensive exercise that does not yield much information since every state in 2016 has a very high fraction of road segments covered by 3G, according to the FCC 477 files. Although we do not carry-out additional tests surrounding

<sup>22</sup>In 2009, AT&T sued Verizon over misleading coverage maps (Diaz, 2009).



(a) 2005



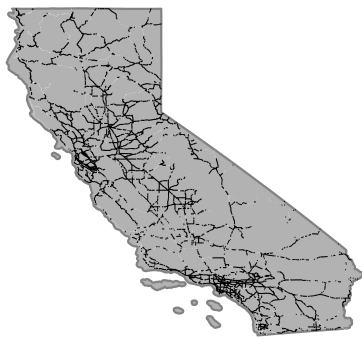
(b) 2007



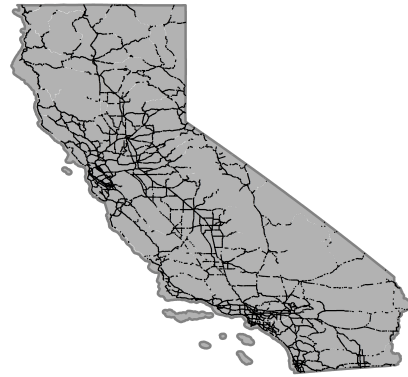
(c) 2009



(d) 2011



(e) 2013



(f) 2016

Figure 2: Predicted 3G Coverage (black) and No Coverage (white) by Year

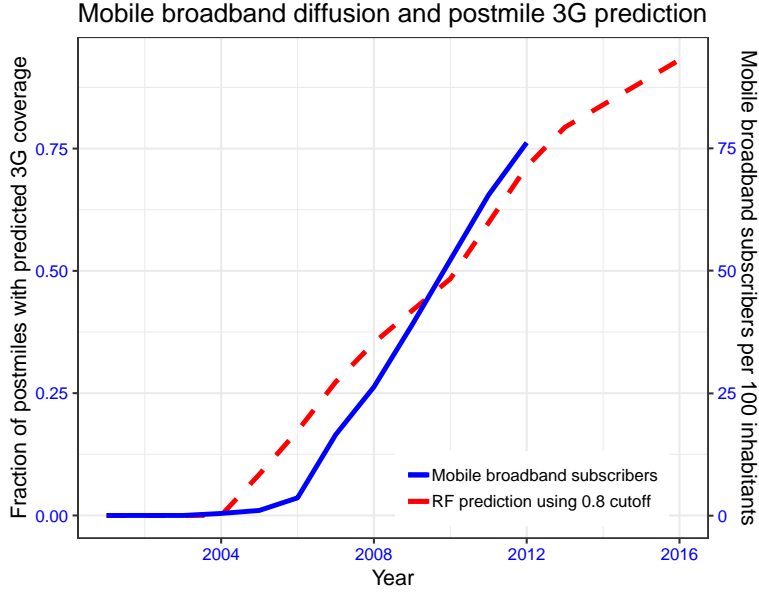


Figure 3: Mobile broadband diffusion and postmile 3G prediction over time

the accuracy of 3G coverage, the combination of the high level of accuracy using our test data, the correlation with mobile broadband subscription rates and the pattern of 3G coverage growth throughout the state over time suggest that our estimates of annual 3G coverage are reasonably accurate.

## D. Car Accident and Traffic Data

The previous sections combine recent 3G coverage data along road segments with tower information to estimate the annual growth in 3G coverage between 2001 and 2013. A potential consequence of the increase in 3G coverage is that automobile drivers will be more distracted by their phones and the accident rate will rise. To explore this possibility, we merge 3G coverage information to the number of accidents that took place along a postmile each year. 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. In most incidents, the age of the drivers in the accident are reported, but whether the cause of the accident is inattention or alcohol involvement is less reliable, as detailed recording likely differs across police jurisdictions.

The dependent variable in our analysis is constructed by first aggregating the number of



accidents along a road segment each year. Each accident along a road segment is assigned to the nearest postmile to the west or south of the accident. We also utilize information on the volume of traffic along a road segment, which allows us to construct an accident rate. Traffic volume is reported annually by the California Department of Transportation (CalTrans) through their Traffic Census Program.<sup>23</sup> Their specific metric is the Annual Average Daily Traffic (AADT), which is the total number of vehicles that travel along a road segment in a year, divided by 365. The AADT provides a measure of how busy the road is on an average day in a particular year.

Each year, Caltrans publishes traffic volume in a spreadsheet for approximately 4,000 locations in both directions. The locations are defined by county, route number and postmile. This information is available for every year between 2001 and 2013 except 2009, in which there was an error in the administrative data. We interpolate values for 2009 using 2008 and 2010. We assign AADT values to the nearest postmile west or south of the reporting location and take the average of the two directions.

Using this process yields precise traffic volume data for 3,709 postmiles in our dataset. This is only a small subset of postmiles in our sample, so we use this data to construct average AADT measures for routes within counties. For example, imagine we only have traffic information for three postmiles of a route with 10 postmiles in a particular county. We take the average of the AADT on the three postmiles and apply that average to all 10 postmiles on the route in that county. Using this process, we are able to construct traffic value data for 61,804 of the 63,733 postmiles in our sample.

Because the sample of postmiles with traffic is a subset of all available postmiles, it is important to note that the accident counts do not change when different samples are analyzed. Appendix figure 14 shows that the trend in accidents is the same for all postmiles, postmiles with traffic data, all postmiles that have at least one accident between 2001 and 2013 and postmiles with at least one accident between 2001 and 2013 that has traffic data. Accidents in all four postmile subsets are increasing until 2005, decrease from 2007 to 2010, then remain

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<sup>23</sup>See <http://www.dot.ca.gov/trafficops/census/> for more information.

relatively stable until 2013.<sup>24</sup>

In the previous subsection, the most accurate measure of 3G coverage along a road segment occurs when the predicted probability of coverage is greater than 0.8. This distinct cutoff allows us to evaluate how traffic accident rates change as a result of 3G coverage. Table IV presents accident rate averages for all postmiles, postmiles that did not have coverage in 2005 but gained coverage by 2013 (“Changers”), postmiles that gained 3G coverage in 2005 (“Always Covered”) and postmiles that did not gain 3G coverage by 2013. The first column of Table IV shows that the final dataset includes 51,727 postmiles and 70 percent of those postmiles gained coverage between 2006 and 2013.

Table IV: Descriptive Statistics

		AADT	Accident Rate				%Δ Accident Rate
	Postmiles	All Years	All Years	2001	2005	2013	2005-2013
All	51,727	61,784	0.94	1.07	0.99	0.77	-22%
Changers	36,305	61,493	0.92	1.05	0.97	0.75	-23%
Always Covered	3,904	100,192	0.87	0.91	0.90	0.64	-28%
Never Covered	11,518	49,680	1.06	1.18	1.12	0.89	-20%

Predicted Coverage Threshold=0.8

The second column of Table IV reports the Annual Average Daily Traffic average for each group and shows that there is a noticeable difference in the level of traffic across the three subsets of postmiles. The postmiles that are always covered have a relatively high AADT average (100,192), compared to postmiles that gained 3G coverage between 2006 and 2013 (61,493). Areas that do not gain 3G coverage have a lower AADT average (49,680) than both postmiles that were always covered and the postmiles that gained coverage in our analysis.

The accident rate for all years, 2001, 2005 and 2013 are reported for each subset of postmiles, as well as the universe of all postmiles in the data. The average accident rate on a road segment in all years is 0.94 per 10,000 AADT. This means that road segments that average 10,000 vehicles per day average 0.94 accidents per year. The AADT average for all years of 61,784 implies that the average road segment has 5.807 accidents per year.

<sup>24</sup>In the empirical analysis, we employ a fixed-effect count model, which omits the 16 percent of postmiles that do not experience at least one car accident over the time period of interest.

Although the subsets of postmiles may be inherently different regarding their location and traffic patterns, the relative change in accident rates across the postmile subsets suggest that 3G coverage could have had an observable impact on accidents. Specifically, in 2005, the subset of postmiles that gained 3G coverage had an accident rate of 0.97 per 10,000 AADT, which decreased to 0.75 in 2013, a 23 percent decrease. Postmiles that had 3G coverage starting in 2005 observed a 28 percent reduction in their accident rate (0.90 to 0.64).

Table IV only provides information on three specific years making the comparison of accident rates across postmiles over time limited. Nonetheless, a first glance at the data suggests that areas that gained 3G coverage between 2006 and 2013 had a lower reduction in accidents than postmiles that had 3G coverage beginning in 2005. To more completely understand how accident rates change in response to 3G coverage, the next section explores the relationship in a fixed-effects regression framework.

## IV. Empirical Analysis

### A. 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 car accidents and 3G coverage within a postmile. Assuming that the conditional mean assumption holds, the estimates are consistent with robust standard errors clustered on postmile (Cameron and Trivedi, 2005; Gourieroux et al., 1984).<sup>25</sup>

The exposure variable is average annual daily traffic (AADT) along the postmile route for a given year, so it enters the specification with its coefficient constrained to equal one.<sup>26</sup> The

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<sup>25</sup>Although not provided, we also estimate these models with a fixed-effects negative binomial, fixed-effects Poisson with bootstrapped standard errors and the quasi-maximum likelihood estimator with robust standard errors suggested by Wooldridge (1999) and Simcoe (2008). All of the results yielded from these estimation strategies are similar in magnitude and statistical significance.

<sup>26</sup>If the coefficient is not constrained to one, the estimated coefficient of interest is not meaningfully altered.

resulting Poisson specification is the following:

$$E[Accident_{it}|\cdot] = \exp(\alpha_1 PredictedCoverage_{it} + \ln(AADT_{it}) + \gamma_i + \tau_t + v_{it}). \quad (1)$$

The variable  $Accident_{it}$  represents the number of accidents that occur at postmile  $i$  in year  $t$ .  $PredictedCoverage_{it}$  represents a measure of predicted 3G coverage. The analysis will initially use a continuous measure of predicted coverage between zero and one and then an indicator variable defined by a threshold between zero and one.  $AADT_{it}$  is the estimated annual average traffic volume for the postmile,  $\gamma_i$  is a postmile fixed effect and  $\tau_t$  is a time fixed effect.

Specification 1 allows us to calculate the percentage change in the accident rate when a postmile gains 3G coverage.<sup>27</sup> When using a strict cutoff to define 3G coverage,  $\alpha_1$  is used to calculate the percentage difference in the accident rate between all the years in which  $PredictedCoverage_{it}$  equals zero and all the years in which  $PredictedCoverage_{it}$  equals one. The identifying assumption in equation 1 is that the change in 3G coverage in a postmile, caused by the construction of new cellular towers, is not related to unobservable characteristics that could influence the accident rate. While the regression does not have a large number of controls, the analysis is able to control for changes in the AADT along postmiles, reducing concerns that the results are capturing a change in traffic patterns. Postmile fixed-effects control for time-invariant road segment characteristics associated with traffic accidents, further strengthening our identification strategy.

Although specification 1 is able to capture many elements that explain traffic accidents, the regression is unable to show the dynamic change in accident rates before and after a postmile gains 3G coverage. To examine the annual effects of 3G coverage, we construct an event study specification with a four year lead and lag, which illustrates how the number of accidents changes when a postmile gains 3G coverage. The omitted category is the first full year of cell

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<sup>27</sup>The percentage change in the accident rate is equal to  $e^{\alpha_1} - 1$ .

phone coverage.<sup>28</sup> The general equation is:

$$E[Accident_{it}|\cdot] = \exp\left(\sum_{k=-4+}^{-1} \theta_k S_{it+k} + \sum_{j=1}^{4+} \theta_j S_{it+j} + \ln(AADT_{it}) + \gamma_i + \tau_t + v_{it}\right). \quad (2)$$

The term  $S_{it}$  equals one when the postmile has its first full year of 3G coverage in time  $t$  and zero otherwise. The event study can only facilitate the use of binary treatment variables. The previous section suggests that the most accurate cutoff occurs when a road segment is defined as having 3G coverage when the predicted probability is above 0.8. However, we show results when defining the coverage threshold as 0.4, 0.6, 0.8 and 1.

## B. Results

Table V shows the results from the fixed-effects Poisson specification (Equation 1). The first two columns report results using continuous predicted 3G coverage. In column (1), the AADT or traffic volume, enters the regression as a control. According to the coefficient of interest, accidents in a postmile increase by 1.6 percent when predicted coverage increases from 0 to 1. When traffic volume is the exposure variable in column (2), the coefficient on traffic volume is restricted to one, effectively changing the dependent variable into the number of accidents per 10,000 AADT. In column (2), the strength of the results are unchanged and increasing predicted coverage from zero to one is associated with a 1.7 percent increase in the accident rate.

Columns (3) through (6) of table V report the change in the accident rate when 3G coverage is defined as a binary variable. In column (3), all postmile-year observations are defined as covered if the continuous predicted 3G coverage measure is 0.4 or above. The coefficient of interest in column (3) suggests that when predicted coverage in a postmile crosses the threshold of 0.4, the accident rate increases insignificantly by 0.58 percent. When the threshold is changed to 0.6 in column (4), the results show that accident rates increase significantly by 0.84 percent when a postmile gains 3G coverage.

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<sup>28</sup>A postmile is said to have coverage for the full year if the tower was built before January 1st of the given year.

Table V: Fixed Effect Poisson Regressions: Accidents and 3G Coverage

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Coverage	0.0158*** (0.00613)	0.0170*** (0.00613)				
ln(Traffic Volume)	0.571*** (0.0357)					
I(Coverage $\geq$ 0.4)			0.00581 (0.00408)			
I(Coverage $\geq$ 0.6)				0.00834** (0.00410)		
I(Coverage $\geq$ 0.8)					0.0111** (0.00493)	
I(Coverage $\geq$ 0.99)						0.01686*** (0.00484)

p<0.01, \*\* p<0.05, \* p<0.10. Dependent variable is annual number of accidents at a postmile. All regressions include 672,451 observations, which represent 51,727 postmiles over 13 years. The exposure variable in columns (2) through (6) is traffic volume.

Our preferred definition of 3G coverage is when predicted 3G coverage in a postmile is 0.8 or above. Column (5) of table V suggests that when a postmile gains 3G coverage the accident rate increases significantly by 1.1 percent. In column (6), postmiles are not considered covered by 3G unless predicted coverage is greater than 0.99. Even when this extreme definition of coverage is used, the relationship between coverage and traffic accidents continues to be significant at conventional levels.

In the preferred specification, a postmile is considered to have 3G coverage if the predicted probability of coverage is 0.8 or greater. Using this threshold aligns with subscription rates for mobile broadband coverage, but the results in table V are not sensitive to the threshold used over a relatively large range of cutoffs. Figure 4 shows the coefficient estimates and 95 percent confidence intervals when the coverage threshold is defined by every value from 0.01 to 1.00, in increments of 0.01. For nearly every threshold above 0.57, the coefficient of interest from equation 1 is significant at the 95% level. Of the thresholds between 0.58 and 0.99, only the cutoffs 0.65 and 0.75 are insignificant. The 0.8 cutoff is our preferred threshold, but the cutoff choice over a wide range of values does not meaningfully alter our findings.

Table V and figure 4 provide evidence that the introduction of 3G coverage is associated

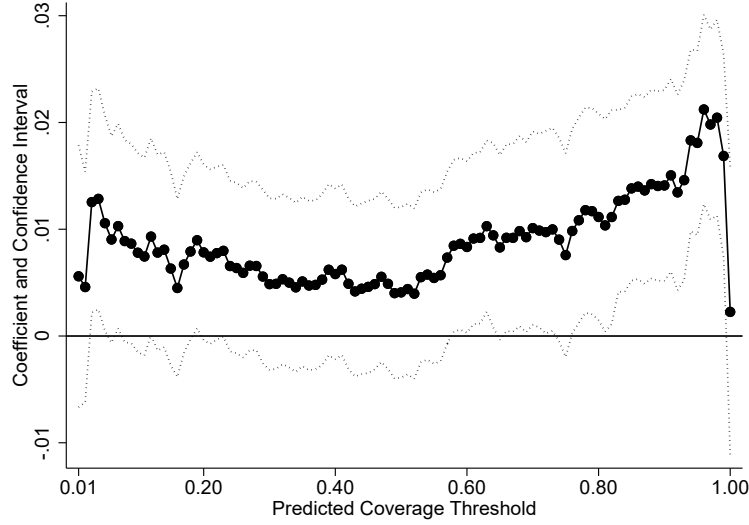


Figure 4: Coefficient Estimates and Confidence Intervals for Panel Regression by Predicted Coverage Threshold

Notes: This figure shows the coefficient estimate in a panel regression framework on an indicator variable equal to one if the predicted 3G coverage for a postmile is above a defined threshold.

with a significant increase in the traffic accident rate. However, the results are not able to provide insight as to whether or not our results are picking up a larger trend in accident rates that could lead to a spurious correlation between 3G coverage and accidents. In order to better understand the dynamic changes in accident rates when 3G coverage is introduced, table VI reports the results from event study regressions, equation 2.

The four columns in table VI define 3G coverage using a different threshold. Consistent with the previous table, there is not a significant relationship between 3G coverage and traffic accidents when coverage is defined at a threshold of 0.4 or 0.99. Columns (2), (3) and (4) use the thresholds of 0.6, 0.8 and 0.99, respectively. The columns all show that 2 years after a postmile gains coverage, there is a significant increase in the accident rate. The increase in the accident rate persists 3 and 4 or more years after gaining coverage. In the years immediately preceding 3G coverage, there is not a significant difference in accident rates.

The results in table VI are conveyed visually in figure 5. Figure 5 shows the plots of the coefficients from table VI, along with the 95 percent confidence intervals. In panel (a), the threshold of 0.40 is used to define 3G coverage. There is a slight upward trend in the accident rate prior to the year 3G coverage is gained (year 0), an insignificant increase in the accident

Table VI: Event Study Coefficients

	(1) I(Coverage $\geq$ 0.40)	(2) I(Coverage $\geq$ 0.60)	(3) I(Coverage $\geq$ 0.80)	(4) I(Coverage $\geq$ 0.99)
4+ years before	-0.016** (0.0075)	-0.020*** (0.0073)	-0.015** (0.0076)	-0.0093 (0.0096)
3 years before	-0.018*** (0.0060)	-0.014** (0.0059)	-0.0058 (0.0062)	0.0027** (0.0081)
2 years before	-0.0093* (0.0052)	-0.00035 (0.0052)	-0.0028 (0.0054)	-0.0186 (0.0073)
1 year before	-0.0053 (0.0042)	-0.0066 (0.0043)	-0.0062 (0.0046)	-0.0071 (0.0062)
1 year after	-0.0058 (0.0045)	0.0052 (0.0046)	0.0070 (0.0057)	0.0097 (0.0064)
2 years after	0.0040 (0.0059)	0.013** (0.0058)	0.021*** (0.0071)	0.0227** (0.0099)
3 years after	0.0092 (0.0083)	0.022*** (0.0082)	0.030*** (0.0086)	0.033*** (0.0123)
4+ years after	0.040*** (0.010)	0.061*** (0.010)	0.076*** (0.0091)	0.0490*** (0.0163)
Observations	632,216	597,246	531,401	315,627
Postmiles	48,632	45,942	40,877	24,279

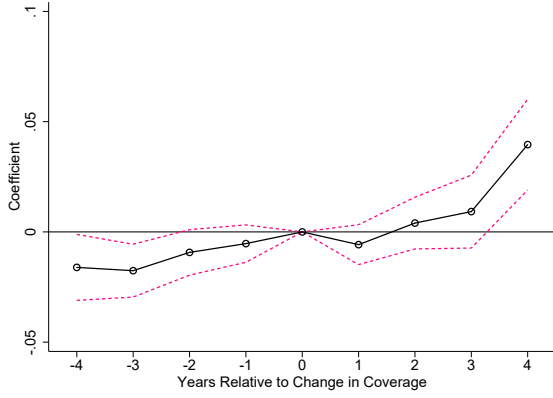
\*\*\* p<0.01, \*\* p<0.05, \* p<0.10. Dependent variable is annual number of accidents at a postmile. Traffic volume is the exposure variable in every column. Observations vary based on the number of postmiles that cross the defined predicted coverage threshold between 2001 to 2013.

rate in years 2 and 3 and a significant increase 4 or more years after coverage is gained.

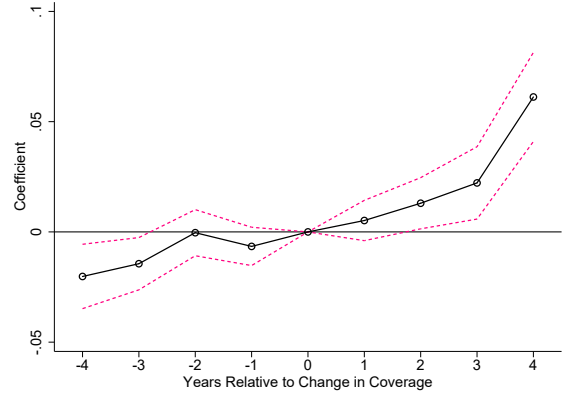
Using the threshold of 0.6 to define coverage in panel (b) generates a similar graph as panel (a). There are two noticeable differences between panels (a) and (b). First, in panel (b), there is essentially no change in the accident rate in the two years leading up to the change in coverage. Second, within two years after gaining coverage, the accident rate in panel (b) is significantly greater than in the year 3G coverage was acquired.

Panel (c) uses our preferred threshold of 0.8. The trend in the accident rate prior to the change in coverage is relatively flat. There is a noticeable rise in the accident rate after a postmile is defined as having coverage. When the threshold of 0.99 is used to define coverage in panel (d) a similar, but more pronounced pattern exists. It is worth noting the event study regressions only include postmiles that crossed the defined threshold. This causes each event

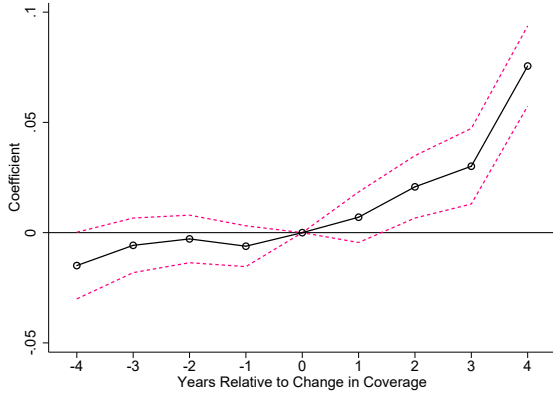




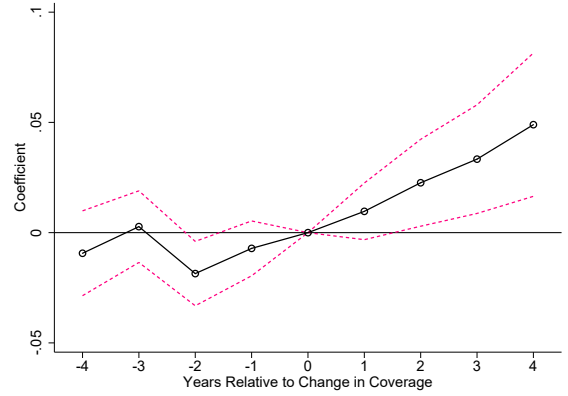
(a)  $\geq 0.40$  Threshold, N=48,632



(b)  $\geq 0.60$  Threshold, N=45,942



(c)  $\geq 0.80$  Threshold, N=40,877



(d) Threshold=0.99, N=24,279

Figure 5: Accident Event Studies Over Different Predicted Coverage Thresholds

study result to have a different number of postmiles, which are reported in the figure.

The results in tables V and VI, along with figures 4 and 5 provide evidence that there is a significant relationship between gaining 3G coverage and the traffic accident rate. Although event study results are only reported for four unique thresholds, any threshold between 0.58 and 0.99 yields similar figures, further strengthening the robustness of the results.

### C. Heterogeneous Effects

Using the universe of highway postmiles in California shows that introducing 3G coverage is associated with a significant increase in the accident rate. However, the effect of using a cell phone while driving may depend on many factors, such as the traffic patterns along a postmile, the age of the driver at fault and the severity of the accident.

## Postmile Traffic Volume

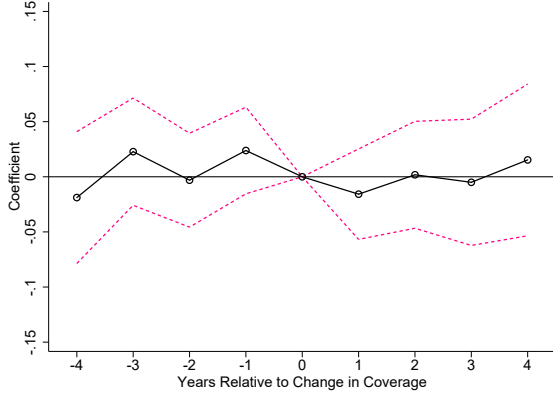
Postmile fixed-effects do control for many unobserved, fixed characteristics associated with a road segment, but it is possible that areas with less traffic are impacted by 3G coverage differently than areas with more traffic. Figure 6 shows event study results using our preferred threshold of 0.8 after creating subsets of postmiles based on the average traffic volume in the postmile between 2001 and 2013. In panel (a) the results using postmiles with an average AADT below the first quartile are reported. No pattern emerges and none of the coefficients are significant at conventional levels. Similar conclusions are drawn when examining the second and third quartiles of traffic. The postmiles with the most traffic are reported in panel (d). One year following the onset of 3G coverage, there is a significant increase in the traffic accident rate and there is no evidence of a trend prior to coverage.

The results from figure 6 provide evidence that postmiles with high traffic volume are responsible for the main results above. Postmiles with less traffic do not have significantly different accident rates before and after 3G coverage becomes available. Although we cannot weigh in on differences in driving behaviors across the quartiles of traffic, 3G coverage appears to be more detrimental when traffic volume is high.

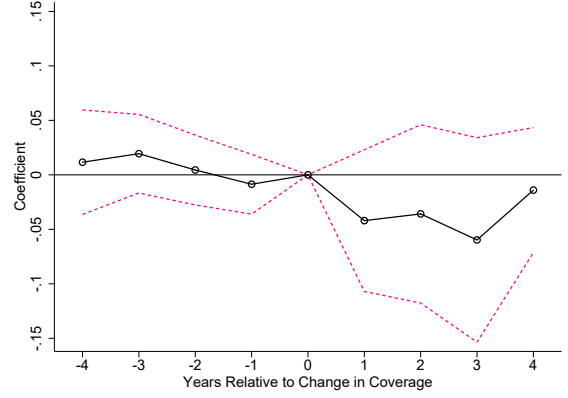
## Age of the Driver At Fault

Although many details of the traffic accident data are not consistently reported within and across police jurisdictions, we are reasonably confident that the age of the driver at fault in an accident is accurately reported. According to multiple studies discussed above, younger individuals are more likely to use and own a smartphone, compared to older individuals. This would suggest that younger drivers would respond more strongly to 3G coverage than older drivers. However, it is possible that younger drivers are better at using a smartphone than older drivers and an older driver with a smartphone may be more likely to get in an accident than a younger driver with a smartphone.

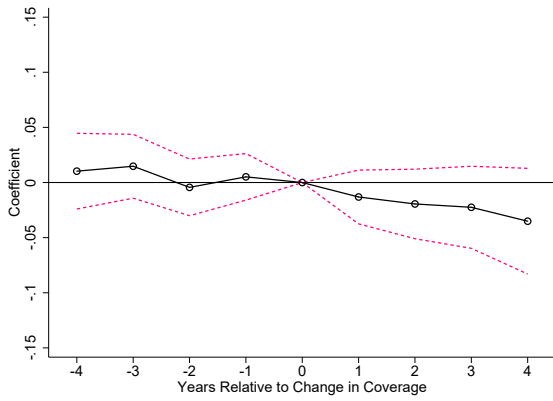
Figure 7 shows the results of event study regressions, again using 0.8 as the threshold for coverage, and stratifying the sample based on the age of the driver deemed at fault in the



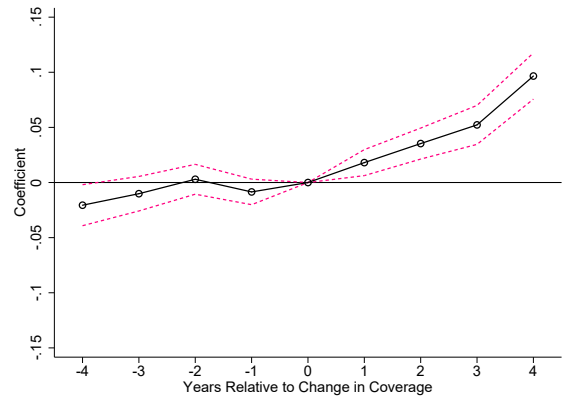
(a) First Traffic Quartile, N=9,301



(b) Second Traffic Quartile, N=10,207



(c) Third Traffic Quartile, N=10,131

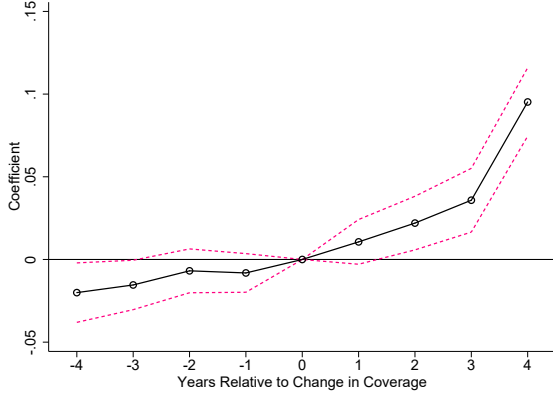


(d) Fourth Traffic Quartile, N=11,238

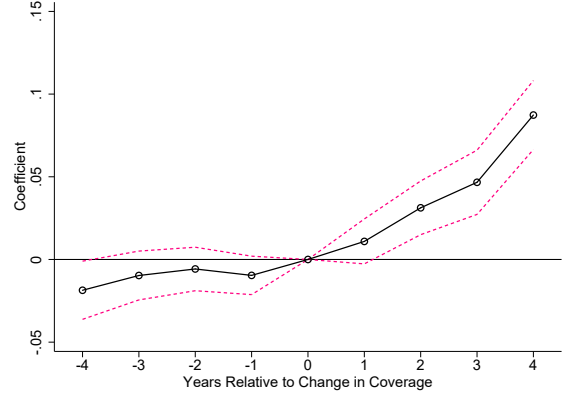
Figure 6: Heterogeneous Effects: Traffic Volume, Predicted Coverage Threshold=0.80

accident. In panel (a), the effect of 3G coverage on accident rates where the driver at fault is younger than 29 years old is reported. There is not a significant difference in accident rates prior to 3G coverage, but accident rates increase significantly two years after a postmile obtains 3G coverage. Panels (b) and (c) report the results for accidents where the driver at fault is between 30 and 49 years old, and 50 and 64 years old, respectively. The same pattern is seen between all three age groups in panels (a), (b) and (c). In panel (d), 3G coverage does not change the accident rate in crashes where the driver at fault is 65 years old or older.

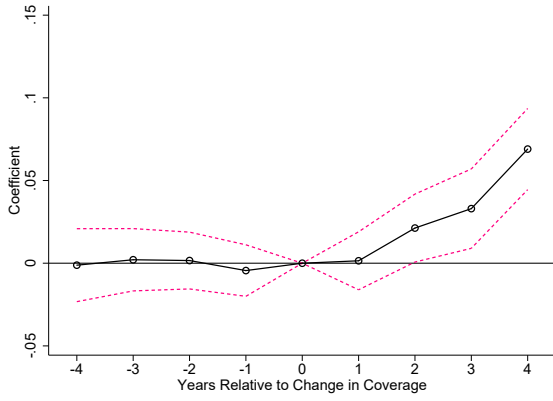
The age-specific event study results in figure 7 show that accidents caused by older individuals do not change when a postmile gains 3G coverage. Accidents caused by individuals between 16 and 64 increase in a postmile when 3G coverage is gained. The results suggest that 3G coverage has an impact on the driving behavior across a wide age range. However, we are



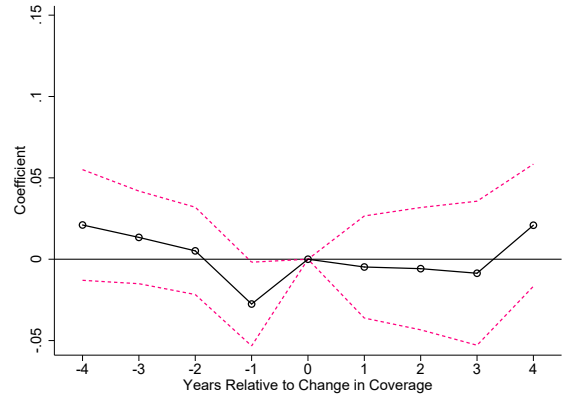
(a) 29 Years and Younger, N=36,880



(b) Between 30 and 49 Years, N=37,377



(c) Between 50 and 64 Years, N=33,857



(d) 65 Years and Older, N=27,494

Figure 7: Heterogeneous Effects: Age, Predicted Coverage Threshold=0.80

unable to decipher whether this is because there is an equal increase in cell phone use across the majority of ages while driving when 3G coverage is available or because cell phone use impacts drivers differently, depending on their age.

### Severity of the Accident

Each accident reported in the data is assigned to one of five general severity categories. Accidents that only damage vehicles are labeled as "property damage only". The category of "no visible bodily harm" captures accidents where the most severe outcome is that an individual says they feel pain, but it is not visible. Whiplash falls into this category. Accidents categorized as "Non-Severe, Visible Bodily Harm" have individuals with cuts or bruises, but the wounds are not severe. "Severe Bodily Harm" implies that an individual requires immediate assistance and

has a critical injury. Accidents with a fatality are graded as the most severe type of accident.

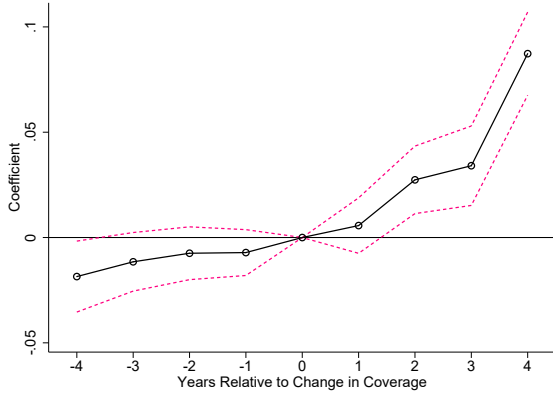
Figure 8 shows the effect of 3G coverage on accidents, by severity. Event study results from "property damage only" accidents are presented in panel (a) and mimic event study results above. After a postmile gains 3G coverage, less severe accidents increase and there is no evidence of a strong trend prior to gaining coverage.

Results for accidents where an individual has a non-visible injury are reported in panel (b). There are similarities between the pattern found in panel (b) and the least severe accidents in panel (a), but the estimates using accidents with non-visible injuries are relatively noisy. Panels (c), (d) and (e) report accidents that are increasingly severe. There is not a strong relationship between 3G coverage and accidents that involve visible injuries, severe bodily harm or fatalities.

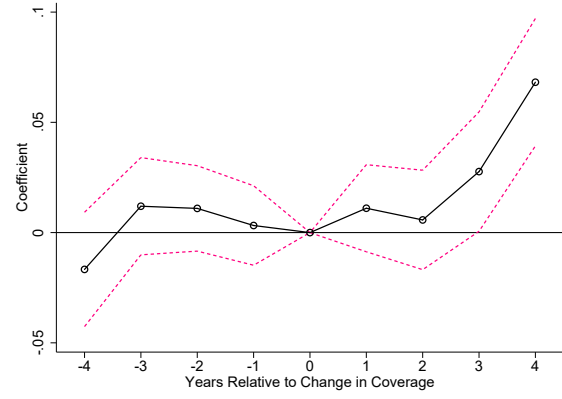
The results in figure 8 suggest that minor traffic accidents are driving the main results in the previous section. The relationship between accidents and 3G coverage becomes weaker as the severity of the accident increases. It is noteworthy that the number of postmiles in the regressions decrease significantly as the severity of the accident being examined rises. This is because there are relatively few postmiles that have a fatal accident in the data and those postmiles without a fatal accident between 2001 and 2013 are automatically dropped from the regression. Nonetheless, the insignificant relationship between severe accidents and 3G coverage is consistent with many of the previous studies that find a limited relationship between cell phone use and fatal accidents.

### **Additional Regressions**

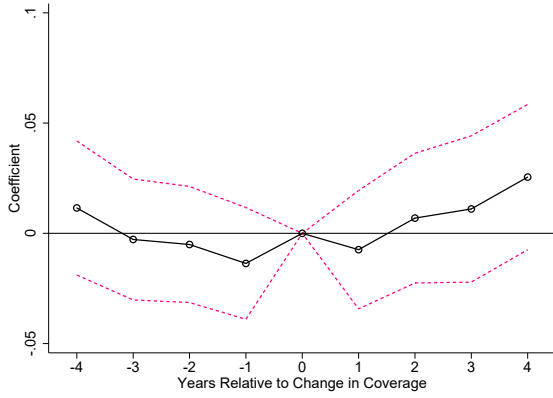
Earlier results suggest that 3G coverage is more likely to increase the accident rate when the volume of traffic is relatively high. This finding is emphasized in panel A of table VII where accidents are separated into peak (6-10am and 4-8pm) and non-peak traffic times, according to the California Department of Transportation. Using our preferred specification where road segments with predicted coverage over 0.8 are defined as having 3G coverage, the first row suggests that the accident rate during peak traffic times increase by 1.22 percent when a postmile gains 3G coverage. In the second row, we find that 3G coverage is associated with a 1.02 percent increase in the accident rate during non-peak hours, but the coefficient is only significant at



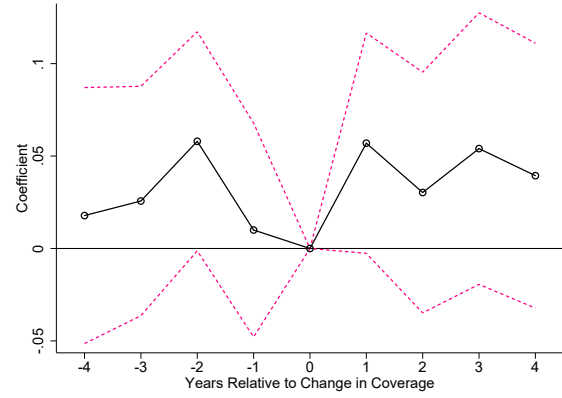
(a) Property Damage Only, N=37,765



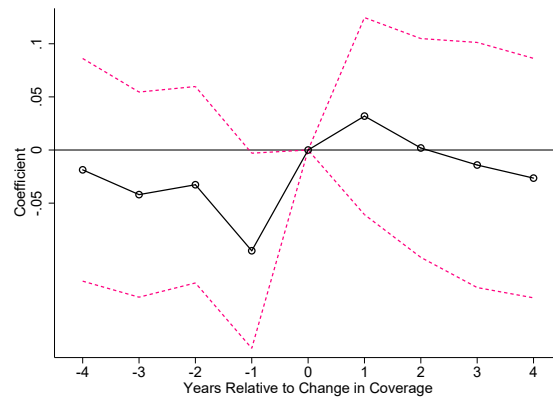
(b) No Visible Bodily Harm, N=30,601



(c) Non-Severe Visible Bodily Harm, N=28,617



(d) Severe Bodily Harm, N=12,254



(e) Fatal, N=8,367

Figure 8: Heterogeneous Effects: Severity of Accident, Predicted Coverage Threshold=0.80

the 10 percent level of significance.

The next panel of table VII analyzes road segments based on the year that 3G coverage was gained. The first regression in panel B only includes postmiles that gained coverage between 2005 and 2007. The relationship between 3G coverage and the accident rate is relatively strong, with the accident rate increasing 2.58 percent when 3G coverage is gained in these early adopting areas. In areas where 3G coverage was gained around the time of the Great Recession (2008 to 2010), there is not a significant relationship between 3G coverage and the accident rate. The accident rate increases by 3.56 percent when 3G coverage is gained in road segments that obtained coverage after the Great Recession (2011 to 2013).

In the time period of our analysis, California enacted two cell phone laws and our data is able to determine whether the bans were more or less effective in areas with 3G coverage. A hand-held cellular device ban while driving was enacted on July 1, 2008. Panel C of table VII uses monthly accident data in 2008 and regresses accidents in a road segment on monthly dummy variables and an interaction variable equal to 1 if an accident took place after July 1st on a road segment with 3G coverage. Road segment fixed effects are included and traffic is the exposure variable. Consistent with Burger et al. (2014), we do not find any evidence that the hand-held ban impacted accidents and the ban is not more influential in areas with 3G coverage.

California also enacted a specific texting ban six months later on January 1, 2009. In order to test whether this ban is more effective in areas with 3G coverage we restrict our sample to the 6 months before and after the texting ban went into effect (July, 2008 to June, 2009). We do not find any evidence that the texting ban influenced the accident rate in areas with or without 3G coverage. The original hand-held ban in July, 2008 may be masking an effect of the texting ban or the bans may not be effective in altering the accident rate.

A final set of regressions are reported in panel D of table VII. The last two regressions show results of our preferred specification using a logit and linear probability model to predict 3G coverage instead of a random forest. When a logit is used to predict coverage, the accident rate increases by 2.3 percent after gaining 3G coverage. Using a linear probability model to predict coverage suggests that the accident rate increases by 4.7 percent after 3G coverage is gained.

Table VII: Robustness Checks

	Coverage	Coverage x Law	Postmiles
Baseline Result	0.0111** (0.00493)		51,727
<i>Panel A: Time of Day</i>			
Peak Accidents (6-10 AM & 4-8 PM)	0.0122** (0.0054)		45,848
Off-Peak Accidents	0.0102* (0.0057)		48,680
<i>Panel B: Year Coverage Gained</i>			
Gained Coverage 2004-2007	0.0258*** (0.0071)		13,782
Gained Coverage 2008-2010	0.00128 (0.0135)		10,401
Gained Coverage 2011-2013	0.0356*** (0.012)		16,694
<i>Panel C: California Cell Phone Laws (Monthly Regressions)</i>			
Handheld Ban (July 1, 2008)		-0.00765 (0.0111)	
Texting Ban (January 1, 2009)		0.0131 (0.0111)	
<i>Panel D: Non-RF 3G Predictions</i>			
Logit Prediction	0.0234*** (0.0086)		51,727
LPM Prediction	0.0467*** (0.0141)		51,727

\*\*\* p<0.01, \*\* p<0.05, \* p<0.10. The dependent variable is annual number of accidents at a postmile. Coverage refers to the predicted 3G probability being greater than 0.80.



Our results using a random forest to predict 3G coverage find that the accident rate increases by 1.1 percent after coverage is gained. Using a random forest to predict 3G coverage appears to lead to a more conservative estimate of the relationship between accidents and cell phones, compared to using a logit or LPM.

In unreported regressions, we find that the results are not dependent on the exclusion of a particular year. When any single year is dropped from the sample, there is not a meaningful change in the results.

## V. Discussion

Many studies exist that examine the relationship between cell phone use and driving behavior. 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. We overcome many of the limitations in previous research by exploring how all traffic accidents respond to changes in 3G coverage.

Our analysis first attaches cellular tower information to postmiles for each year of data. The FCC reports 3G coverage data in 2016 and we assume that 3G coverage was not available prior to 2005. Machine learning techniques allow us to estimate how the construction of cellular towers change the predicted level of 3G coverage along a postmile for every year that accident data is available.

Poisson fixed-effects regressions compare postmile accident rates before and after the introduction of 3G coverage. We find that accident rates increase in a postmile after a tower is constructed and a postmile gains 3G coverage. The identifying assumption in the empirical analysis is that unobserved characteristics that influence traffic accidents are unrelated to the construction of cellular towers. Although we cannot directly test whether or not our identifying assumption holds, we are confident in our results. Regressions incorporate changes in traffic volume, reducing concerns that the effect of 3G coverage is being confounded by an increase in traffic. Postmile fixed-effects capture many important unobservable characteristics of a road segment that are related to accidents, such as road quality, line-of-sight and unchanging traffic

patterns. Event study results mitigate concerns that the increase in accidents is part of a larger trend that began prior to a postmile gaining 3G coverage. Any remaining endogeneity in our analysis comes from a systematic change in driving behavior that is unrelated to cell phone use and happens to occur when a cellular tower is constructed.

In summarizing the results above, a plausible story emerges. Cell phone tower construction increases the likelihood that a road segment has 3G coverage. Postmile accident rates in the years preceding 3G coverage are statistically similar to the year coverage is acquired. In the year after gaining coverage, there is a subtle increase in the accident rate. Two, three and four or more years after a postmile gains coverage, the accident rate increases significantly. Because changes in 3G coverage results are determined largely by the construction of cellular towers, the delayed accident rate response is not surprising. Historically, cellular towers have not been constructed by cellular carriers such as Verizon or AT&T. Instead, firms that specialize in cellular tower construction build the towers and then lease the tower to cellular providers. This suggests that it is possible for a tower to be constructed near a postmile, leading us to assign the postmile 3G coverage, but a lag between tower construction and service suggests that users may not change their driving behavior until the following year.<sup>29</sup>

Gaining 3G coverage does not influence all road segments in the same way. Road segments that have relatively low traffic volume do not see a significant change in traffic accidents after 3G coverage becomes available. Accidents where the driver at fault is over 65 years old are not impacted by 3G coverage. The trend in severe accidents where bodily harm is visible or there is a fatality does not change when 3G coverage becomes available. This suggests that 3G coverage increases the likelihood of a non-severe accident occurring in areas of high traffic and for drivers under the age of 65. In other words, when a road segment gains 3G coverage, fender benders in high traffic areas where the driver at fault is relatively young are more likely.

The magnitude of the results are comparable to previous research using traffic accidents as an outcome. Our point estimates suggest that the accident rate in a postmile is 1.1 percent higher when there is 3G coverage, compared to there being no 3G coverage. The average

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<sup>29</sup>In 2017, Verizon and AT&T signed a contract with the cellular tower construction company, Tillman Infrastructure, where Tillman builds towers specifically for Verizon and AT&T, reducing the time between tower completion and usage (Reuters, 2017).

postmile in our data over all years has an accident rate of 0.94 per 10,000 AADT and an average AADT of 61,784. If all 51,727 postmiles in the data gained 3G coverage, a 1.1 percent increase would translate into 3,305 more accidents per year in California.

A 1.1 percent increase in the accident rate is comparable to work by Adams et al. (2012), but noticeably less than Carpenter and Dobkin (2009) and Faccio and McConnell (2018). Adams et al. (2012) use changes in state-level minimum wages to show 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 motor vehicle fatalities increase by 15 percent after an individual becomes legally allowed to drink at the age of 21. Faccio and McConnell (2018) conclude that Pokémon Go was responsible for 134 crashes, a 47 percent increase, in Tippecanoe County between July 6, 2016 and November 30, 2016, the 5-month time period in which the game Pokémon Go 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 by nature. Both alcohol consumption and motor vehicle fatalities decrease as individuals age (Carpenter and Dobkin, 2009). Pokémon Go users peaked at approximately 25 million users per day in July, 2016 then quickly fell to less than 7 million users by January, 2017 (Windels, 2017). General cell phone use grew throughout the 2000s and continues to grow today (Deloitte, 2017).

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 cell phone 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, observing a change in accidents is difficult to detect.

Using the introduction of 3G coverage to capture cell phone use is beneficial because in areas without 3G coverage, the benefits of a smartphone are limited; only calling and texting are available in areas with 2G coverage. This does highlight a limitation of using 3G coverage to identify effects. If an area that gains 3G coverage previously had 2G coverage, we are capturing the effect of a postmile moving from 2G to 3G coverage. Assuming that a driver is texting

when there is 2G coverage and using other smartphone functions when there is 3G coverage, our positive findings then suggest that the functionality of the smartphone is more distracting than texting. It is possible that a driver is less likely to use a smartphone to text when there is not 3G coverage and entering 3G coverage increases the use of all smartphone functions. We cannot observe what drivers are doing when they enter an area with 3G coverage, and are unable to provide more insight into the exact mechanism causing the increase in accidents when 3G coverage becomes available. Despite this limitation, the use of 3G coverage as a measure of cell phone use improves upon previously used proxies.

In many of the studies, fatal traffic accidents are used (Abouk and Adams, 2013; Kolko, 2009). In figure 8, less severe accidents increase when 3G coverage becomes available, but more severe accidents and fatal accidents are not impacted by 3G coverage. Our results suggest previous studies may not find a persistent relationship between cell phone use and accidents because fatal accidents are used as the dependent variable. Additionally, the current paper is able to examine traffic accidents at the postmile level as opposed to the state level, which allows us to capture important unobservable characteristics that may influence accident rates. Using machine learning techniques to estimate the relationship between traffic accidents and 3G coverage at a fine geographic level yields an important finding that researchers have been unable to identify: cell phone use leads to a persistent increase in traffic accidents.

## VI. Conclusion

This paper uses the construction of cellular towers between 2001 and 2013 in California to show that accident rates increase when a road segment gains 3G coverage. Estimates of 3G coverage are derived from historical cellular tower information, current 3G coverage and machine learning techniques. The main results show that traffic accidents in a postmile increase after gaining 3G coverage. Event study results show there is not a trend in accidents within a postmile prior to gaining coverage and the rise in accidents is most noticeable two, three and four or more years after gaining coverage. The findings are not sensitive to the threshold used to define coverage, the time-of-day that the accident took place or using a logit model to predict coverage instead

of machine learning.

We contribute to the literature on cellular phone use and accidents. Unlike much of the previous work, we show that there is a significant and persistent increase in accidents following the introduction of 3G coverage. Although we cannot identify changes in specific driver behavior, heterogeneous results show that accidents that increase after 3G coverage is introduced do not involve severe injuries, occur in highly trafficked areas and are caused by drivers younger than 65.

These detailed results speak directly to policy makers. Banning cell phone use by drivers has not effectively reduced traffic fatalities, but laws requiring cars to have certain safety features may prove to be more influential. Blind spot monitoring, lane drift alerts and collision avoidance systems are becoming increasingly common. Effective in May, 2018, back-up cameras are required on all new vehicles less than 10,000 pounds (Bomey, 2018). Advancing car safety features may be able to overcome the increase in distraction caused by increasing cell phone usage by drivers.

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## VII. Online Appendix

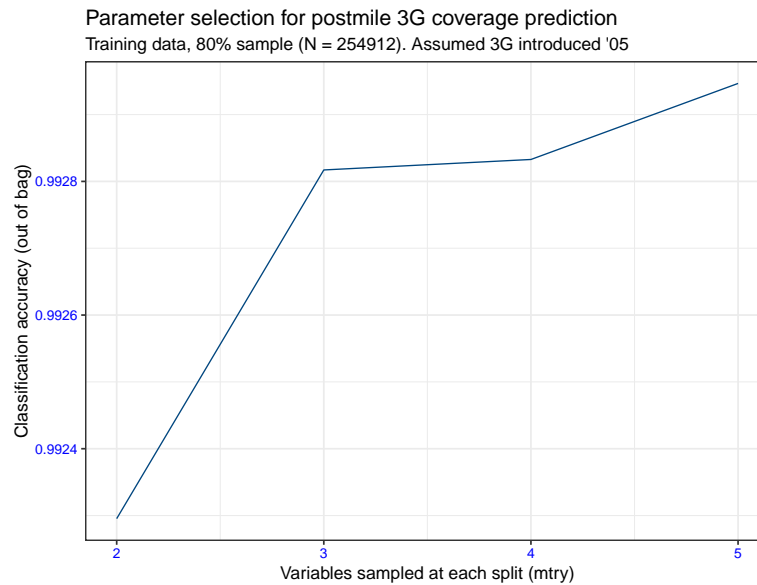


Figure 9: Random forest parameter selection

This plot shows cross-validated performance varying the number of variables sampled at each split. This is implemented by cross-validating over the parameter *mtry* in the *caret* package.

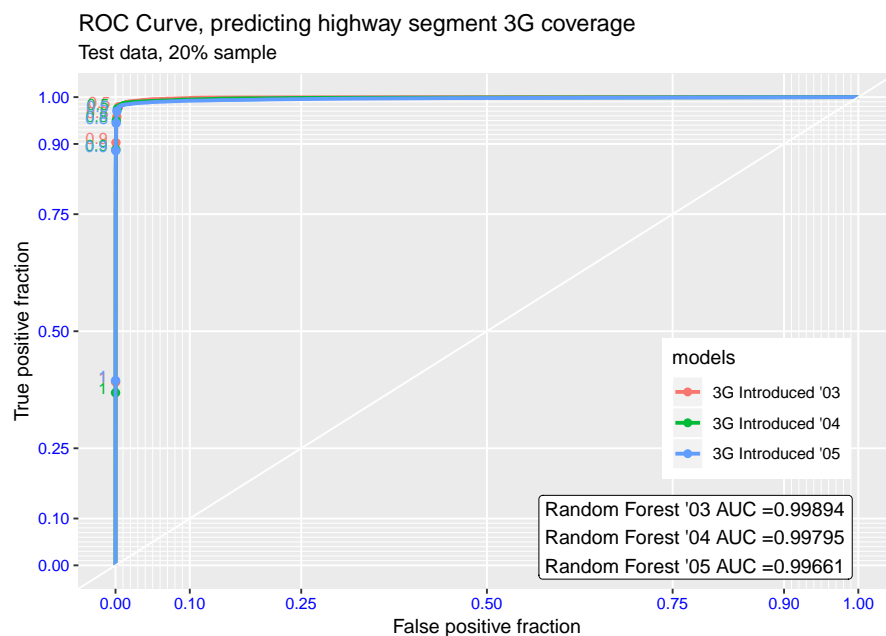


Figure 10: ROC plot varying date of 3G introduction.

This plot shows three ROC curves, one for each model where the date of 3G introduction is varied.

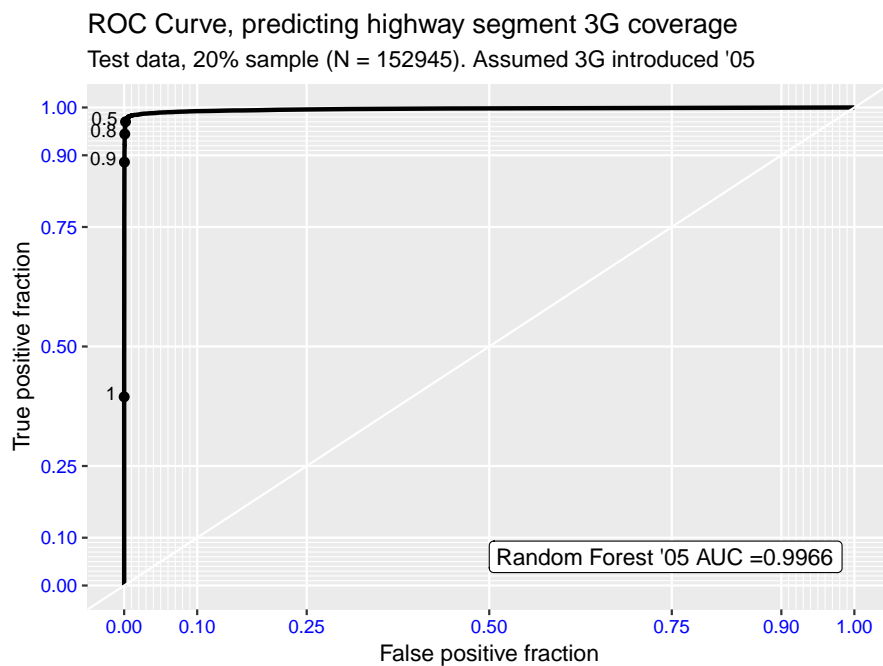


Figure 11: ROC Curve

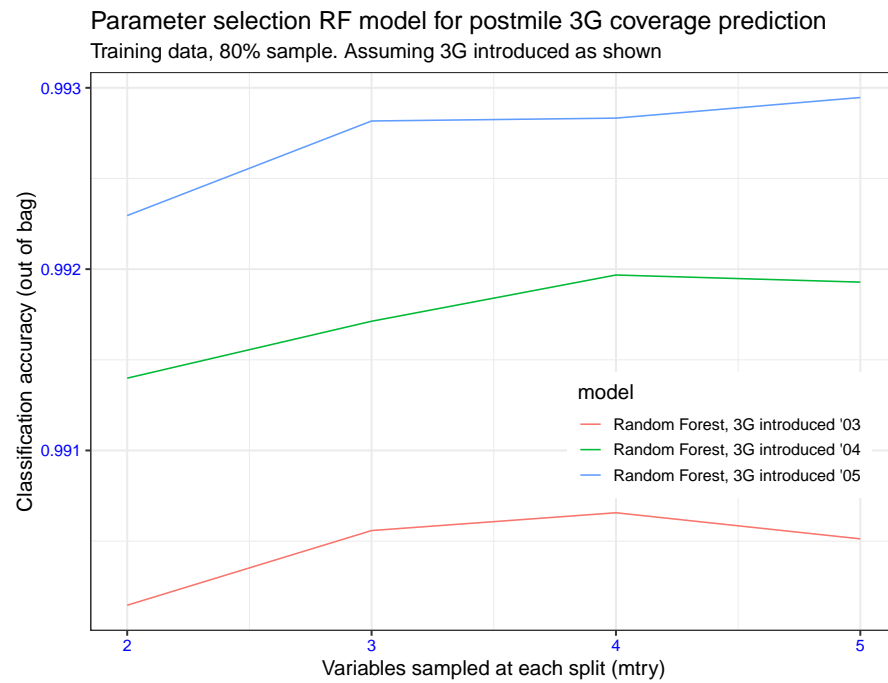


Figure 12: Parameter selection for models varying assumption of 3G introduction  
This plot shows cross-validated performance varying the assumed year of 3G introduction, and varying the number of variables sampled at every decision node.

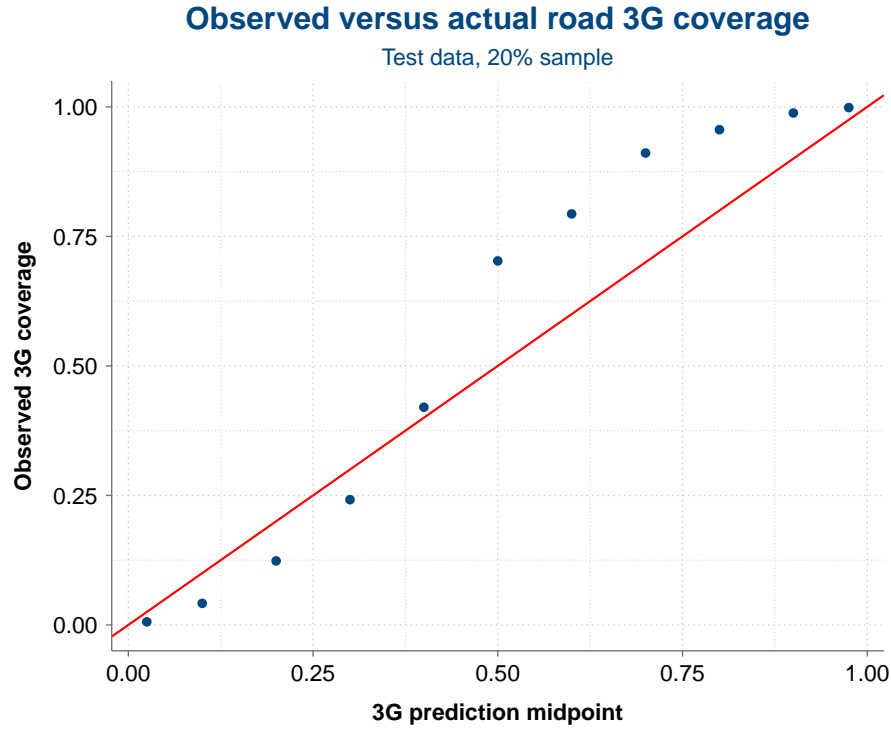


Figure 13: Calibration plot

This plot shows prediction calibration by binning the 3G predictions into eleven bins, and for each bin calculating the observed 3G coverage. According to (Dawid, 1982), forecasts are "well calibrated if, for example, the long-run proportion of forecast 75 percent credible intervals that succeed in covering the actual value of the predicted quantity turns out to be 75 percent." This corresponds to observed event percentages on the y-axis lining up with the bin midpoints on the x-axis, shown in the red line.

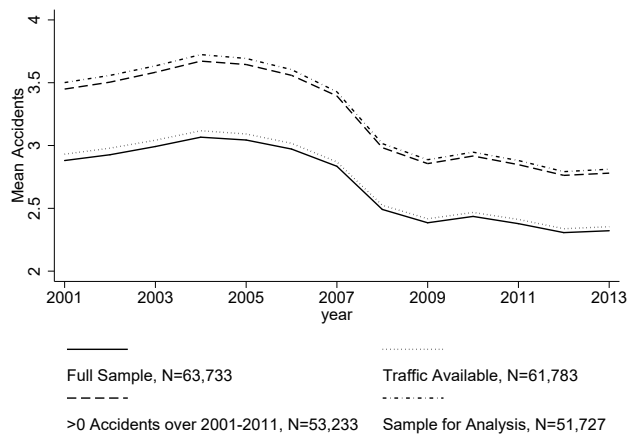


Figure 14: Average Accidents Over Time by Sample of Postmiles (N)