ABSTRACT

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In the first chapter of my dissertation, I assess the affect of wires alerts for exteme weather on hazard mitigation. Wireless alerts delivered through mobile phones are a recent innovation in regulatory efforts towards preparation for extreme weather events including flash floods. In this article, I use difference-in-differences models of car accidents and traffic volume, respectively, from days with government issued alerts for flash flood in the State of Virginia. I find that wireless messages for flash flood reduced car accidents by -17.3 percent and reduced traffic volume by -5.2 percent, relative to the predicted level using standard, non-wireless alert protocols. These results imply that wireless warning

messages effectively contribute to reductions in exposure to hazards associated with extreme weather.

In my second paper, I analyze the effects of a unique forest conservation policy on residential development and assess the additionality in forest cover due to this policy. I combine panel data on forest cover change from satellite imagery and parcel-level modeling on residential development, including residential subdivisions occurring before and after policy adoption. My results indicate that after introducing the policy, there was a 23% increase in forest cover within subdivisions relative to the amount without the policy.

In my third and final paper, I assess the effect of a California 1992 wildfire hazard disclosure law on parcel level probability of development using panel data on the location and timing of residential development. I find that after the introduction of the hazard disclosure law, annual probability of development is reduced by -13% and -24%, for parcels located in high and very high severity areas, respectively. Based upon these results, the 1992 hazard disclosure law was at least moderately effective at updating homeowners' subjective perception of exposure to wildfire risk and reducing the rate of development in the highest severity locations.

ESSAYS ON NATURAL HAZARD MITIGATION AND FOREST COVER CHANGE

By

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Chapter 1: Wireless Alerts for Extreme Weather and the Impact on Hazard Mitigating Behavior

Nearly every community in the United States is periodically threatened by extreme weather events including hurricane, tornado or flash flood. The National Weather Service actively monitors weather events as they develop and in the case of an imminent threat, issues emergency alerts to affected areas. To complement existing warning protocols, the Wireless Emergency Alert (WEA) system was adopted in the US in 2012 and is designed to issue warnings directly to mobile devices in case of national emergency, extreme weather and AMBER alerts. Wireless messages in cases of extreme weather are targeted to mitigate potential risk from individuals facing life-threatening exposure to inclement weather. The purpose of this article is to study the effect of WEA messages for extreme weather on daily car traffic conditions based upon a sample of flash flood events from counties located in the State of Virginia between 2011 and 2013. I evaluate hazard mitigation outcomes in response to WEA messages through an empirical examination of car accidents and assess mechanisms for hazard mitigation through an analysis of traffic volume patterns following WEA messages.

The growth of mobile phone usage has changed how people communicate and altered the global economy. The United Nations (UN) estimates that mobile phones have spread faster than any other technology in world history (UN 2010). Previous research has examined the impact of access to mobile phones on micro-economic development outcomes. This includes studies of the impact of mobile phones on markets for fish (Abraham 2006; Jensen 2007), agriculture (Chowdhury and Wolf 2003; Muto and Yamano 2009; Aker 2010) and textiles (Chowdhury and Wolf 2003; Jagun, Heeks, and Whalley 2008). These studies suggest that access to mobile phones reduces costs of communication and price dispersion, improving both consumer and producer welfare in the process. However, mobile phone use can have a broader impact on individuals' lives, including changes in the mode of communication between governments and citizens. In case of extreme weather emergency, government agencies in the US and other developed nations traditionally rely on conventional media sources, including television and radio, to distribute warning messages. With the advent and near ubiquity of mobile devices, governments can now send tailored and geographically explicit warning messages directly to individuals with the highest risk of exposure to dangerous weather conditions.

Previous research has assessed the effect of product warnings on consumer health risks and other hazard mitigating behavior. This includes studies of hazardous cleaning products (Viscusi, Magat and Huber 1986), work place chemical hazards (Viscusi and Connor 1984), and food safety (Loureiro and Umberger 2007; Wang, Mao and Gale 2008). Findings of these studies support the hypothesis that an individual's willingness to undertake hazard mitigating behavior generally increases with the perceived level of risk presented by the product. Driving conditions are often adversely affected by extreme weather events. Many studies have found weather conditions such as precipitation and poor visibility to be significant determinants in predicting car accident outcomes

(Levine et al., 1995; Eisenberg 2004; Brijs, Karlis and Wets 2008; Jung, Quin and Noyce 2010). However, no previous research has evaluated the effect of emergency weather alert protocols on hazard mitigation outcomes such as automobile collisions or other observed traffic patterns.

This study is based upon a panel database of daily car accidents and traffic volume from all counties located in the State of Virginia in the years 2011 to 2013. The econometric model is a Poisson model of the daily count of car accidents per county and I identify the effect of WEA messages based upon difference-in-differences variation. The treatment group includes all counties that received a WEA message for flash flood, during the post-WEA period (July, 2012 – December 2013). The first control group consists of all counties that received a non-wireless flash flood warning in the pre-WEA period (July, 2011 – June, 2012). The second control group includes counties that received a less severe and non-wireless alert for a flash flood watch during either the pre- or post-WEA period. Other control variables used to predict car accident counts include: time of day the alert was issued, weather related variables for daily precipitation and average wind speed, day of the week, as well as fixed effects at the county and month-year level. I also assess potential mechanisms for reductions in car accidents due to WEA messages utilizing hourly traffic volume from counties that received flash flood warnings during the pre-WEA and post-WEA period. I identify the differential effect of WEA messages on traffic volume using a difference-in-differences regression discontinuity (RD) analysis from the hours just prior, and immediately after the issuance of an alert. I control for trends in traffic volume by time of day and utilize a local linear regression control function to account for the impact of inclement weather and other time varying traffic volume trends in the neighborhood of the discontinuity.

My analysis highlights several main conclusions. On average, car accidents are elevated, in both the pre- and post-WEA periods, in counties that received a flash flood warning versus a flash flood watch. This is consistent with the hypothesis that flash flood warnings are issued primarily on days with more car accidents due to extreme weather conditions. I find that WEA messages for flash flood reduced a statistically significant average of -17.3 percent daily car accidents relative to the number of car accidents using non-wireless warning protocols. Based upon estimates for the average car accident cost from the National Highway Traffic Safety Administration (NHTSA), WEA messages resulted in an expected reduction in the cost of car accidents by -$3.5 million in Virginia during the post-WEA period. I also find changes in driving behavior in response to WEA from my investigation of traffic volume trends. At the boundary, I estimate that WEA messages lead to a statistically significant reduction of approximately -4.0 percent of cars travelling per hour, relative to traffic conditions following non-wireless flash flood warnings. These results suggest that at least some individuals respond to WEA messages by delaying or canceling travel plans during extreme weather periods. Thus, observed reductions in car accidents may be due, in part, to reduced traffic volume following the issuance of a WEA message.

This study makes several important contributions to the literature. This is the first study to empirically examine the effect of mobile emergency alerting protocols on car accident outcomes or other hazard mitigating behaviors. I utilize a difference-in-differences natural experimental design to isolate the effect of WEA messages on car accident and traffic volume outcomes. This study design helps to eliminate bias from several potential sources including: correlation between severe weather trends and days with flash flood warnings as well as changes in weather and other traffic trends from the pre-WEA to the post-WEA period. WEA is currently one of only a handful of nationally operated systems designed to deliver geographically explicit emergency alert messages to mobile devices. Results of this analysis suggest that wireless messages for extreme weather successfully reduce the number of car accidents and traffic volume compared to existing non-wireless protocols. The US experience with WEA implementation may serve as an example to other countries and municipalities considering the adoption of similar mobile warning systems.

The remainder of this article is organized as follows. In the next section, I provide an overview of WEA policy adoption as well as the study area chosen for this analysis. Next, I describe the econometric model and data used to estimate the effect of WEA messages on car accident outcomes. This is followed by the empirical results and several robustness checks. I then present an analysis of potential mechanisms for car accident reductions using traffic volume data. I conclude with some summary remarks as well as implications for future research.

I. Policy Overview and Study Setting

The Wireless Emergency Alert (WEA) system was established in the United States in 2012 and is designed to warn citizens of potential and imminent threats by issuing an alert to WEA capable cellphones through mobile carrier networks. WEA capable cellphones include most smartphones, which as of 2013 the majority (56 percent) of Americans own (Smith 2013). All WEA enabled smartphones may receive an alert unless the subscriber has specifically opted out of alerts online. The WEA system is operated by several coordinating federal agencies including the Federal Emergency Management Agency (FEMA), Federal Communications Commission (FCC), the Department of Homeland Security (DHS) and the National Weather Service (NWS). WEA protocol may issue warnings, typically at the county level, related to extreme weather events, local emergency, AMBER alerts or presidential alerts during a national emergency.

Emergency messages in case of extreme weather are primarily the responsibility of the National Weather Service (NWS). The NWS distributes non-wireless emergency alerts through NOAA Weather Radio, local news broadcast, and the Emergency Alert System on radio and television. In addition, local governments may have their own emergency alert systems such as outdoor sirens as well as email and mobile alerts delivered to subscribing residents. However, all other local systems for emergency weather alerts that are distributed through mobile devices are strictly opt-in systems, requiring the individual to subscribe in order to receive weather updates. The NWS actively monitors storm systems as they develop from weather monitoring stations distributed across the US. In cases of flash flood, for instance, the NWS ranks oncoming storm systems into categories of flash flood watch and warning. A flash flood watch generally indicates conditions that may develop into a flash flood event but the occurrence is neither imminent nor certain. A flash flood warning, on the other hand, indicates that a flash flood is in progress, imminent, or highly likely.[1]

Protocols for WEA messages are in addition to existing NWS procedures for emergency weather alerts, which did not otherwise change after WEA introduction. WEA messages may be issued in case of tsunami, hurricane, typhoon, dust storm, extreme wind and flash flood. The WEA system for extreme weather events was activated nationally beginning June 29, 2012. When a storm system develops into an imminent threat, the NWS will nominate an alert for WEA message. This recommendation is then passed on to the DHS and then to mobile carriers for distribution to mobile devices.[2] All individuals located within affected areas with a WEA capable cellphone will receive an alert unless the individual has opted out of WEA messages online. WEA messages are less than 90 characters in length and are designed to warn citizens of the nature of the weather emergency, the area affected and advise individuals of appropriate precautionary behavior. WEA is reserved only for the most severe weather conditions, so as an example, WEA messages would be distributed when a storm

[1] For a full list of NWS flash flood watch and flash flood warning criteria, see sections 4.2.2 and 5.2.2, respectively: http://www.nws.noaa.gov/directives/sym/pd01009022curr.pdf

[2] WEA messages may only be issued to areas with cell phone coverage, gaps in service most often overlap with locations of protected lands (e.g. national parks). For a map of Verizon cell phone coverage (the largest cellphone network provider in the US) see http://vzwmap.verizonwireless.com/dotcom/coveragelocator/default.aspx?requestfrom=webagent.

is upgraded to flash flood warning status but would not be issued in cases of flash flood watch.

The WEA program is intended to provide an integrated and flexible system to alert American people in case of emergency or other hazards to public safety. Several countries either have adopted, or are experimenting with the adoption of wireless protocols for extreme weather. This includes systems currently being developed by countries in the European Union as well as active wireless alert systems in Japan, Chile, Israel and the US.[3] By distributing messages through mobile phone networks, government regulators hope to communicate directly with individuals facing the greatest exposure to risk and encourage appropriate hazard mitigating behavior. In cases of extreme weather like a flash flood, one of the principle aims of WEA messages are to encourage safer driving behavior during severe weather periods. Flash floods often entail elevated levels of precipitation that may directly imperil driving conditions. In addition, one of the greatest hazards posed by flash flood result from roadways deluged with excess rainfall and as little as two feet of water can carry away most automobiles.[4] WEA messages signify that extreme weather conditions are imminent or ongoing and the purpose is to allow individuals time to seek cover and avoid driving during these periods. With enough warning, WEA messages

[3] For more information on other national systems for wireless emergency messages, see http://www.gsma.com/mobilefordevelopment/wp-content/uploads/2013/01/One2Many-Cell-Broadcast-Emergency-Alerts.pdf

[4] For more information on how flash floods develop and the hazards associated with these events see http://www.srh.noaa.gov/images/fwd/pdf/floodsandfloods.pdf

may help to prevent increases in automobile collisions, injuries and fatalities that often accompany extreme weather events.

The State of Virginia is the primary study region used to analyze the effect of the WEA system on car accidents in this analysis. There are a total of 134 counties and independent cities in Virginia. Weather conditions in Virginia are generally temperate climate but with warm and humid summer months. Severe weather most often occurs due to large thunderstorms, which may occasionally develop into flash floods. Tornadoes occur less frequently and Virginia typically averages approximately six tornadoes per year.[5] NOAA has issued several warnings for emergency weather in the case of flash flood and tornado in the pre-WEA (July, 2011 – June, 2012) and post-WEA (July, 2012 – December, 2013) periods, summarized in table 1.1. Based upon their greater frequency, analyzing the effect of WEA messages for flash flood on traffic outcomes in Virginia is the primary focus of this article.

Generally speaking, any weather event that is elevated to flash flood or tornado warning status will trigger the dissemination of a WEA message. However, the distribution of WEA events was hampered for much of 2012 due to software malfunction and scheduled system maintenance. As a result, after July 2012, there exist several instances of weather events which triggered non-wireless, NWS warnings for either flash flood or tornado which were not recorded as receiving a WEA message. Unfortunately, software malfunction impacted both the dissemination of WEA messages and the recording of WEA events. It is

[5] For a list of average yearly count of tornado incidence by state, see http://www.erh.noaa.gov/cae/svrwx/tornadobystate.htm

therefore impossible to determine the exact reason why WEA messages were not recorded in these cases. For this reason, in subsequent analyses, I drop any observations from counties that were recorded as receiving a NWS warning in the post-WEA period that lack a record of receiving a corresponding WEA message.

Overall, between July 2011 and December 2013 there were 131 days and 775 counties with extreme weather alerts for flash floods or tornado. Flash flood warnings make up the majority of alerts, representing approximately 74 percent of all extreme weather warnings and 84 percent of WEA messages. The incidence rate of flash flood warning was similar in the pre- and post-WEA periods. There were approximately 0.16 flash flood warnings per county per month in the pre-WEA period and 0.13 during the post-WEA period. A total of 269 counties received a WEA message, which represents approximately 35 percent of all warnings issued. Since program inception in July of 2012, WEA messages have been distributed relatively evenly across the State of Virginia. Figure 2 displays the frequency of WEA messages by county in Virginia from July, 2012 to December, 2013. WEA messages have been issued in 80 percent of counties, with a mean of 2.01 alerts per county over this time period. Albemarle County received a total of 11 WEA messages, the most recorded by any county in my sample.

II. Econometric Model of Daily Car Accidents

In this section, I develop an econometric model to evaluate the effect that the introduction of the Wireless Emergency Alert (WEA) system has on county level daily car accident counts. The daily count of car accidents are observed for each county that received either a non-wireless flash flood warning in the pre-WEA period (July, 2011 – June, 2012) or a wireless alert during the post-WEA period (July, 2012 – December, 2013). I also observe car crashes in control counties that received an alert for a flash flood watch that did not also receive a wireless or non-wireless warning for other severe weather events. Car accidents that occurred on other days without a flash flood warning or watch are not otherwise considered. In this way, estimated model parameters and unobserved daily heterogeneity in weather conditions are all specific to counties on days with conditions that may generate either a flash flood watch or flash flood warning.

The econometric model for this analysis is a Poisson model of daily car crash counts, clustered by date. Let $Y_{it} \in \mathbb{N}^{+}$ be the observed number of car crashes for county i in period t. W_{it} is a binary variable for flash flood warning treatment status, taking on a value of one if county i received either a wireless or non-wireless warning for flash flood in period t and is equal to zero otherwise. τ is a post regulatory dummy that takes on a value of one for all periods after the introduction of the WEA system. Let $\mathbf{X_{it}}$ be a vector of other control variables such as time of day the alert was issued, day of the week, as well as weather related variables for daily precipitation and average wind speed. The variable $\mathbf{C_i}$ is a vector of fixed effects at the county level and $\mathbf{M_{it}}$ represents fixed effects at the month by year level. The probability that $Y_{it} = y$ is represented in Equation 1 below

(1) $$\Pr\left[Y_{it}=y\right]=$$

$$\frac{e^{-\exp(W_{it}\otimes\tau\beta+\mathbf{X_{it}}\alpha_1+\mathbf{C_i}\alpha_2+\mathbf{M_t}\alpha_3+\sigma\eta_t)}\left(\exp\left(W_{it}\otimes\tau\beta+\mathbf{X_{it}}\alpha_1+\mathbf{C_i}\alpha_2+\mathbf{M_t}\alpha_3\right)\right)^{y}}{y!}.$$

Here, $\beta,\alpha_1,\alpha_2,\alpha_3$ are parameters to be estimated and clustering by date accounts correlation in daily storm level heterogeneity between counties and allows for over-dispersion (Cameron and Trivedi 2005).

The effect of the WEA system in Equation 1 is identified based upon difference-in-differences (DD) variation to compare the daily number of car accidents in treatment counties that received a WEA message for flash flood to (i) control counties that received a less severe flash flood watch message and (ii) counties that received a non-wireless flash flood warning in the pre-WEA era. Equation 2 displays the interaction of flash flood warning status (W_{it}), and the post-regulatory dummy (τ) included in Equation 1

(2) $$W_{it}\otimes\tau\beta=W_{it}\beta_1+\tau\beta_2+W_{it}\tau\beta_3.$$

The parameter β_1 accounts for baseline differences in car accident trends in flash flood warning counties versus watch counties. This parameter captures both the differential effect of flash flood warnings protocols on car accident outcomes as well as correlation in extreme weather conditions on these days, relative to days that receive only a flash flood watch. The parameter β_2 captures changes in car accident trends and extreme weather conditions during the post-WEA period. Finally, the effect of the WEA system is identified in Equation 2 based upon the interaction parameter β_3, which accounts for spatial and temporal heterogeneity in which counties are selected for WEA messages. However, as Ai and Norton (2003) and Puhani (2012) note, sign and significance of parameters for interaction terms from non-linear models cannot be interpreted directly. For this reason, I therefore stress the importance of marginal effects for interpreting the impact of WEA messages on the count of daily car crashes.

Marginal effects are calculated for all parameters in the model. For non-interaction terms, let $x_{it} \in \mathbf{X_{it}}$ and $\alpha_1^x \in \alpha_1$, Equation 3 represents the marginal effect of the covariate x_{it} on the daily count of car accidents

$$\text{(3)} \qquad \frac{\partial E\left[Y_{it}\right]}{\partial x_{it}} = \alpha_1^x \exp\left(W_{it} \otimes \tau\beta + \mathbf{X_{it}}\alpha_1 + \mathbf{C_i}\alpha_2 + \mathbf{M_t}\alpha_3\right).$$

For interaction terms, the formulation of marginal effects is slightly more complicated. In a linear regression, estimates from DD models are recovered through the assumption of additive separability of the conditional expectation function. In a non-linear model, cross-group differences between counties and over time need not be equal (Puhani 2012). Instead, the treatment effect of WEA messages on the treated group is recovered as the difference between the observed outcome, Y_{it}, with a WEA message to the counterfactual potential outcome without WEA message, Y_{it}^0. Let $\mathbf{\Omega_{it}} = \left\{\mathbf{X_{it}}, \mathbf{C_i}, \mathbf{M_t}\right\}$, the conditional expectation for the observed count of car accidents is

$$\text{(4)} \qquad E\left[Y_{it} \mid W_{it} = 1, \tau = 1\right] = \exp\left(\beta_1 + \beta_2 + \beta_3 + \mathbf{\Omega_{it}}\alpha\right).$$

Although the counterfactual outcome without WEA message cannot be directly observed, Y_{it}^{0} can be parametrically estimated using parameters from Equation 1 (Puhani 2012). The conditional expectation for the counterfactual count of car accidents without WEA message is

(5) $$E\left[Y_{it}^{0} \mid W_{it}=1, \tau=1\right]=\exp\left(\beta_1+\beta_2+\mathbf{\Omega_{it}}\alpha\right).$$

Equation 6 displays the difference between Equations 4 and 5 and represents the estimated marginal effect of WEA messages on daily car accidents

(6) $$E\left[Y_{it} \mid W_{it}=1, \tau=1\right]-E\left[Y_{it}^{0} \mid W_{it}=1, \tau=1\right]=$$

$$\exp\left(\beta_1+\beta_2+\beta_3+\mathbf{\Omega_{it}}\alpha\right)-\exp\left(\beta_1+\beta_2+\mathbf{\Omega_{it}}\alpha\right).$$

Estimates from Equation 5 may be interpreted as the additive effect that the introduction of the WEA system has on daily incidence of car accidents relative to the previous, non-wireless system that existed prior to WEA introduction. Because the exponential function is strictly monotonic, the treatment effect of WEA messages in Equation 6 will have the same sign as the estimated parameter β_3, though significance of these terms may differ (Puhani 2012). A negative and significant estimate from Equation 6 would indicate that WEA messages tend to reduce the incidence of car accidents by conveying new information regarding the imminent threat of extreme weather. For instance, individuals that received a WEA message may be more likely to delay travel and avoid roadways during extreme weather periods, thereby reducing car accidents. Alternatively, car accidents may be reduced because individuals are more likely to adopt precautionary driving behaviors in response to WEA messages, such as reducing speed and defensive driving techniques.

Equation 1 allow for heterogeneity in which counties are selected for WEA treatment across space as well as baseline differences in the incidence of car crashes over time. The primary identifying assumption in Equation 6 is that controlling for other observables, there are no other unobservable factors that impact the incidence of car crash on days with WEA messages that are not common to either flash flood watch days, or days with flash flood warnings in the pre-WEA period. In robustness checks discussed in the results section, I test sensitivity of my results to this assumption by running several falsification tests. I conduct a temporal falsification test using observations from the pre-WEA period (July, 2011 – June, 2012) with false treatment beginning in January, 2012. This exercise is used to check for differential time trends in car accident patterns between flash flood warning and flash flood watch counties which may confound estimates of the effect of WEA messages on car accident outcomes. To test for unobserved spatial heterogeneity in which counties were selected for WEA messages, I also conduct a spatial falsification test. In this model I compare car accident outcomes in counties that share a border with a county that was issued a non-wireless flash flood warning or WEA message to counties that share a border only with a flash flood watch county.

III. Available Data

Data used for this study are collected from two primary sources: emergency alert system (EAS) data from the National Oceanic and Atmospheric Administration (NOAA) and traffic outcome data from the Virginia Department of Transportation (VDOT). Emergency alerts are issued by the National Weather Service (NWS) for weather events impacting communities across the United States. NOAA maintains an online daily log of all WEA messages issued since program inception.[6] Using these data, I collect information regarding the location and time of WEA messages for flash flood issued between July, 2012 and December, 2013 in the State of Virginia. To compare the effect of WEA messages for flash flood to warnings issued for similar weather events in the pre-WEA era (July, 2011- June, 2012) and in flash flood watch counties, I collect data on all flash flood warnings and watches from NOAA's Interactive Products Database. Data for historical flash flood warnings are available from 1986 to the present day but information on historical flash flood watches only exist since July, 2011. For both WEA and non-WEA events, alert logs contain information on the time the alert was issued, locations affected and type of weather event.

I acquired car accident data from the Virginia Department of Transportation (VDOT), which collects information on the location and date for each car accident that occurs on public roads and highways in the State of Virginia. Using these data I determine the total number of car accidents for each day between 2011 and 2013 and for all counties and independent cities in

[6] WEA message logs are located here: http://weather.noaa.gov/pub/logs/heapstats/2013/

Virginia. Once aggregated to the county level, I merge the car accident database with the record of NOAA emergency alerts issued by county and by day. The outcome variable for this analysis is the daily count of car accidents per county. To allow sufficient time for alerting protocols to impact car crash patterns, if an emergency alert was issued after 10pm, I use accident totals from the day following the alert.[7] I also determine the number of licensed drivers per county, in hundreds of thousands, based upon data provided by VDOT from the year 2012.

My sample includes one treatment group and two overlapping control groups that serve as a basis of comparison to isolate the effect that WEA messages have on car crash patterns. The treatment group for this analysis comprises all counties that received a WEA message for flash flood on the day that the alert was issued in the post-WEA period. The first control group consists of all counties that received a non-wireless flash flood warning in the pre-WEA period. The second control group includes counties that were issued a less severe alert for a flash flood watch in either the pre- or post-WEA period but that were not also issued a flash flood warning. Observations from counties on days that do not fall into either the treatment group or one of the control groups are not considered in this analysis.

In order to explain daily incidence of car accidents I collect data for several other important control variables. Table 1.2 provides summary statistics for covariates included in this analysis. The time of day the alert was issued is included as a categorical variable with six four-hour groups (12am-4am, 4am-

[7] For reference, less than 5 percent of flash flood warnings were issued between 10pm - 12am

8am, 8am-12pm, etc.), with 12am-4am serving as the baseline category. This variable is used to capture differences in car accident patterns from alerts issued at different times of day, which may be common to both flash flood warnings and watches. In addition, I interact the dummy variable for flash flood warning status with emergency message time categories to assess the differential effect that emergency message timing has in counties that received a flash flood warning versus a flash flood watch.

Time of alert may be important to explain car crash incidence, especially as alert timing overlaps with daily commute schedules. As an example, figure 1.1 displays average hourly traffic volume for weekdays and weekends based upon VDOT data from 2011-2013. For weekdays, traffic volume peaks with morning and evening commuting traffic between 7am-9am and 4pm-7pm, respectively. On the weekends, traffic volume varies more smoothly throughout the day but reaches its highest level in the afternoon and early evening. Traffic volume is at its lowest level from approximately 12am-4am, which also serves as the baseline time category in my model. Emergency alerts that are timed to coincide with heavier volumes of traffic that occur as the population commutes to and from work may have a greater influence on both driver behavior as well as the number of cars on the road. I also include dummy variables for the day of week, with Sunday set as the baseline, to account for cyclical patterns in traffic volumes, which tend to peak during the workweek (Monday – Friday) and fall over the weekend. Month by year intercepts are used to account for other unobserved sources of temporal heterogeneity such as seasonal weather patterns and changing rates of smartphone ownership. I also include county specific fixed effects to control for unobserved sources of spatial trends such as average daily traffic volume that may also impact car accident outcomes.

To control for heterogeneous weather conditions that may impact car crash incidence, I collect data on per county daily averages for precipitation and wind speed from historical weather station data managed by NOAA's National Climactic Data Center.[8] For each day in my sample, I match counties to the closest neighboring active weather station collecting information on relevant weather related variables. For the vast majority of counties (85 percent), daily weather data are determined from weather stations located within county borders. Precipitation, measured in millimeters of rainfall per day, is expected to positively affect car crashes by decreasing road traction and visibility.[9] Based upon previous research (Levine et al. 1995), which has generally found an insignificant relationship between wind and car accidents, I anticipate an ambiguous sign for wind speed, which is measured in meters per second.

Table 1.3 provides a breakdown of the average daily counts of car accidents that occurred during the pre- and post-WEA periods among flash flood warning and watch counties. I report the number of accidents overall as well as per 100,000 licensed drivers. The average count of car accidents is elevated in counties that received a flash flood warning relative to conditions in flash flood watch counties. In the pre- and post-WEA periods, counties that received a flash

[8] NCDC queryable database of weather station data is located here http://www.ncdc.noaa.gov/

[9] I also calculate total daily snowfall for each county in my analysis but because most flash flood events occur in the spring and summer, no snowfall occurred on any of the dates in my analysis

flood warning averaged approximately 26 percent and 19 percent more car accidents per 100,000 licensed drivers than flash flood watch counties, respectively. This increase in the number of car accidents is most likely due to inclement weather conditions that tend to accompany warning messages. On average, flash flood warning counties report approximately 24.1 mm of precipitation on alert days versus 10.0 mm in flash flood watch counties. Overall, there is a decrease in the number of car accidents reported in flash flood warning counties in the post-WEA versus the pre-WEA period. However, these numbers are not directly comparable because of differing populations of flash flood warning counties as well as heterogeneous weather conditions between the pre- and post-WEA periods. It is therefore necessary to examine the model of daily car crash counts developed in the following section to determine the aggregate effect of WEA messages on car crash outcomes.

IV. Results

Table 1.4 reports results of the Poisson model of daily car accident incidence in Virginia Counties clustered by date.[10] All counties and dates included in this analysis received either a flash flood WEA message (during the post-WEA period), a flash flood warning (during the pre-WEA period), or a less severe flash flood watch (during either period). Table 1.5 provides average marginal effects for covariates included in this analysis. Coefficients from table 1.5 may be

[10] A negative binomial model of daily car accident counts yielded virtually identical results

interpreted as the average marginal effect of a deviation in observed covariate values on the daily count of car accidents per county. Standard errors are calculated using the delta method.

Based upon results of table 1.6, day of the week has a significant effect on predicting car accidents. As expected, car accidents peak during the workweek when traffic volume is highest. Tuesdays and Fridays report the highest average count of car accidents and Sunday reports the lowest levels of car accidents. Consistent with previous studies, higher levels of precipitation tend to increase the daily count of car accidents, though this coefficient is significant only at the ten percent level.

On average, slightly more daily car accidents occurred during the post-WEA period, though this effect is not statistically significant and sensitive to which months are set as the baseline. Flash flood warning counties, from all periods, average more car accidents than flash flood watch counties and this result is significant at below the one percent level. This is consistent with the interpretation that that flash flood warning events are timed to coincide with the most extreme weather conditions. Thus, car accidents may be elevated on these days due to the more severe weather conditions which tend to accompany these events.

The timing of alert messages for flash flood is an important predictor of the expected number of crashes. On average, days with emergency messages issued between 4am-8am report an increase in car accidents for both flash flood warning and watch counties, which is statistically significant at below the one percent level. This may be due to the fact that alerts issued during this time immediately precede the typical morning rush hour traffic commute. As a result, peak inclement weather conditions may arrive during the time of day with the largest number of drivers on the road, causing a spike in car accidents. Compared to flash flood watch counties, flash flood warning counties report an average of -1.52 fewer car accidents for alerts issued between 8am-4am, which is significant at below the one percent level. The large reduction in car accidents among flash flood warning counties during this time may be due to drivers responding to the perceived severity in weather conditions by delaying their morning commute until after the most extreme weather conditions have passed. However, only 1.2 percent of observations and 4.7 percent of flash flood warnings were reported between 4am-8am, the lowest share of any time category. Thus, the large magnitude of this effect could also be explained by some other unusual correlation of county and weather driving conditions among the small set of observations reported during this period.

The impact of WEA messages for flash flood is estimated based upon the interaction parameter of flash flood warning status and the post-WEA dummy variable. Table 1.6 provides a breakdown of the predicted change in car accidents due to the introduction of WEA messages, which is estimated based upon Equations 4-6. I calculate average change in car accidents overall, per 100,000 licensed drivers and as a percentage change from the total number accidents without WEA message. Based upon these results, I predict an average of 3.38 car accidents with WEA message and 4.09 car accidents without WEA message. This represents a difference of approximately -0.71 daily car accidents, or a reduction of approximately -17.3 percent compared to conditions without WEA message. Both of these results are statistically significant at below the one percent level.

The National Highway Transit Safety Administration (NHTSA) estimates that the average cost of a car accident is approximately $22,000 in 2013 dollars (Blincoe et al. 2014).[11] In total, 764 car accidents were reported in Virginia counties that received WEA messages for flash flood. Based upon predictions from this model, the introduction of the WEA system resulted in an expected reduction of approximately -160 car accidents relative to what would have occurred without WEA. Assuming that the national average cost of car accidents applies to observations from this model, WEA messages for flash flood contributed to an expected reduction of -$3.5 million in damages from car accidents in Virginia alone.

A. Robustness Checks

In this section, I test robustness of previous results to a variety of alternative specifications. Although my estimation results allow for heterogeneity in which counties are selected for flash flood warnings and WEA messages, my estimates may be confounded if diverging car accident trends exist between flash flood warning and watch counties over time. To test sensitivity of my results to unobserved time trends I conduct a temporal falsification tests using data from the

[11] NHTSA estimates that there were approximately 13.6 million car accidents in 2010 that caused economic damages of approximately $277 billion

pre-WEA period (July, 2011 – June, 2012) with hypothetical WEA treatment occurring in January of 2012. Covariate marginal effects are reported in table A1 located in Appendix A, with marginal effects for the false WEA treatment effect reported in table A2. Based upon these results, there is no significant difference in the effect of flash flood warnings after false treatment (January, 2012 – June, 2012) as compared to the period before (July, 2011 – December, 2011).[12]

Previous results may also be biased, for instance, if regulators routinely and non-randomly target flash flood warnings to specific areas of the state, or if these warning procedures significantly changed after the introduction of WEA. Therefore, in table A3 I conduct a spatial falsification exercise to test sensitivity of results to unobserved sources of spatial heterogeneity. In table A4 I provide marginal effects for false WEA treatment. In this estimation I include observations from the pre- and post-WEA periods from untreated counties that share a border with a flash flood warning county, as well as untreated counties that exclusively border flash flood watch counties. Untreated counties that border areas that received flash flood warnings are considered false-treatment observations and counties that border flash flood watch counties are considered false-control observations. Based upon these results, I find no significant baseline differences in car accident patterns between flash flood warning versus flash flood watch counties or between flash flood warnings issued during the pre-WEA and post-WEA period.

[12] In unreported results, I also try estimating models with false treatment beginning variously in November, 2011, December, 2011, February, 2012 and March, 2012 with no change in significance of false treatment results.

In previous results, I cluster by date to account for correlation in storm severity, along with other daily varying car accident trends between counties. However, correlation may also exist between observations within the same county over time. To account for serial correlation in observations over time, I estimate an alternative fixed effect Poisson model of the daily count of car accidents with fixed effects at the county level. Unfortunately, average marginal effects are impossible to interpret from fixed effect Poisson models due to the exclusion of the fixed effects from the condition expectation function. As an alternative, table A5 provides the incident rate ratios (IRRs) for covariates from this model. Statistical significance for covariates are determined based upon the deviation of the IRR from one. IRRs can be interpreted as the multiplicative effect of covariates from the baseline and the deviation of the IRR from one indicates the percentage change in the count of car accidents due to a marginal increase in the covariate of interest. Significance levels of covariates from table A5 are little changed from those of table 1.5. In addition, table A5 suggests a reduction in the count of car accidents due to WEA messages that is comparable in magnitude and significance to results of tables 1.5 and 1.6.

In table A6 I estimate a county fixed effect linear model, which is two-way clustered at the date and county level and includes all variables from table 1.4. Two-way clustered standard errors are calculated using the formulation proposed by Cameron, Gelbach and Miller (2011). Coefficients for covariates from linear models may be interpreted directly as marginal effects and are independent of other parameters from the model. Although the distribution of count data is often highly non-normal, as noted by Angrist (1999), the conditional expectation function for discrete covariates can be linearly parameterized using a saturated model, regardless of the support of the dependent variable. Not all covariates in table A6 are discrete: daily precipitation and wind are represented as continuous variables. However, so long as the conditional expectation function is reasonably saturated, table A6 may still provide an approximation of the average marginal effect and significance for other saturated parameters, including the effect of WEA messages on daily car accident outcomes. Based upon table A6, I find a significant WEA messages for flash flood reduce an average of -0.86 daily car accidents, which is significant at below the one percent level. Compared to table 1.6, I predict a slightly larger reduction in car accidents, though this difference is statistically insignificant. Marginal effects for other parameters from this model are generally of the same sign as those reported in table 1.5, though magnitudes and significance levels do differ somewhat.

In addition to the models discussed above, I also estimate a county fixed effect Poisson model using observations from all counties on all days, regardless of extreme weather warning status. In other models, I repeat results of tables 1.4-1.6 but drop the months July, 2013 – December, 2013, to provide symmetric pre- and post-WEA time windows. I also estimate a model including additional intercepts for alert time with twelve two hour time blocks (i.e. 12am-2am, 2am-4am, etc.). Additionally, I estimate other models with discretized decile categorical ranges for precipitation and wind speed and cubic polynomials for these parameters. Results of these alternative models are available upon request but conclusions from these models conform to those reported in tables 1.5-1.6.

V. Mechanisms for Car Accident Reduction

In this section, I address potential mechanisms for car accident reductions due to WEA messages for flash flood. There are two non-mutually exclusive hypotheses that may explain the observed reductions in car accidents. One explanation is that individuals who receive a WEA message abandon or delay their travel plans until after the severe weather period has elapsed. Another explanation is that in response to WEA messages, drivers adopt defensive driving behaviors that help reduce their chances of being involved in a car accident. Whereas the later hypothesis could be discerned by analyzing individual behavioral outcomes, the former hypothesis is testable through an analysis of traffic flow data on days with WEA messages.

Reductions in traffic volume may decrease hazard exposure to individuals who opt to avoid driving and may also result in spillover benefits to other drivers by reducing congestion during severe weather periods. I utilize a difference-in-differences regression discontinuity (RD) model to assess the differential effect of WEA messages on traffic volume. I compare traffic volume in the hours before and after the issuance of a WEA flash flood warning during the post-WEA period (July, 2012 – December, 2013) and traffic volume before and after the issuance of a non-wireless flash flood warning during the pre-WEA period (July, 2011 – June, 2012). Based upon the RD approach and assuming that commuting patterns and other weather trends vary in a predictable manner throughout the day, flash flood warning treatment is as good as randomly assigned in the neighborhood of the discontinuity (Lee and Lemieux 2010). Under the hypothesis that WEA messages impact an individual's driving decisions, we may expect that traffic volume is lower immediately following the issuance of a WEA message than would be predicted using existing non-wireless warning protocols. Previous research has estimated RD models with fixed effects (Hoxby 2000; Pettersson-Lidbom 2008). However, to the best of my knowledge, this is the first study to implement a difference-in-differences RD model.

The econometric model used for this analysis is estimated as follows. Let V_{iqdh} be the count of cars per hour for station i in quarter q (e.g. July, 2011 – September, 2011), on day d and hour h. $\bar{V}_{iqh}$ represents the average count of cars from station i for the quarter q, which is calculated separately for every hour of the day and for each day of the week. $\bar{V}_{iqh}$ is based upon an average of n_q observations per quarter, typically about 13, as this is the approximate number of weeks per quarter. As demonstrated in figure 1.1, traffic volume tends to follow a predictable daily pattern due to daily commuting schedules. Therefore, I construct the dependent variable $\tilde{V}_{idh}$, displayed in Equation 7

(7) $$\bar{V}_{iqh} = \sum_{d \in q} \frac{V_{iqdh}}{n_q}$$

$$\tilde{V}_{idh} = V_{iqdh} - \bar{V}_{iqh} \; .$$

$\tilde{V}_{idh}$ represents traffic volume net average hourly and station specific quarterly trends and controls for the influence of cyclical commuting patterns on traffic volume. Positive values of $\tilde{V}_{idh}$ indicate above trend traffic conditions and negative values indicate below trend conditions. Deviations in traffic volume from mean trends may be due to extreme weather conditions, weather alerting protocols, or other unobserved sources of heterogeneity.

Let $c_{idh} = h - \theta_{id}$ be the running variable, where $\theta_{id} \in \mathbb{R}^{+}$ represents the time of day that the alert was issued. E_{idh} is a dummy variable that takes on a value of one for all hours after an extreme weather warning (i.e. $c_{idh} > 0$). $\mathrm{T} \in \{0,1\}$ designates the type of alert sent; $\mathrm{T} = 0$ indicates a non-wireless flash flood warning from the pre-WEA period and $\mathrm{T} = 1$ indicates a wireless flash flood warning from the post-WEA period. Let μ_{id} be fixed effects at the station by day level and ε_{idh} be a disturbance term clustered at the traffic monitoring station level. Equation 8 displays the predicted effect of WEA messages on traffic volume

$$\tilde{V}_{idh}^{\mathrm{T}} = E_{idh}^{\mathrm{T}} \lambda^{\mathrm{T}} + f^{\mathrm{T}}\left(c_{idh}^{\mathrm{T}}\right) + \mu_{id}^{\mathrm{T}} + \varepsilon_{idh}^{\mathrm{T}} \ , \tag{8}$$

$$\text{where } h^{-} \leq c_{idh}^{\mathrm{T}} \leq h^{+} \text{ and } \mathrm{T} \in \{0,1\} .$$

Equation 8 is estimated separately for pre-WEA and post-WEA flash flood warnings and λ^{T} is the parameter to be estimated. I include fixed effects at the station by day level to de-mean the regression of any unrelated trends in traffic volume that are common to the traffic monitoring station on days when flash flood warnings are issued. The variables h^{-} and h^{+} represent the bandwidth of the data used. The function $f^{\mathrm{T}}\left(c_{idh}^{\mathrm{T}}\right)$ is the control function and is included to capture unobservable trends in traffic volume such as the effect inclement weather, which may differ on the left hand side versus right hand side of the discontinuity (i.e. before and after the alert). However, for purposes of identification these baseline trends in traffic volume are assumed to vary smoothly in the region of the discontinuity.

The parameter λ^{T} represents the average treatment effect on the treated (ATT) for non-wireless and wireless alerts. A negative and significant estimate of λ^{T} would indicate a statistical decrease in traffic volume in response to flash flood warning messages. Let $\lambda^{WEA} = \lambda^{1} - \lambda^{0}$, which is identified through difference-in-differences variation. Assuming that WEA messages contribute to a greater adoption of hazard mitigating behavior than would be observed using existing non-wireless protocols, we may expect $\lambda^{WEA} < 0$, with all other conditions being equal. This implies a larger statistical decrease in traffic volume for post-WEA flash flood warning messages than for pre-WEA messages.

Traffic volume for this analysis is reported in hourly increments and is based upon continuous traffic monitoring station data provided by the VDOT. There are a total of 435 traffic monitoring stations in Virginia, located in 92 out of 134 counties in the state. The locations of these stations are displayed in figure A2, in Appendix A. Monitoring stations tend to be concentrated primarily near large urban centers, such as Virginia Beach and Richmond, as well as on interstates and highways. My sample consists of hourly traffic volume from the day of alert for stations located in counties that received either a pre-WEA or post-WEA flash flood warning. Table 1.7 lists the average count of cars per hour and deviation in vehicle count from quarterly station level trends in hourly traffic volume for pre-WEA and post-WEA messages. For all hours of the day, vehicle count is between 10-20 percent lower for post-WEA messages than for pre-WEA messages. However, both alert types follow similar trends throughout the day, consistent with the weekday commuting patterns displayed in figure 1.1. On average, vehicle count is below station level hourly trends for both alert types. Previous research has found that traffic volume tends to decrease in response to increased precipitation (Keay and Simmonds 2005). Thus, below trend traffic volume may be due in part to the arrival of extreme weather conditions.

The running variable for this analysis is hours from the issuance of a flash flood warning, which may take a value in the interval -12 to 12. Negative values indicate hours prior to the alert and positive values indicate hours afterward. I adjust the running variable to account for the minute within the hour that the alert was issued. Thirty minutes passed the hour is treated as the zero point for the discontinuity. As an example, for a flash flood warning issued precisely at 8:20am, the value of the running variable for the periods of 7-8am and 9-10am would be -0.83 and 1.17, respectively. This is due to the fact that the period 7-8am is closer, on average, to the boundary than the period 9-10am. In my primary specification, I also drop any hour during which a flash flood warning was issued if the alert was sent after the 15^{th} minute and before the 45^{th} minute of the hour.[13] For instance, from the previous example, I would drop the hour 8-9am. This is due to the fact that a substantial share of the hour occurred before as well as after the alert was issued and would tend to attenuate my ATT estimates near the boundary.

To estimate the effect of WEA messages on traffic volume, I use a non-parametric, local linear regression discontinuity model. The dependent variable is the count of cars per hour, net quarterly station specific trends by day of week and hour of day, as illustrated in Equation 7. I proceed by first de-meaning the data of average station by day fixed effects. Then I use these residuals to fit a local linear regression of the running variable using a triangular kernel function and optimal bandwidth calculated based upon the method proposed by Imbens and Kalyanaraman (2012). I calculate the Local Wald Estimate of the impact of pre-WEA and post-WEA flash flood warnings on hourly traffic volume. The difference between these two calculations represents the difference-in-differences estimate of the effect of WEA messages on traffic volume. This entire process is bootstrapped 1000 times to provide asymptotically consistent RD estimates for purposes of hypothesis testing.

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[13] In unreported results, I also experiment with alternative restrictions from the hour of the discontinuity such as dropping observations after the 10th minute and before the 50th of the hour, or after the 20th minute and before the 40th minute, as well as dropping no observations and dropping all observations from the hour of the discontinuity.

A. Traffic Volume Results

Table 1.8 reports the results of a set of RD models of the impact of WEA messages on traffic volume. I estimate several alternative specifications and for each model, I report the estimated average treatment effect on the treated (ATT) of non-wireless flash flood warnings, issued during the pre-WEA period, wireless alerts issued during the post-WEA period and the difference between these two estimates. Model 1 is estimated based upon Equations 7-8 and includes observations from alerts issued during all times of day. I exclude station by day fixed effects in model 2. Finally, in models 3 and 4 I conduct falsification tests using data from the day immediately preceding flash flood warnings, as well as data from counties neighboring non-wireless and wireless flash flood warning counties, respectively. These falsification models are estimated with restrictions identical to those of model 1. Assuming that the RD method is valid for models 1 and 2 we should expect no significant RD effect in either model 3 or 4.

In models 1 and 2, the baseline effect of non-wireless alerts on traffic is positive but insignificant. On the other hand, compared to trends immediately prior, traffic volume decreases by a statistically significant amount following a WEA flash flood warning. Relative to traffic volume conditions following non-wireless alerts, I find that WEA messages reduced traffic volume by approximately -38 cars per hour. These results are statistically significant at below the one percent level and support the hypothesis that WEA messages help contribute to reductions in traffic volume by encouraging individuals to delay or cancel travel during severe weather periods. An average of 947 cars per hour were recorded during the hour WEA messages were sent, a -38 car reduction, as predicted in model 1, represents a decrease in traffic volume by -4.0 percent relative to traffic volume using only non-wireless alerting protocols.

Figure 2 provides a graphical representation of the effect of pre-WEA and post-WEA messages based upon the local linear regression estimated in model 1. Traffic volume is represented on the vertical axis, controlling for hourly volume trends and station by day fixed effects. Hours from alert is listed on the horizontal axis. Pre-WEA traffic volume trends are represented by the solid black line and pre-WEA trends are represented by the dashed line. The vertical line in the middle of the figure represents the time the alert was issued. Observations to the left of the vertical line occurred prior to the issuance of an alert and observations to the right occurred after the alert. For pre-WEA observations prior to the alert, traffic volume is decreasing over time and reaches a nadir approximately three hours before the non-wireless flash flood warning. After this, volume begins to rise. Traffic volume reaches a peak approximately seven hours after the alert before falling back to pre-alert levels. As is the case with pre-WEA observations, traffic volume is decreasing in the hours prior to the issuance of a wireless alert during the post-WEA period. At the discontinuity, there is a sharp decrease in traffic volume, and in the hours after the WEA message is sent, traffic volume gradually rises back to pre-alert levels but does not reach a new peak, as is the case with non-wireless flash flood warnings.

Due to daily commute schedule and other driving activity, traffic volume is generally at its highest during the daytime hours and lowest during the night. I therefore explore potential heterogeneity in the effect of WEA messages by time of day by dividing the sample of flash flood warning messages into four six hour groups. This includes alert messages sent between 12am-6am, 6am-12pm, 12pm-6pm and 6pm-12am, respectively. Results of these models are reported in table A7 in Appendix A and are estimated with restrictions identical to model 1. I predict statistically significant reductions in traffic volume for all times of day ranging between -34 to -49 cars per hour, with slightly larger reduction in traffic volume coinciding with the rush hour traffic periods of 6am-12pm and 12pm-6pm. WEA messages may have a more pronounced effect on traffic volume during the high volume, daytime hours due to the larger share of potential drivers on the road.

To test sensitivity of the control function to unobserved trends in traffic volume, I conduct temporal falsification tests in models 3-4, reported in table 1.8. Model 3 uses data from the day immediately preceding the issuance of flash flood warnings and is estimated with the same restrictions as model 1.[14] There is no evidence of a statistically significant false treatment effect for pre-WEA or post-WEA messages, nor is there a significant difference between these estimates. Figure A3, located in Appendix A provides a graphical representation of control functions from model 3. Finally, in model 4 I conduct a falsification test using data from neighboring counties that did not receive wireless or non-wireless flash flood warning. Figure A4, provides a graph of the control functions from this

[14] The slightly differing sample populations in Model 5, versus Model 1, is due to a handful of continuous monitoring stations that were active on the day of a flash flood warning that were inactive the day prior

model. Although the graph of the control functions for the neighboring counties looks similar to those of figure 1.2, at the boundary, I find no statistically significant effect of either wireless or non-wireless alerts on traffic volume.

VI. Concluding Remarks

WEA is among the only emergency message systems in the world that distributes geographically explicit emergency messages directly to mobile devices on a strictly opt-out basis. This allows regulators to send tailored emergency messages directly to individuals in harm's way and suggest hazard mitigating behaviors to minimize their exposure to risk. In this article, I investigate the impact of WEA messages for flash flood on car accident outcomes and traffic volume in the State of Virginia between 2011 and 2013. I isolate the effect of WEA messages by using a difference-in-differences model to compare car accidents in treatment counties that received a WEA message for flash flood to counties that received a non-wireless flash flood warning during the pre-WEA period and to control counties which received an alert for a less severe flash flood watch during either the pre- or post-WEA periods. Compared to the existing non-wireless alert system, my analysis suggests that WEA messages may reduce daily car accident counts by -17.3 percent in the event of flash flood. This result is statistically significant at below the one percent level.

I also address potential mechanisms for reductions in car accidents through an analysis of traffic volume following wireless and non-wireless flash flood warnings. This analysis uses hourly traffic volume data from just before and just after a flash flood warning message is distributed during either the pre-WEA or post-WEA period. I identify the effect of WEA messages using a differences-in-differences regression discontinuity model. I find that traffic volume is reduced by approximately -38 cars per hour (-4.0 percent) following the issuance of a WEA message relative to traffic volume conditions following non-wireless flash flood warnings. These results suggest that some individuals respond to WEA messages by avoiding roadways during inclement weather periods, thereby lowering their exposure to risk and contributing to reductions in car accident totals.

For purposes of this analysis, I have focused on reductions in car accidents as indication of overall hazard mitigation in response to WEA messages. Future research could be used to study the effect of WEA messages on other traffic outcomes such as car accident injuries and fatalities. The empirical strategy used in this analysis could easily be applied to study the effect of WEA messages on car accident outcomes in other regions of the United States. Expanding the region of analysis could also be used to study the effect of WEA messages for a more diverse set of extreme weather events, such as hurricanes, dust storms or in regions with a more frequent occurrence of tornadoes.

TABLE 1.1: TOTAL NUMBER OF EXTREME WEATHER ALERT DAYS AND COUNTIES IN THE PRE-WEA PERIOD (JULY, 2011 – JUNE, 2012) AND POST-WEA PERIOD (JULY, 2012 – DECEMBER, 2013)

	Pre-WEA Period		**Post-WEA Period**			
	Non-wireless Warning		**Wireless Warning**		**Other Warnings**	
Warning	**Days**	**Counties**	**Days**	**Counties**	**Days**	**Counties**
Flash Flood	49	259	40	226	27	86
Tornado	22	131	8	43	8	30
All	59	390	44	269	31	116

TABLE 1.3: MEAN AND STANDARD DEVIATION OF CAR CRASHES FOR FLASH FLOOD WARNING AND FLASH FLOOD WATCH COUNTIES (STANDARD DEVIATION IN PARENTHESES)

	Pre-WEA Period		**Post-WEA Period**	
Warning	**Warning**	**Watch**	**Warning**	**Watch**
Total Daily Crashes	5.247	2.563	3.381	2.897
	(9.265)	(5.844)	(7.489)	(5.777)
Crashes per 100,000 Licensed Drivers	6.697	5.318	7.701	6.438
	(6.877)	(6.917)	(12.450)	(7.174)

TABLE 1.2: COVARIATE SUMMARY STATISTICS FOR FLASH FLOOD WARNINGS AND WATCHES

Variables	Mean	Standard Deviation	Min	Max
WEA Period x Warning County				
WEA Period	0.5968	0.4907	0	1
Warning County	0.2622	0.4399	0	1
WEA Period x Warning County	0.1222	0.3276	0	1
Alert Time of Day				
12am - 4am	0.1022	0.3029	0	1
4am - 8am	0.1016	0.3022	0	1
8am - 12pm	0.1497	0.3569	0	1
12pm - 4pm	0.1665	0.3726	0	1
4pm - 8pm	0.3595	0.4800	0	1
8pm - 12am	0.1205	0.3257	0	1
Day of Week				
Sunday	0.1108	0.3140	0	1
Monday	0.1670	0.3731	0	1
Tuesday	0.1557	0.3626	0	1
Wednesday	0.1724	0.3779	0	1
Thursday	0.1622	0.3687	0	1
Friday	0.1341	0.3408	0	1
Saturday	0.0978	0.2972	0	1
Weather Controls				
Precipitation (mm)	13.7334	21.8326	0	181.1
Wind Speed (m/s)	1.4414	1.7595	0	9.8000
Licensed Drivers (100,000s)	0.5161	1.1024	0.0197	7.8890
Observations	1850			
Number of Dates	133			

TABLE 1.4: DIFFERENCE-IN-DIFFERENCES (DD) POISSON MODEL FOR DAILY COUNT OF CAR ACCIDENTS

Variables	Coefficient	Standard Error
WEA Period x Warning County		
WEA Period	0.0496	0.2162
Warning County	0.2921***	0.0934
WEA Period x Warning County	-0.1903***	0.0668
Alert Time of Day[a]		
4am - 8am	0.1404***	0.0492
8am - 12pm	-0.0075	0.0657
12pm - 4pm	0.0181	0.0867
4pm - 8pm	0.0197	0.0686
8pm - 12am	0.0331	0.1576
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.4403***	0.1655
Warning County x 8am - 12pm	0.1075	0.3482
Warning County x 12pm - 4pm	0.0698	0.1298
Warning County x 4pm - 8pm	0.0610	0.1085
Warning County x 8pm - 12am	-0.1901	0.1871
Day of Week		
Monday	0.4106***	0.0698
Tuesday	0.5675***	0.0865
Wednesday	0.4388***	0.0756
Thursday	0.4423***	0.0622
Friday	0.5049***	0.0711
Saturday	0.4055***	0.0844
Weather Controls		
Precipitation (mm)	0.0014*	0.0008
Wind Speed (m/s)	-0.0287	0.0177
Constant	0.0034	0.3304
Fixed Effects		
County	Yes	
Month x Year	Yes	
Observations	1850	
Number of Dates	133	

***Significant at the 1% level; **Significant at the 5% percent level; *Significant at the 10% level

[a]Baseline time category of 12am-4am

TABLE 1.5: AVERAGE MARGINAL EFFECTS FOR COVARIATES ON DAILY COUNT OF CAR ACCIDENTS

Variables	**Coefficient**	**Standard Error**
WEA Period x Warning County		
WEA Period	0.1450	0.6170
Warning County	1.1087***	0.3190
WEA Period x Warning County	-0.7086***	0.2637
Alert Time of Day[a]		
4am - 8am	0.4705***	0.1651
8am - 12pm	-0.0234	0.2043
12pm - 4pm	0.0569	0.2732
4pm - 8pm	0.0622	0.2154
8pm - 12am	0.1052	0.5044
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-1.5868***	0.5299
Warning County x 8am - 12pm	0.4362	1.4877
Warning County x 12pm - 4pm	0.2850	0.5204
Warning County x 4pm - 8pm	0.2485	0.4319
Warning County x 8pm - 12am	-0.6927	0.7389
Day of Week		
Monday	1.0822***	0.1897
Tuesday	1.6281***	0.2687
Wednesday	1.1743***	0.2020
Thursday	1.1857***	0.1678
Friday	1.4000***	0.2093
Saturday	1.0658***	0.2354
Weather Controls		
Precipitation (mm)	0.0044*	0.0025
Wind Speed (m/s)	-0.0919	0.0567
Fixed Effects		
County	Yes	
Month x Year	Yes	
Observations	1850	

Number of Dates	133

***Significant at the 1% level; **Significant at the 5% percent level; *Significant at the 10% level
[a]Baseline time category of 12am-4am

TABLE 1.6: CHANGE IN CAR ACCIDENT COUNT CONDITIONAL ON FLASH FLOOD WARNING STATUS AND IN POST-WEA PERIOD (STANDARD ERRORS IN PARENTHESES)

Warning	**With WEA**	**Without WEA**	**DD Treatment Effect**	**Per 100,000 Licensed Drivers**	**Percent Change**
Flash Flood	3.381***	4.089***	-0.709***	-1.388***	-17.329***
	(0.125)	(0.254)	(0.264)	(0.507)	(5.522)

***Significant at the 1% level; **Significant at the 5% percent level; *Significant at the 10% level

TABLE 1.7: AVERAGE TRAFFIC VOLUME (COUNT OF CARS) BY HOUR OF THE DAY FOR PRE-WEA AND POST-WEA FLASH FLOOD WARNINGS

	Raw Traffic Volume		**Deviation from Hourly Average**	
Hour	**Pre-WEA Volume**	**Post-WEA Volume**	**Pre-WEA Volume**	**Post-WEA Volume**
12am - 1am	292	259	-59	1
1am - 2am	204	178	-36	-1
2am - 3am	172	155	-31	0
3am - 4am	185	164	-26	1
4am - 5am	318	266	-27	6
5am - 6am	704	602	-38	12
6am - 7am	1211	1054	-51	17
7am - 8am	1694	1365	-52	-5
8am - 9am	1726	1383	-61	-1
9am - 10am	1567	1339	-92	8
10am - 11am	1568	1351	-105	1
11am - 12pm	1629	1405	-113	11
12pm - 1pm	1715	1487	-112	16
1pm - 2pm	1725	1510	-130	-3

2pm - 3pm	1823	1577	-151	5
3pm - 4pm	1958	1731	-160	-6
4pm - 5pm	2041	1753	-188	-29
5pm - 6pm	2059	1778	-201	-36
6pm - 7pm	1706	1489	-194	-40
7pm - 8pm	1329	1135	-162	-46
8pm - 9pm	1026	912	-164	-29
9pm - 10pm	803	750	-120	-22
10pm - 11pm	665	511	-109	-14
11pm - 12am	442	394	-85	-4

TABLE 1.8: REGRESSION DISCONTINUITY MODELS OF IMPACT OF PRE-WEA AND POST-WEA FLASH FLOOD WARNINGS ON TRAFFIC VOLUME (BOOTSTRAPPED STANDARD ERRORS LISTED IN PARENTHESES)

	WEA Flash Flood Warning		**Falsification Tests**	
	(1)	**(2)**	**(3)**	**(4)**
Pre-WEA	8.83	8.86	-4.1	3.12
	(7.79)	(7.21)	(7.75)	(5.49)
Post-WEA	-29.02***	-30.5***	-0.39	-14.87
	(8.91)	(8.76)	(9.19)	(9.97)
Difference	-37.85***	-39.35***	3.71	-17.99
	(11.21)	(10.92)	(12.08)	(11.2)
Station-Day FE	Yes	No	Yes	Yes
Stations	368	368	368	389
Observations	34769	34769	34557	53051

***Significant at the 1% level; **Significant at the 5% percent level; *Significant at the 10% level

Based upon 1,000 bootstrapped replications

Model 1 uses a sample of alerts from all hours of the day and includes station by day fixed effects, Model 2 excludes station by day fixed effects but is otherwise identical to Model 1. Models 3 and 4 present falsification tests using data from the day immediately prior to flash flood warnings and from counties neighboring flash flood warning counties, respectively.

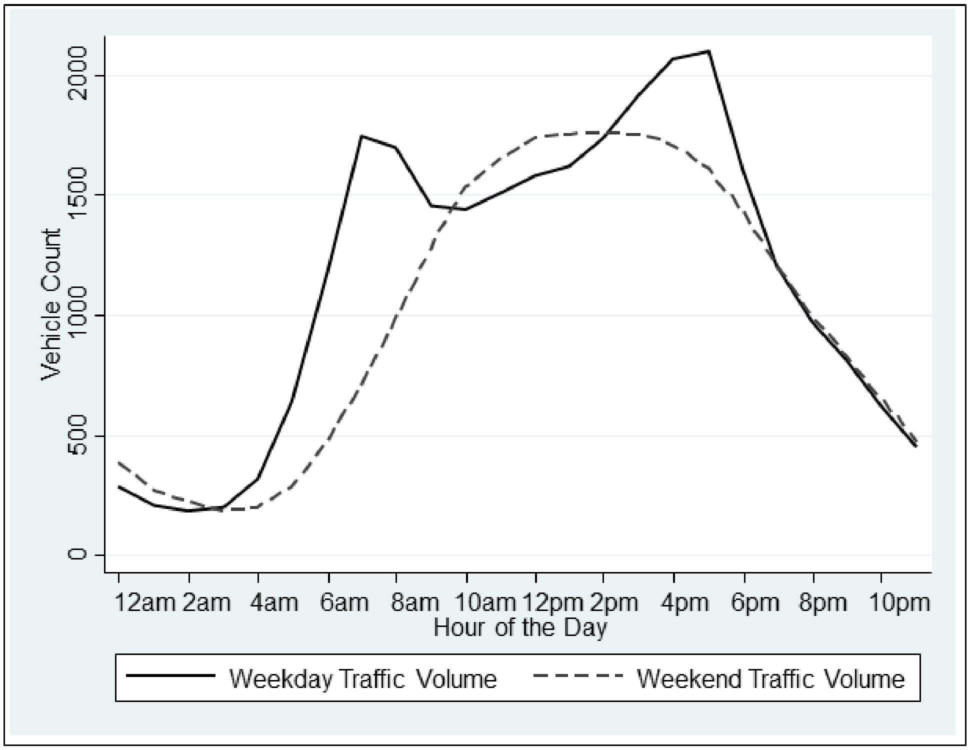
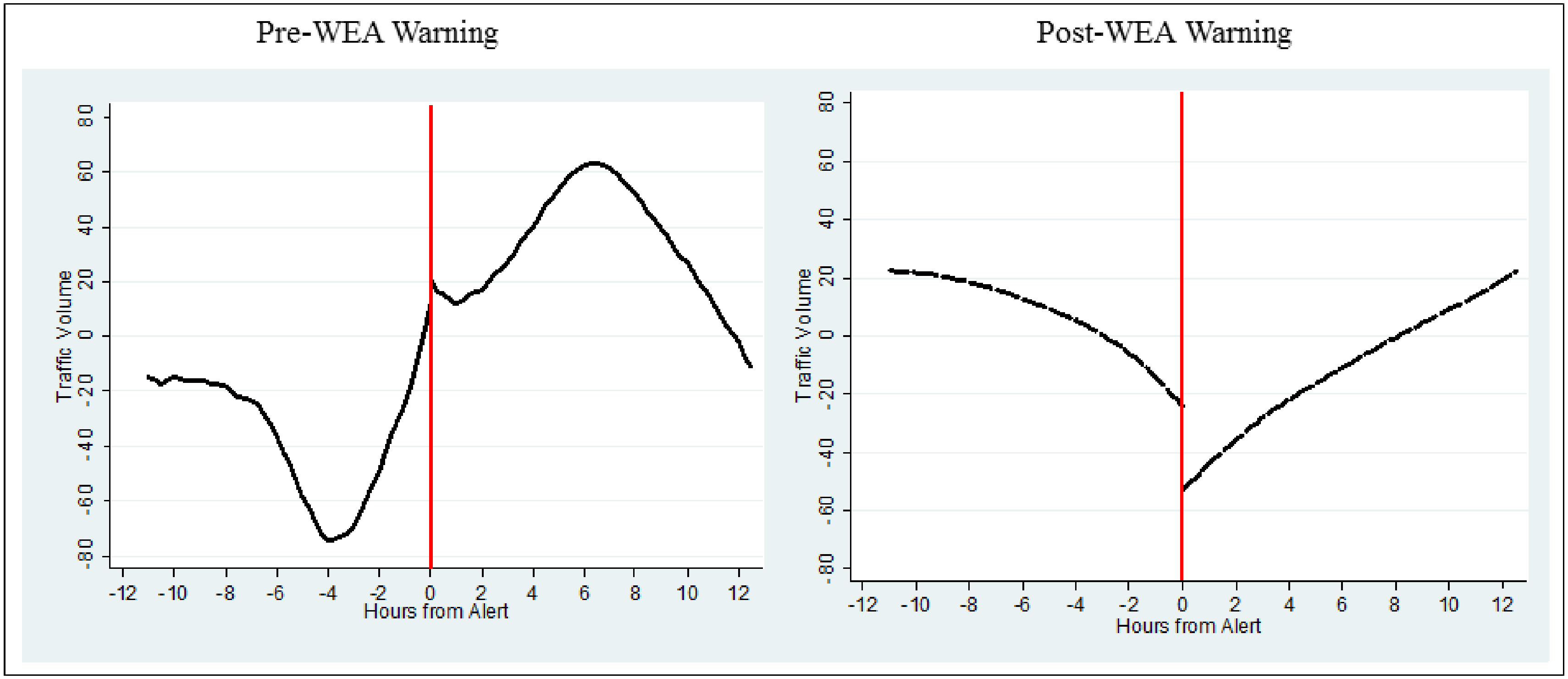


FIGURE 1.1. HOURLY TRAFFIC VOLUME BY WEEKDAY AND WEEKEND IN VIRGINIA (2011-2013)



Notes: Controlling for hourly trends by quarter-station and station by day fixed effects

FIGURE 1.2. LOCAL LINEAR REGRESSION OF HOURS FROM ALERT ON TRAFFIC VOLUME FROM MODEL 1

Chapter 2: Additionality and Forest Conservation Policy for Residential Development

Forest cover provides ecosystem services and amenities that are not fully considered in private landowner decisions. Substantial work has analyzed the targeting of voluntary incentive payments for rural landowners to encourage forest cover retention and the provision of ecosystem services and amenities (e.g., Nelson et al. 2008; Lewis, Plantinga and Wu 2009; Lewis et al. 2011; Lawler et al. 2014). The incentive-based policies in these studies have incorporated important aspects into targeting payments such as the incomplete information on landowner opportunity costs and nonlinear forest benefits for habitat preservation. Other research has focused on land-use regulatory policies using parcel-level models of residential development to examine the effects of regulations such as open space clustering requirements (Irwin and Bockstael 2004), zoning (Newburn and Berck 2006; Lewis, Provencher, and Butsic 2009; Butsic, Lewis, and Ludwig 2011), and permitting (Wrenn and Irwin 2015). Meanwhile, the effect of forest conservation regulations on residential development has received less attention. Two exceptions are Lichtenberg, Tra, and Hardie (2007) and Lichtenberg and Hardie (2007) who assess how the Forest Conservation Act (FCA) in Maryland influences residential density and the provision of open space amenities within subdivisions. They find that forest conservation requirements crowd out public non-forested open space and reduce residential density. Their analysis, however, relies only on parcels already converted to subdivision after the FCA was adopted rather than analyze the effect of FCA regulations on the dynamic process of residential land conversion.

The purpose of this study is to analyze the heterogeneous effect of the FCA on residential development and estimate the additionality in forest cover due to this regulation. We use a spatially explicit panel dataset of residential subdivisions during 1985-2000 in Baltimore County, Maryland. The econometric model is a panel Heckman selection model with two stages that are jointly estimated. The first stage is a panel probit model of the landowner decision to develop or remain undeveloped. In the second stage, we estimate the change in the percentage of forest cover on the property, conditional on development in the first stage. The FCA was adopted in 1993 allowing us to model landowner development decisions during periods before (1985-1992) and after (1993-2000) the FCA. Land-use decisions are assumed to be a function of the existing forest cover, zoning, distance to Baltimore City, riparian buffer area, slope, neighborhood housing prices, and other parcel attributes. To characterize parcel-level forest cover change, we utilize satellite-based data from the North American Forest Dynamics Project measuring forest cover on roughly a biennial basis between 1985 and 2004.

Our analysis yields several main results. Prior to the FCA, forest cover decreased following residential development across the entire distribution of existing forest cover values. After the FCA, forest cover increased on average for developed parcels with lower levels of existing forest cover between 0-60%.

However, parcels with the highest levels of existing forest cover have significant decreases in forest cover even after the FCA, suggesting that parcels with the most intact forest cover continue to have fragmentation. Overall, there is an expected increase in total forest cover of approximately 23% on subdivisions with the FCA relative to without the regulation, according to landscape-level simulation analysis in the region.

This research makes several contributions to the literature. This is the first study, to our knowledge, that combines analyses of fine-scale panel data on forest cover change from satellite imagery and spatially explicit parcel-level modeling on residential development decisions. Importantly, we are able to more accurately assess the initial level of existing forest cover on developable parcels and the partial loss in forest cover that occurs on residential subdivisions. Forest land converted to urban development in prior studies is often implicitly assumed to result in a complete loss of forest, thereby overestimating the environmental damages from development. In our study, we empirically estimate forest cover change with data from satellite imagery in contrast to previous studies relying on assumptions between development and forest cover loss. Furthermore, because our analysis spans periods before and after the FCA, this allows us to provide baseline estimates of forest loss in the pre-regulatory period in order to provide potential estimates of additionality in forest cover achieved in the post-regulatory period. The FCA in Maryland is the only statewide forest conservation regulation in the United States that focuses on forest retention and replanting requirements within residential subdivisions. Our analysis suggests that the implementation of the FCA provided an increase in the level of forest area and could provide guidance to other regions interested in implementing similar policies to promote forest conservation in areas threatened by residential development.

I. Policy Background on Maryland's Forest Conservation Act

Forest cover loss is a major concern for states, such as Maryland, that have experienced rapid urban development. The proportion of developed land in the entire state of Maryland more than doubled from 8.9% in 1973 to 18.2% in 2000; and of the 546,000 acres of newly developed land, low-density residential development accounts for 62% (Irwin and Bockstael 2007).[15] Forest cover in urban areas can provide amenity values to nearby residents as found in hedonic studies (e.g., Tyrväinen and Miettinen 2000; Sander, Polasky, and Haight 2010), in addition to other social benefits such as carbon sequestration and storage and reduction in air pollution, stormwater runoff and urban heat island effects. Meeting goals for water quality improvements in local waterways and the Chesapeake Bay has increased attention on the importance of maintaining and restoring forested areas. Priority areas for forest protection and restoration include environmentally sensitive areas, such as riparian buffers, 100-year floodplains, steep slopes and critical habitat.

The Forest Conservation Act (FCA) was passed as a statewide law by the Maryland legislature in 1991 and implemented locally by county and municipal

[15] Irwin and Bockstael (2007) point out that the urban footprint in Burchfield et al. (2006) is based on land cover classification from Landsat imagery which can only accurately detect higher density urban development at approximately greater than one housing unit per acre; however, it often cannot distinguish lower density exurban development on septic systems at less than one housing unit per acre from extensive land uses (e.g., agricultural and forestry uses).

governments in 1993. Starting in January 1993, the law applies to any subdivision development with grading over 40,000 square feet (approximately one acre) and is designed to reduce forest loss following property development. The FCA does not apply to existing uses on parcels, such as working farms that are not undergoing subdivision development. Prior to subdivision development, a landowner completes a forest conservation plan (FCP) that specifies the forest conservation requirement on the property, including a plan for retaining existing forest cover and new tree plantings (Galvin, Wilson and Honeczy 2000).[16] The FCP must be approved by county planning agencies as part of the overall subdivision approval process for land use and environmental permitting.

Thresholds for afforestation and conservation under the FCA regulations are determined based on the existing forest cover and the prevailing zoning. The afforestation threshold is twenty percent in regions zoned for either agricultural and resource areas or medium residential areas. For parcels with less than twenty percent existing forest cover, the landowner must plant new trees up to the afforestation threshold, even if no trees are cleared in the process of development. The conservation threshold is fifty percent in regions zoned for agricultural and resource areas and twenty-five percent when zoned for medium residential areas. In order to avoid replanting requirements entirely, a landowner must retain at least twenty percent of existing forest cover above the conservation threshold, which is referred to as the break-even point. Forest land cleared below the break-even

[16] The landowner may also meet the conservation requirement through offsite mitigation. Offsite forest mitigation is relatively uncommon for our study region in rural Baltimore County, representing less than 10% of forest acres conserved based on available data.

point but above the conservation threshold must be replanted at one-fourth the amount the forest is cleared. Forest land must be replanted at twice the amount cleared below the conservation threshold.[17] Prior to the adoption of FCA regulations, there were no afforestation or conservation thresholds for the entire region.

II. Conceptual Model

We present a simple illustrative economic model on how the introduction of regulatory costs related to compliance with the FCA are expected to influence landowner decisions on the timing of development and forest cover change. We assume that the landowner is a profit-maximizing agent that presently owns a parcel in an undeveloped land use (e.g., agriculture, forestry) and is considering the irreversible decision to convert the parcel to residential development at some time T. The undeveloped parcel has percent existing forest cover F and a vector of other parcel attributes X that affect the benefits and costs of the returns in the existing and developed land uses.

If the parcel is developed, the amount of existing forest cover removed on the subdivision development is d, where $d \geq 0$. Forest cover after development is $\varphi = F - d + \lambda(d, F, \alpha, \gamma)$, which is the existing forest cover before development F minus existing forest cover removed d plus forest planting mandated under the FCA $\lambda(d, F, \alpha, \gamma)$. Mandated forest planting $\lambda(d, F, \alpha, \gamma)$ depends upon the

[17] For further details on FCA requirements, see the Chesapeake Bay Foundation "A Citizen's Guide to the Forest Conservation Act in Maryland" http://www.cbf.org/document.doc?id=148.

amount of forest cover removed, existing forest cover as well as the afforestation and conservation thresholds, α and γ, respectively. For simplicity, here we focus on the conservation threshold but not the break-even point, though similar results would be obtained if considering both. For parcels with percent existing forest cover below the afforestation threshold $0 \le F \le \alpha$, the landowner must meet the afforestation requirement equal to $\alpha - F$ and must also replant any forest cover removed at double the amount cleared, such that $\lambda(d, F, \alpha, \gamma) = \alpha - F + 2d$. Parcels with existing forest cover above the afforestation threshold but below the conservation threshold $\alpha < F \le \gamma$ have no afforestation requirements but must replant any forest cover removed at double the amount cleared, such that $\lambda(d, F, \alpha, \gamma) = 2d$. Parcels with percent existing forest cover above the conservation threshold $\gamma < F \le 100$ have excess forest cover $F - \gamma$ that may be cleared without penalty and only are required to replant for the portion of forest cover removed that falls below the conservation threshold. Hence, parcels with high existing forest cover in the range $\gamma < F \le 100$ have excess forest cover, such that $\lambda = 2\left[d - (F - \gamma)\right]$ for $d > F - \gamma$ and $\lambda = 0$ for $d \le F - \gamma$. Note that $\lambda = 0$ in the absence of the FCA for all parcels.

Following the conceptual framework of Capozza and Helsley (1989), the landowner choses the optimal timing of development T^* and the removal of existing forest cover on the subdivision d^* to maximize profits

(1) $$\max_{T,d}\left\{\int_0^T R^u\left[F,X\right]e^{-rt}dt+\int_T^\infty R^s\left[\varphi\left(F,d,\lambda\right),X,t\right]e^{-rt}dt-C\left[d,\lambda,X\right]e^{-rT}\right\},$$

where r is the interest rate. The first term in equation 1 is the present value of rent in the undeveloped use $R^u\left[F,X\right]$ from time $t=0$ to the conversion time T^*, which is a function of parcel attributes X related to land quality (e.g., soil quality) and the existing forest cover F for forestry or cleared for agriculture. The second term is present value of rents from subdivision development $R^s\left[\varphi,X,t\right]$ from the conversion time T^* onward. The rent in subdivision development is a function of the forest cover after development φ, other parcel attributes X (e.g., accessibility to employment, parcel area, etc.), and is assumed to be increasing over time due to income and population growth. The last term is the fixed cost of residential development, which occurs at conversion time T^* and is discounted to the present. The fixed cost of residential development $C\left[d,\lambda\left(d,F,\alpha,\gamma\right),X\right]$ includes the costs for the amount of forest cover removed, regulatory costs related to compliance with the FCA, and other parcel attributes affecting development costs (e.g., steep slopes, riparian buffers).

The landowner's decision on the optimal timing of development is determined from the first-order condition of equation 1 with respect to the conversion time T

(2) $$R^s\left[\varphi,X,T\right]-R^u\left[F,X\right]-rC\left[d,\lambda\left(d,F,\alpha,\gamma\right),X\right]=0\ .$$

The optimal timing of development T^* occurs when the rent in residential use equals the opportunity costs of forgone rent from the undeveloped land use plus the costs of borrowing capital for residential conversion. The optimal forest cover removal is determined from the first-order condition of equation 1 with respect to d

(3) $$\int_T^{\infty} \frac{\partial R^s}{\partial \varphi}\left(\frac{\partial \varphi}{\partial d}+\frac{\partial \varphi}{\partial \lambda}\frac{\partial \lambda}{\partial d}\right)e^{-rt}dt-\left(\frac{\partial C}{\partial d}+\frac{\partial C}{\partial \lambda}\frac{\partial \lambda}{\partial d}\right)e^{-rT}=0.$$

Consider the landowner's optimal choice of forest removal d_0^* in the absence of the FCA, where $\lambda = 0$. The first-order condition with respect to d in equation 3 simplifies to $\int_T^{\infty} \frac{\partial R^s}{\partial \varphi}\frac{\partial \varphi}{\partial d}e^{-rt}dt-\frac{\partial C}{\partial d}e^{-rT}=0$. The first term represents the marginal effect of an increase in forest removal on the present value of marginal returns in residential use, which is expected to be increasing with forest removal at a decreasing rate. Note that $\frac{\partial \varphi}{\partial d}=-1$ because an increase in forest removal results in a corresponding decrease in forest cover after development. Higher levels of forest cover retained on the subdivision, due to less forest removal, reduces the profitability of development by limiting the number of developable lots, meaning that $R^s\left[\varphi, X, t\right]$is concave and decreasing with respect to φ. The second term reflects the marginal cost of residential development due to forest cover clearing, which is expected to be increasing with forest removal. It is thus expected that, without the FCA, the partial derivative of forest cover removal with respect to existing forest cover is $0<\frac{\partial d_0^*}{\partial F}<1$. Conditional on a parcel in a given location, the amount of forest cover removed increases with the initial amount of existing forest cover because some, but not all, of a marginal increase in existing forest cover is cleared to accommodate the residential buildings and other aspects of the subdivision, such as roads, driveways, and lawns.

Figure 1 provides a graphical illustration of forest cover change Φ as a function of existing forest cover *F*. Without the FCA, forest cover change Φ_0 is equal to the forest cover after development $\varphi_0 = F - d_0^*$ minus existing forest cover *F* prior to development. This means that $\Phi_0 = -d_0^*$, as depicted in figure 1 showing an increasing amount of forest removal d_0^* for higher levels of existing forest cover. The amount of forest removal d_1^*, with the FCA, and existing forest cover *F* generates the planting requirement $\lambda\left(d_1^*, F, \alpha, \gamma\right)$. With the introduction of the FCA, the landowner is expected to have the same or lower amount of forest removal, such that $d_1^* \le d_0^*$, to reduce the FCA planting requirements. Hence, forest cover change with the FCA is $\Phi_1 = \lambda\left(d_1^*, F, \alpha, \gamma\right) - d_1^*$. Let $\Delta\Phi$ be the difference in forest cover change with versus without the FCA

(4) $$\Delta\Phi = \Phi_1 - \Phi_0 = \lambda\left(d_1^*, F, \alpha, \gamma\right) + \left(d_0^* - d_1^*\right).$$

Total forest cover change $\Delta\Phi$ includes both the effect of the FCA from replanting requirements $\lambda\left(d_1^*, F, \alpha, \gamma\right)$ and avoided deforestation $\left(d_0^* - d_1^*\right)$.

Figure 1 depicts forest cover change with versus without the FCA, showing the heterogeneous impact of $\Delta\Phi$ across the distribution of existing forest cover values. For parcels with percent existing forest cover below the afforestation threshold $0 \le F \le \alpha$, the replanting requirement is

$\lambda\left(d_1^*, F, \alpha, \gamma\right) = \alpha - F + 2d_1^*$ and thus $\Delta\Phi = \alpha - F + d_0^* + d_1^*$. At $F = 0$, although no forest is cleared either with or without the FCA, $d_0^* = d_1^* = 0$, total forest cover change is $\Delta\Phi = \alpha$ due to the afforestation requirement. At $F = \alpha$, the total forest cover change is $\Delta\Phi = d_0^* + d_1^*$ because the afforestation requirement is no longer needed but replanting is required for forest cover removal. A local minimum occurs at $F = \alpha$ unless $d_0^* + d_1^* \geq \alpha$, as shown in figure 1.

Parcels with percent existing forest cover $\alpha < F \leq \gamma$ must replant double the amount of forest cover removed with the FCA, meaning that $\lambda\left(d_1^*, F, \alpha, \gamma\right) = 2d_1^*$ and $\Delta\Phi = d_0^* + d_1^*$. The amount of forest removal that the landowner would have chosen without the FCA d_0^* is increasing with higher existing forest cover in figure 1. With the FCA, the combined effect of replanting requirements due to forest clearing and avoided deforestation are increasing, such that $\Delta\Phi$ is increasing over the range $\alpha < F \leq \gamma$ and reaches a maximum at $F = \gamma$.

Parcels with existing forest cover above the conservation threshold $\gamma < F \leq 100$ have excess forest cover $F - \gamma$ that may be cleared without penalty. That is, the landowner is required to replant only for the portion of forest removal occurring below the threshold, such that for $d_1^* > F - \gamma$, then $\lambda\left(d_1^*, F, \alpha, \gamma\right) = 2\left[d_1^* - \left(F - \gamma\right)\right]$ and thus $\Delta\Phi = d_0^* + d_1^* - 2\left(F - \gamma\right)$. Total forest cover change $\Delta\Phi$ has a maximum at the conservation threshold $F = \gamma$ and is declining in magnitude as existing forest cover increases above the conservation threshold in the range $\gamma \le F \le 100$. For parcels with high existing forest cover, excess forest cover may be greater or equal to forest cover removal even without the FCA, $d_0^* \le F - \gamma$. In this case, when no forest cover removal occurs below the conservation threshold, the landowner has no incentive to change their behavior, such that $\lambda = 0$ and $\Delta\Phi = 0$ for parcels with existing forest cover above the critical value $F \ge F_c = \gamma + d_0^*$ as depicted in figure 1.[18]

The FCA may affect other aspects of the landowner's development decisions. Although the FCA planting requirements only directly affect parcels undergoing subdivision, there is also potential for indirect effects on the timing of development. In the absence of the FCA, the effect of existing forest cover on timing of development is ambiguous. Parcels with higher levels of existing forest cover may provide amenities valued by future residents but may also raise development costs due to increased forest clearing costs. With the introduction of the FCA, lower returns to development are expected particularly for parcels with higher costs due to the FCA planting requirements. Under these conditions, development may be delayed on parcels with higher FCA planting costs compared to those parcels with comparatively lower FCA planting costs, such as those parcels with $F \ge F^c$ from figure 1. Given the expected heterogeneity in the effect of the FCA by existing forest cover values, an empirical model is necessary

[18] This critical value may not exist at F=100% in the case when forest cover removal d_0^* without the FCA is large. Nonetheless, excess forest cover is increasing over the range $\gamma \le F \le 100$ such that the total forest cover change $\Delta\Phi$ declines over this range.

to understand how the FCA affects landowner decisions on the timing of development and forest cover change.

III. Econometric Model

In this section, we develop a panel Heckman selection model to estimate the effect of the FCA on land development and forest cover change decisions. The landowner is assumed to be a profit-maximizing agent who decides either to develop parcel i or remain undeveloped in each period t. Conditional on a parcel being selected for development, the landowner determines forest cover change on the parcel after subdivision. A positive level of forest cover change indicates a net gain in forest area while negative forest cover change indicates a net loss. We use a bivariate sample selection model because land development and forest cover change decisions may be correlated (Heckman 1979). For the first stage, let Y_{it}^* represent the unobserved latent variable on the value from residential development for the landowner on parcel i in period t net the value from remaining undeveloped in the existing use. Conditional on a parcel being undeveloped, parcel i develops in period t if $Y_{it}^* > 0$, and conversion decisions are assumed to be irreversible. Let Y_{it} be a binary variable to indicate when a parcel develops such that

(5) $$Y_{it} = 1 \quad if\ Y_{it}^* > 0, \quad Y_{it} = 0 \quad if\ Y_{it}^* \leq 0 \ .$$

In the first stage, a panel probit model is used to estimate land development decisions as a function of parcel attributes. We expect the effect of the FCA on land development decisions to vary based primarily on the parcel-level existing forest cover. Due to the afforestation and conservation thresholds under the FCA requirements described above, we expect the effect of the FCA to vary nonlinearly over the distribution of existing percent forest cover. Therefore, we use categorical ranges of existing percent forest cover to allow flexibility in the model specification to represent the potential nonlinear relationship between land use decisions and existing percent forest cover. Let F_{it} be a vector of existing forest categories grouped into quintile values (i.e., 0-20%, 20-40%, 40-60%, 60-80%, 80-100%), with the lowest quintile of 0-20% existing forest cover as the baseline category. Let τ be a post-regulatory dummy variable equal to one for any period after the introduction of the FCA in 1993. We also include interactions terms between the forest cover categories F_{it} and post-regulatory dummy variable τ to estimate whether the effect of existing forest cover in the period after the FCA changes relative to the baseline period prior to the FCA. Let X_{it} represent a vector of control variables, such as riparian buffer area, slope, and other parcel attributes. Let Z_{it} represent a vector of exclusion restrictions included in the first stage model but omitted from the second stage in the Heckman selection model. The model is theoretically identified without any exclusion restrictions given the nonlinear functional form assumption in the first stage; however, for practical purposes, estimation of the Heckman selection model may require at least one regressor to be excluded from the second stage

(Cameron and Trivedi 2005). Let T_t represent annual time dummy variables. Equation 6 shows the specification for the first stage panel probit model for the probability of development where the error term ε_{it} is an independently and identically distributed and clustered at the parcel level

$$(6) \qquad Y_{it}^{*} = F_{it}\beta_1 + \tau\beta_2 + \tau F_{it}\beta_3 + X_{it}\beta_4 + Z_{it}\beta_5 + T_t\beta_6 + \varepsilon_{it} \ .$$

In the second stage, we estimate the percent forest cover change after development, represented by the variable ΔF_{it}. It should be noted that we only observe forest cover change for parcels actually selected for development. Let ΔF_{it}^{*} represent a latent variable of forest cover change, such that forest cover change is observed as $\Delta F_{it} = \Delta F_{it}^{*}$ when parcel i is developed in period t, $Y_{it}^{*} > 0$, and otherwise it is not considered. Equation 7 shows the specification for forest cover change which is similar to equation 6 except we drop the exclusion restriction Z_{it} from the second stage for identification purposes

$$(7) \qquad \Delta F_{it}^{*} = F_{it}\gamma_1 + \tau\gamma_2 + \tau F_{it}\gamma_3 + X_{it}\gamma_4 + T_t\gamma_5 + \mu_{it} \ .$$

Land development and forest cover change decisions in equations 6 and 7 are estimated simultaneously using a full information maximum likelihood (FIML) approach. We assume that errors are correlated between equations 6 and 7, which are jointly and normally distributed

$$(8) \qquad \begin{bmatrix} \varepsilon_{it} \\ \mu_{it} \end{bmatrix} = N\left(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{bmatrix} 1 & \rho \\ & \sigma^2 \end{bmatrix} \right) .$$

The correlation coefficient between the first and second stage is represented by the parameter ρ. If ρ is significant, this implies that ignoring the correlation between these two land use decisions would yield inconsistent parameter estimates.

We calculate the marginal effects of covariates on the probability of development in the first stage and forest cover change in the second stage. Let $\Omega_{it} = \{F_{it}, X_{it}, Z_{it}, \tau, T_t\}$ be a vector of covariates included in equations 6 and 7, and let $\omega_{it}^k \in \Omega_{it}$ be the covariate *k* for subsequent marginal effects. For the first stage, the marginal effect of covariate ω_{it}^k on the annual probability of development is calculated as

(9)
$$\frac{\partial \Pr\left[Y_{it} = 1 \mid \Omega_{it}\right]}{\partial \omega_{it}^k} = \frac{\partial \Phi\left[\Omega_{it}\beta\right]}{\partial \omega_{it}^k} .$$

As noted in Ai and Norton (2003), coefficients need not have either the same sign or significance as marginal effects for interaction terms in nonlinear models, such as the interaction term τF in our case. For this reason, we emphasize the interpretation of statistical significance based on the marginal effects in equation 9 rather the coefficient estimates in equation 6. Marginal effects of covariates on forest cover change decisions are represented in equation 10 and are calculated conditional on a parcel being selected for development

(10)
$$\frac{\partial E\left[\Delta F_{it} \mid Y_{it} = 1, \Omega_{it}\right]}{\partial \omega_{it}^k} = \gamma_k - \rho\left(\frac{\phi\left[\Omega_{it}\beta\right]}{\Phi\left[\Omega_{it}\beta\right]}\right)\left(\Omega_{it}\beta + \frac{\phi\left[\Omega_{it}\beta\right]}{\Phi\left[\Omega_{it}\beta\right]}\right) .$$

Marginal effects in equation 10 account for the direct effect of covariate *k* on the forest cover change decision, represented by coefficient γ_k, as well as the indirect effect on which parcels are selected for development.

To assess the potential effect of the FCA, we compute the expected forest cover change conditional on development for the periods before and after the FCA

$$E\left[\Delta F_{it} \mid Y_{it} = 1, \tau = 1, \Omega_{it}\right] - E\left[\Delta F_{it} \mid Y_{it} = 1, \tau = 0, \Omega_{it}\right] . \tag{11}$$

In general, we expect an increase in forest cover change on subdivisions after the FCA, relative to before. We calculate the forest cover change in equation 11 separately for each existing forest cover quintile to examine whether heterogeneity in the potential effect of the FCA varies by the existing forest cover categories. In addition to the change in the FCA, we recognize that there are other factors potentially influencing land use decisions that may change over time and will discuss these potential effects and robustness tests in the Results section. These robustness tests includes alternative specifications that use a more narrow time window of subdivision activity in 1988-1997, temporal falsification tests that only use either the pre-FCA data or post-FCA data and move the regulatory event to an arbitrary time within those time periods, and sensitivity tests to the specification using quintile categories of existing forest cover by examining the model specification using decile categories.

IV. Data

Baltimore County is located adjacent to the City of Baltimore, and the majority of residents commute to work in the county or Baltimore City (see figure A1 in Appendix B). Land-use decisions that disturb forest cover affect water quality in local waterways and the Chesapeake Bay. Furthermore, the rural area in Baltimore County has three large reservoirs that provide the regional drinking water supply for over 1.8 million residents in the Baltimore Metropolitan Region. An urban growth boundary (UGB) was implemented in Baltimore County in 1967, also referred to as the urban-rural demarcation line (URDL). An UGB is designed to reduce development and conserve agricultural and forested land in rural areas by restricting municipal sewer and water access exclusively to parcels located within the UGB. Although the UGB may limit higher density development on sewer service, it does not prevent lower density residential development in rural areas where subdivisions are instead served by individual private septic systems and groundwater wells. Despite the efforts of smart growth policies, the majority of acreage developed in Maryland occurs as low density residential development on septic systems in rural areas.

Our study region focuses on the rural area located outside the UGB to understand the effect of the FCA on residential development and forest cover change in this region with the majority of forest area and land conversion. This rural area covers 387 square miles, which is approximately two-thirds of the county land area. Resource conservation (RC) zoning was created in the rural area in 1976 and includes three main zoning types (figure A1). RC2 zoning for agricultural preservation covers the majority of the rural area and designated minimum lot size zoning at fifty acres per housing unit. RC4 zoning was created for watershed protection and designated minimum lot size zoning at five acres per housing unit. RC5 zoning was created to allow rural residential development and has minimum lot size zoning at two acres per housing unit. RC2 and RC4 zoning represents the majority of the land area and are considered agricultural and resource areas under the FCA regulations outlined above, with a conservation threshold of fifty percent. RC5 zoning is considered a medium residential area and thus has a conservation threshold of twenty-five percent. All three zoning types have an afforestation threshold of twenty percent.

Data used to estimate the residential land-use conversion model in Baltimore County rely on spatially explicit parcel data from the Maryland Department of Planning. We manually reconstruct the panel of residential subdivisions using historic archives for all recorded plats from 1985 to 2000. We determine the landowner's decision on the timing of subdivision development based on the initial recorded year of approval from historic subdivision plat maps. All parcels from the same subdivision are aggregated to recover the original "parent" parcel and we reconstruct the landscape for parcel boundaries in 1985. We also recorded the total number of buildable residential lots allowed for each subdivision in the approval process. For the land-use conversion model, we determine all developable parcels that, as of 1985, were eligible for residential development in the RC zoning area with more than five acres and could subdivide into two or more buildable residential lots.[19] There were a total of 3,043 developable parcels starting in 1985, of which 413 residential subdivisions occurred during 1985-2000. This includes 230 subdivisions in 1985-1992 prior to the FCA and 183 subdivisions in 1993-2000 after the FCA.

Forest cover data are obtained from the North American Forest Dynamics Project, a NASA funded project under the North American Carbon Program (NACP) (Goward et al. 2012). The NACP collects detailed forest cover data starting in 1984 for 55 selected locations across the United States, including the Baltimore-Washington corridor, based on Landsat satellite imagery at approximately 30-meter resolution. The Vegetation Change Tracker (VCT) algorithm, developed by Huang et al. (2010), is applied to Landsat imagery on an annual to biennial basis to provide forest cover maps, which are used to determine the timing and spatial distribution of deforestation, reforestation, and afforestation.[20] For the Baltimore-Washington corridor, existing forest cover maps are available as raster files for 12 different time periods including the following years: 1984, 1986, 1987, 1988, 1990, 1991, 1994, 1996, 1998, 2000, 2002, and 2004. We intersect these 12 snapshots of forest cover with the parcel boundary layer to create variables for the percentage of existing forest cover on each parcel, calculated as the amount of existing forest cover divided by the total parcel area.

[19] We have screened out areas zoned for non-residential uses (e.g., commercial, industrial, parks, etc.) and parcels already developed. Parcels put into land preservation easements were considered developable from 1985 until the date of easement, after which they were not considered developable.

[20] Validation of the NACP data indicate an overall accuracy of 92% for forest clearing disturbance events (Thomas et al. 2011). It should be acknowledged that Landsat satellite imagery has a 30-meter resolution, which results in increased uncertainty in detecting fine-scale changes in forest cover.

The Landsat imagery used by the NACP did not cover a portion of northern Baltimore County (11% of the county area), and this area was thus excluded from the analysis.

Forest cover change is calculated as the difference between the percent forest cover after development and percent existing forest cover prior to development. For parcels developed in 1985-1992, forest cover change is calculated as the difference between percent forest cover in 1996 and existing percent forest cover prior to subdivision development. For parcels developed in 1993-2000, forest cover change is calculated as the difference between percent forest cover in 2004 and existing forest cover prior to subdivision development. As an example, for a subdivision event occurring in 1989 we would use the existing forest cover prior to subdivision development in 1988 and the forest cover following development in 1996 to determine forest cover change. We use the year of the subdivision event to represent the timing of the landowner development decision because the number of buildable lots and forest conservation plan requirements are determined at the time of subdivision approval. Approximately 93% of all lots have a residential structure built within five years of subdivision.

Figure 1 shows the average forest cover change for subdivisions occurring before the FCA in 1985-1992 and after the FCA in 1993-2000. Prior to the FCA, the average forest cover change was negative across the entire distribution of existing forest cover. The largest losses occurred on subdivisions with higher levels of existing forest cover ranging from approximately 40 to 100%. After the

FCA, a modest gain in forest cover occurred on average for subdivisions with existing forest cover less than 40%; meanwhile, forest cover change decreased continuously for subdivisions with greater than 60% existing forest cover. The largest difference in forest cover change occurred for subdivisions with approximately 50% existing forest cover, where subdivisions had no change in forest cover after the FCA versus an average loss of 9% prior to the FCA. This difference was positive for most of the distribution of existing forest cover, except at the highest forest cover values of 90-100%. This suggests an overall positive effect of the FCA on forest retention and afforestation, albeit heterogeneous effects by parcel-level existing forest cover.

Forest cover change is the dependent variable in the outcome equation for the second stage, while the first stage in the Heckman selection model is a panel probit model for whether the parcel is developed or not. We derive parcel attributes within a geographic information system (GIS) to create explanatory variables for each parcel in our dataset. Summary statistics for these covariates are reported in table 2.1.

We represent existing percent forest cover prior to development in quintile categories. We use quintiles to allow flexibility to capture the potential nonlinear relationship between forest cover change and the existing amount of forest cover. Zoning requirements represent another major land use regulation that pertains to development. We manually reconstruct the historical zoning map in 1976 to represent the zoning designations that existed during the model period of subdivision development in 1985-2000. The zoned capacity variable for the number of allowable lots is created according to the parcel size and maximum density zoning regulations for each parcel. We expect that parcels with higher zoned capacity are more likely to develop. Additionally, the parcel area in acres in quadratic form is included to control for the potential effect of parcel size that is not already accounted for with the zoned capacity variable.

A distinction is made in the subdivision approval process between major and minor subdivisions. Major subdivisions are projects including four or more lots and require a formal public hearing prior to approval, whereas minor subdivisions with two or three lots only requires the planning board approval rather than a public hearing. The variable authorized minor is a dummy variable that takes on a value of one if the zoned capacity on the parcel only allows a minor subdivision with two or three lots. Authorized minor parcels tend to be smaller parcels with fewer development options that are expected to be less likely to develop. The FCA requirements apply the same to both major and minor subdivisions. We therefore treat the authorized minor variable as an exclusion restriction in the first stage and assume that being zoned for minor development may affect the probability of development but not forest clearing, conditional on being selected for development.

We also created an indicator variable for whether the parcel is eligible for a land preservation easement in any of the three major statewide easement programs—Maryland Environmental Trust (MET), Maryland Agriculture Land Preservation Foundation (MALPF), or the Rural Legacy Program (RLP).[21]

[21] MET has eligibility criteria for both parcel size (at least 25 acres or adjacency to equivalent sized protected area) and high quality soils (at least 50% of land area with soil capability class I or

Easement eligibility is expected to decrease the probability of development because the existence of an easement program may delay the decision to subdivide, as found empirically by Towe, Nickerson, and Bockstael (2008) and based on the real options framework for competing land uses in Geltner, Riddiough and Stojanovic (1996). Assuming that a parcel is selected for development, easement eligibility is not expected to affect the forest cover change following development; and therefore, easement eligibility is used as an exclusion restriction in the first stage development equation.

The distance from each parcel to Baltimore City in miles is used to represent accessibility to regional employment opportunities. Similarly, the distance from each parcel to the closest major road or highway is used to represent access to transportation infrastructure. Parcels located farther from either Baltimore City or a major road are expected to have lower likelihood of development. We construct the riparian buffer variable based on the stream hydrology and 100-year floodplains according to the riparian setback requirements in Baltimore County. We represent the riparian buffer variable as the percent of parcel area located within a 50-foot buffer around intermittent and perennial streams starting in 1986. Beginning in 1989, the riparian buffer variable includes a 100-foot buffer around intermittent and perennial streams, due to an update in the setback requirements. When the 100-year floodplain is larger than the minimum riparian setback requirements described above for a given parcel,

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II). MALPF requires meeting criteria for both parcel size (at least 50 acres or adjacency to equivalent sized protected area) and high quality soils (at least 50% of land area with soil capability class I, II, or III). RLP has designated priority areas focused on environmental sensitive watersheds, critical wildlife corridors, and regions of intact agricultural and forest lands.

then the riparian buffer variable is set equal to percent of parcel area within the 100-year floodplain. Riparian buffers are expected to constrain the likelihood of development and forest clearing. Average percent slope and elevation in meters are both calculated for each parcel using the digital elevation model (DEM) at 10-meter grid resolution. We included an indicator variable on whether the parcel is located on prime agricultural soils to reflect the land suitability for profitable agricultural use. Furthermore, the average soil erosion potential is calculated for each parcel based on soil survey data from the USDA Natural Resource Conservation Service to provide a measure of poor soil quality.

Surrounding land use variables are included to control for potential spatial spillover effects from neighboring protected areas and developed land uses. These surrounding land use variables include the percent area within a 500-meter buffer around the boundary for each parcel in non-residential use (e.g., commercial, industrial, etc.), residential use, parks, and undeveloped land use. The variables are lagged temporally to represent the surrounding land uses prior to development, and the undeveloped category is omitted as the baseline. We also create a dummy variable for whether there was an existing house on the parcel.

We also included an index variable on real housing prices at the census tract level to control for how neighborhood housing prices may affect the development decision. To construct our measure of housing prices, we use arm's length housing transaction data between 1985 and 2000 in Baltimore County obtained from Maryland Property View (MDPV). Following the method in Sieg et al. (2002), we run a series of hedonic regressions for each year to separate out the index on the price of housing services at the neighborhood (census tract) level from the structural and lot-specific characteristics of the house. The index on housing prices varies spatially and temporally by census tract and by year, respectively, where higher housing prices are expected to increase the probability of development by increasing the expected returns to development. Additionally, we use the hedonic price model predictions to construct a measure of housing price variability. Capozza and Li (1994, 2002) show theoretically that an increase in housing price uncertainty raises the expected return needed for development. Based on this conceptual framework, Cunningham (2007) finds empirical evidence that an increase in housing price uncertainty tends to delay development (reduce probability of development). Details on the methodology used to create the census tract level variables for both price of housing services and variance in housing prices can be found in Appendix C. The changes in neighborhood characteristics, such as income growth, in theory should be capitalized into the index variable on housing prices. We further include census tract fixed effects to control for any baseline differences in socioeconomic or other neighborhood characteristics. Additionally, we include annual time fixed effects to control for broader economy-wide fluctuations, such as mortgage interest rates or regional employment rates.

V. Results

Table 2.2 reports the FIML estimation results of the Heckman model for a panel probit model of residential development in the first stage and forest cover change in the second stage. The estimated correlation coefficient $\hat{\rho}$ between the first and second stage is 0.70 and is significant at the 1% level. The positive correlation coefficient suggests that, controlling for observable parcels attributes, parcel selected for development have higher levels of forest cover change relative to the undeveloped parcels. In table 2.3, we provide the marginal effects for each covariate computed at the observed values. For the first stage, marginal effects on the average annualized probability of development are calculated based on equation 9. For the second stage, marginal effects for forest cover change conditional on development are calculated based on equation 10, which account for the indirect effects from the selection process of land development in the first stage. Standard errors for marginal effects are calculated using the delta method.

In the first stage, the marginal effects of covariates in table 2.3 on the average annualized probability of development yield the following results. The marginal effects for existing forest cover are not significant for any quintile category, relative to the omitted baseline category of 0-20% existing forest cover. This suggests that, prior to the FCA, there was no significant difference in the likelihood of development for parcels with high existing forest cover relative to those with low existing forest cover. The post-regulatory dummy variable in table 2.2 is not significant, indicating that the overall rate of development was similar between the periods in 1985-1992 and 1993-2000. Additionally, the marginal effects of interaction terms between the post-regulatory variable and existing forest cover are also not significant. Although the conceptual model suggests that, with the introduction of the FCA, there is potential for higher likelihood of development on parcels with the highest levels of existing forest cover; the empirical results suggest that the potential effects are not statistically significant across the forest cover quintiles in the post-regulatory period for the probability of development.

Marginal effects for several other covariates on the probability of development are significant in table 2.3 and generally conform to expectations when significant. Larger parcels tend to have economies of scale that lower development costs. Thus, the average marginal effect for parcel area is positive and significant at the 1% level. Parcels with larger riparian buffer area are less likely to be developed, suggesting that the riparian setbacks requirements and 100-year floodplains reduce the suitability for development, as expected. The presence of an existing house, which may indicate working farmland, tends to delay development. The marginal effect of surrounding residential land use is positive and significant, suggesting that neighboring development potentially provides infrastructure to increase the likelihood of development; meanwhile, the marginal effect for surrounding parks is not significant. The housing price variables are also not significant, presumably because the yearly and census tract fixed effects control for most of the variation in housing prices in our study region in rural Baltimore County.

As expected, the coefficients for authorized minor and easement eligibility, which are used as exclusion restrictions in the first stage, are both negative. In addition, an F-test reveals that these parameters are jointly significant at the 1% level. With two exclusion restrictions, this system of equations is over-identified and we test the suitability of these exclusion restrictions using likelihood ratio tests (Cameron and Trivedi 2005). In these tests, we compare the log-likelihood from table 2.2 in which both variables are excluded from the second stage to the log-likelihood for a model that respectively includes either the authorized minor or easement eligibility variable in the second stage. If the variable is a suitable exclusion restriction, then we should expect no significant difference in the log-likelihood between these models using a chi-squared test with one degree of freedom. The p-value on the chi-squared test is 0.26 for the authorized minor variable and 0.48 for easement eligibility, suggesting that both variables are suitable exclusion restrictions.

The primary interest of our analysis is the marginal effect of existing forest cover on the expected forest cover change conditional on development. The marginal effects for existing forest cover in table 2.3 are negative and significant for all quintile categories, relative to the baseline category for existing forest cover at 0-20%. This implies that larger losses in forest cover occurred for developed parcels with higher levels of existing forest cover during the period 1985-1992 prior to the FCA. For example, developed parcels with 20-40% existing forest cover have on average approximately 5.7% more forest cover loss compared to developed parcels with 0-20% existing forest cover during this period. The post-regulatory dummy variable is positive and significant in table 2.2, suggesting that there was an increase in forest cover on developed parcels in 1993-2000 relative to those developed in 1985-1992. The marginal effects of the interactions between the post-regulatory variable and existing forest cover categories in table 2.3 indicate heterogeneous effects according to the existing levels of forest cover. Consider, for example, the negative and significant interaction effect between existing forest cover at 80-100% in the post-regulatory period. Compared to the baseline category with 0-20% forest cover, this result suggests that larger decreases in forest cover occurred during the period after the FCA for developed parcels with 80-100% forest cover than occurred prior to the FCA.

Regarding the other covariates in table 2.3, the marginal effect of the average percent slope is positive and significant at the 5% level. This indicates that parcels with higher average slope have a lower percentage of forest cover loss, as expected, because steeper slopes may reduce the area suitable for development. The marginal effect is also positive and significant for the riparian buffer variable, presumably because riparian setback regulations provide more forest retention and restoration since they reduce the area allowed for residential development. The marginal effect on parcel area is negative and significant, suggesting that larger parcels have a higher percentage of forest cover loss following development than smaller parcels.

To further investigate the potential effect of the FCA on land use decisions, we provide the expected forest cover change conditional on development in table 2.4 for each quintile category of existing forest cover. We base the results shown in table 2.4 upon the same set of 2,813 parcels that were undeveloped as of 1993, in order to represent those parcels that were developable when the FCA was adopted. Then, according to equation 11, the expected forest cover change is calculated, conditional on development, in the period 1985-1992 and in the period 1993-2000. The difference indicates the expected increase in forest cover after the FCA relative to the period prior to the FCA, while accounting for the selection process of land development.

Table 2.4 shows that the expected forest cover after development decreases on developed parcels in the period 1985-1992 for all existing forest cover categories. Prior to the FCA, forest cover loss ranges from -3.2% on parcels with 0-20% existing forest cover to approximately -11.4% on parcels with 60-80% existing forest cover. After the FCA, a modest increase in forest cover change occurs on average for developed parcels with existing forest cover between 0-60%. However, a decrease in expected forest cover change occurs for developed parcels with greater than 60% existing forest cover.

When considering the difference between the periods after versus before the FCA in table 2.4, an expected net increase in forest cover conditional on development occurs for parcels with 0-60% existing forest cover. The baseline category of 0-20% existing forest cover, for example, reports an expected decrease in forest cover of -3.2% in 1985-1992 and an expected increase of 4.8% in 1993-2000, leading to an overall net increase of 8.1% between these two periods. The largest overall net increase in forest cover is 16.4% for parcels with 40-60% existing forest cover. These results suggest that the afforestation and conservation thresholds implemented under the FCA likely increased the amount of forest cover, relative to what would have occurred without the regulation, but primarily on parcels with lower existing forest cover. In contrast, parcels with the highest levels of existing forest cover at 80-100% have no significant difference in expected forest cover on developed parcels between the periods before and after the FCA. This result may be due to the FCA setting a maximum conservation threshold at 50%, meaning parcels with high levels of existing forest cover above this threshold may deforest large tracts of forest area without penalty. This has consequences for land fragmentation and suggests that the most intact forested areas continue to have the largest losses in forest cover despite the implementation of this forest conservation regulation.

A. Robustness Checks

As mentioned above, it should be acknowledged that, in addition to the effect of the FCA, there may be other market or parcel attributes that vary between these two time periods. It would be desirable to use another neighboring region that is unaffected by the FCA as a control region. However, the FCA is a statewide regulation that was adopted at the same time in neighboring counties in Maryland. Additionally, the forest cover data from the NACP (Goward et al. 2012) only covers the Baltimore-Washington corridor and does not extend into neighboring York County, Pennsylvania. In the absence of such a control region, we conduct several robustness checks to examine the potential sensitivity of our estimation results.

First, we conduct temporal falsification tests that restrict the sample to include either the pre-FCA or post-FCA data only and move the regulatory event to an arbitrary year within those respective time periods. We start by performing a falsification test using only the post-FCA data spanning the period in 1993-2000. We then estimate the model specified in equations 5-7 while hypothetically considering the false regulatory event occurring in 1997, such that 1993-1996 is considered before the regulation versus 1997-2000 after the regulation. If there were significant differences in the forest cover change conditional on development between these two periods, it would suggest potential confounding influence of time-varying unobservable factors affecting forest cover change decisions. Table B1 in Appendix B is analogous to the calculations made for the results in table 2.4. Table B1 shows that there were no significant differences in the expected forest cover change between these two periods in 1993-1996 versus 1997-2000. We repeated this method for the falsification test using only the pre-FCA data spanning 1985-1992 while hypothetically considering the false regulatory event in 1989. Table B2 in Appendix B similarly shows that no significant differences in forest cover change occurs between the periods 1985-1988 versus 1989-1992.

Second, we estimate the model over a shorter ten-year horizon in 1988-1997 as a comparison to our main results over the longer horizon in 1985-2000. By narrowing the time window, we focus the analysis to the period immediately before and after the introduction of the FCA. Hence, this may reduce potential bias from confounding temporally varying unobservable factors. The estimated covariate marginal effects are presented in table B3 in Appendix B. The marginal effects in table B3 change quantitatively but the significance for covariates are qualitatively similar to those in table 2.3. Table B4 shows the expected forest cover change conditional on development for the periods 1988-1992 versus 1993-1997. The results on estimated forest cover change in table B4 are qualitatively the same as those reported in table 2.4. This analysis for a shorter period in 1988-1997, of course, has fewer subdivision events to estimate the model, which is the reason we use the longer period in 1985-2000 for our main results.

Third, we examine the sensitivity to the specification using quintile categories of existing forest cover. We explore the model estimation using decile categories to saturate the potential nonlinear effects. Tables A5 and A6 respectively present the covariate marginal effects and expected forest cover change based on decile forest cover categories. The results are qualitatively the same as those in tables 2.3 and 2.4, respectively. In addition to the discrete categories of existing forest cover as quintiles or deciles, we examine an alternative model where existing forest cover is represented as a continuous variable with a quadratic polynomial to capture the potential nonlinear effects of existing forest cover. Table B7 shows the estimation results for the panel Heckman selection model with the quadratic specification on forest cover, which includes interactions between these forest cover variables and the post-regulatory indicator variable. Tables A8 and A9 shows the covariate marginal effects and expected forest cover change conditional on development, respectively, where the expected effects are calculated at the midpoint of each quintile category (i.e., 10%, 30%, 50%, 70%, 90%). The main results for this continuous quadratic specification are qualitatively the same as those for the discrete categorical specifications in tables 2.3 and 2.4, respectively.[22]

Fourth, we explore whether spatial autocorrelation is significant using a Moran's I test on the residuals for our main results on forest cover change. The Moran's I statistic is estimated to be 0.021 with a p-value of 0.81 when using neighboring observations within a 500-meter radius, and is estimated to be 0.047 with a p-value of 0.35 when using neighboring observations within a 1000-meter radius. These results suggest the presence of positive but statistically insignificant spatial autocorrelation.

Lastly, we examine whether the forest cover change predictions are sensitive to the estimated correlation parameter $\hat{\rho}$ in the Heckman selection model. Because $\hat{\rho} = 0.70$ and is statistically significant (table 2.2), this suggests that model estimates would be inconsistent without controlling how parcels are selected for development. The model estimation, however, relies on the distributional assumptions that the errors are jointly and normally distributed, as stated in equation 8. As a robustness check, we explore the model specification assuming no sample selection, such that the first stage development equation and second stage forest cover change equation are estimated separately (i.e., $\rho = 0$). The corresponding covariate marginal effects and expected forest cover change predictions are provided in tables A10 and A11, respectively. These results are similar in magnitude and sign to the analogous results in tables 2.3 and 2.4. While

[22] We also explored the model estimation that included interactions between the quadratic terms for parcel area and the existing forest cover quintiles for both the baseline and post-regulatory periods. A chi-squared likelihood ratio test comparing a model that includes additional interactions to the main model estimation in table 2 was not significant at the 5% level.

sample selection is significant in table 2.2, the main results for the forest cover change predictions are not overly sensitive to sample selection.[23]

VI. Policy Simulation on Landscape-Level Forest Cover Change

In this section, we provide results of a policy simulation to analyze the landscape-level implications of the FCA on forest cover change in rural Baltimore County. The analysis uses 1,000 bootstrapped samples of the original data set, followed by model estimation according to the specification provided in equations 5-7. Parcels that are developable as of 1993 are used to predict the amount of land development and forest cover change that would occur under the scenarios with and without the FCA during the period 1993-2000. The dummy variable τ is set to one for the scenario with the FCA and set to zero for the scenario without the FCA, while all other variables and coefficients are unchanged between these scenarios.

For each bootstrapped iteration, we predict the parcel-level expected annual probability of development with and without the FCA in each year during 1993-2000. Then, analogous to the methodology in Lewis, Provencher, and Butsic (2009), the expected annual probability of development for each parcel is compared to a random number drawn from a uniform distribution for each parcel and year. The parcel is considered developed in the first year spanning 1993-2000

[23] We also explore sensitivity analysis for the Heckman selection model where the correlation parameter ρ was fixed at 0.3 and 0.5, respectively, and the model results were similar to those reported in tables 3 and 4.

in which the expected annual probability of development is greater than the random number; and otherwise, it is considered to remain undeveloped in 2000. If the parcel is predicted to develop, then the expected forest cover change conditional on development in that given year is calculated.

Simulation results are summarized in table 2.5 showing the land area, existing forest area, and forest cover change on subdivisions under the scenarios with and without the FCA. For all estimates, the means are calculated from the estimated model using the original data set, and bootstrapped 95% confidence intervals (CIs) are calculated based on the 25th and 975th largest simulation results from the 1,000 bootstrap iterations. The null hypothesis is a test on whether the bootstrapped 95% CIs contain zero for the difference between the results under scenarios with and without the FCA. Table 2.5 shows that more total developed land area on subdivisions occurs under the scenario with the FCA compared to without the regulation, specifically 8,400 acres developed with the FCA and 7,504 acres developed without the FCA. This difference, however, is not statistically significant since the bootstrapped CIs range from -4,137 to 3,732. Furthermore, the amount of existing forest cover on subdivisions with and without the FCA is 3,969 acres and 3,743 acres, respectively; but this difference is also not statistically significant.

The results for forest cover change in table 2.5 demonstrate that larger predicted losses in forest cover occur for the scenario without the FCA. We predict a total loss of 893 forested acres out of 3,743 acres of existing forest cover under the scenario without the FCA during 1993-2000, representing about a 24%

loss of forest cover. Meanwhile, we predict a total loss of only 229 forested acres out of 3,969 acres of existing forest cover for the scenario with the FCA. This indicates an overall net difference of 664 forested acres between these two scenarios, approximately a 23% increase in forest cover with the FCA relative to forest cover on subdivisions without the FCA.

Importantly, the results for forest cover change are heterogeneous by the level of existing forest cover. Table 2.5 indicates that significant decreases in forest cover occur for parcels with 20-100% existing forest cover for the scenario without the FCA. With the FCA, there is no significant decrease in forest cover for parcels with 0-60% existing forest cover, whereas there are significant decreases in forest cover for parcels with 60-100% existing forest cover. It is informative to compare the difference in forest cover change between the scenarios by the existing forest cover categories. The largest gain in forest cover occurred on subdivisions for parcels with 40-60% existing forest cover, which had an increase of 324 forested acres compared to the simulation without the FCA. This result suggests that parcels with existing forest cover near the conservation threshold are most significantly affected, which presumably results in either higher retention of existing forest cover or more reforestation to compensate for areas cleared during the subdivision process. For parcels with 80-100% existing forest cover, no significant difference in forest area occurs between the scenarios with and without the FCA. According to the FCA, parcels with high levels of existing forest cover may remove a significant amount of forest acreage above the conservation threshold without requiring reforestation or afforestation. Hence, forest fragmentation may continue unabated for the parcels with the most intact forest habitat.[24]

VII. Conclusion

The purpose of this paper is to analyze the potential heterogeneous effect of the FCA on residential development and assess the change in forest cover occurring with the regulation adoption. Prior to the FCA, forest cover decreases on subdivision developments across the entire distribution of existing forest cover values. After the FCA, forest cover increases on average but only for parcels with existing forest cover between 0-60%. The largest difference in forest cover change between the periods before and after the FCA is for parcels with 40-60% existing forest cover. Meanwhile, parcels with 80-100% existing forest cover have no significant difference in the level of forest loss between the periods before versus after the FCA. Hence, parcels with the highest levels of forest cover at 80-100% continue to have the largest decrease in forest cover, despite the FCA, thereby resulting in forest habitat fragmentation in regions with the most intact forest cover.

Our analysis suggests that an overall significant and positive effect on total forest cover occurred in the region with the FCA. Based upon landscape-level policy simulations, we find that total expected forest cover in rural

[24] We also provide the simulation results with the bootstrapped 90% and 80% CIs in the Appendix in tables B12 and B13, respectively. Both tables B12 and B13 show that there is not a significance difference in the total developed land area under the scenarios with versus without the FCA and there is an overall significant increase in the forest cover with the FCA relative to without it.

Baltimore County increased by approximately 664 acres with the FCA relative to the counterfactual outcome without it, representing a 23% increase in forest area relative to the expected total forest cover that would have occurred on subdivisions without the FCA. Regulatory effectiveness could be further improved, for instance, if regulators increased the conservation threshold. In doing so, landowners subdividing their properties would be required to assume larger amounts of forest conservation and would reduce the amount of forest acreage that could be removed without penalty. Since the most intact forests are currently the least affected by the FCA, another approach would be to target funding from purchase of development rights programs to protect these high priority forested areas. Land managers may find complementary and synergistic strategies between current land-use policies and incentive programs by targeting payments to areas where the FCA is expected be less effective in meeting landscape-level forest conservation goals. However, assessing the tradeoffs needed to set priorities for forest conservation would require a more detailed evaluation of the spatial distribution of ecosystem services provided by forests rather than only the total level of forest cover change provided in this study. Another issue that deserves further evaluation is the potential for the FCA adopted exclusively in Maryland to induce spatial spillovers, thereby increasing development and forest loss in neighboring states without this regulation. Our analysis focuses on the direct effect of the FCA to increase forest cover within our study region; however, to the extent that spillover effects increase development in less regulated regions, it may offset the forest cover gains from the FCA.

There is growing interest and research in programs designed to reduce deforestation and promote afforestation, including both incentive-based payments for ecosystem services (Lubowski, Plantinga, and Stavins 2006; Nelson et al. 2008; Lewis, Plantinga, and Wu 2009; Lewis et al. 2011) and land-use regulations (Lichtenberg, Tra, and Hardie 2007; Lawler et al. 2014). In this study, we integrate parcel-level modeling of residential development decisions with fine-scale panel data on forest cover change from satellite imagery. In doing so, we are able to more accurately assess the partial loss in forest cover that occurs on subdivision developments even prior to regulatory adoption, as well as estimate the additionality of forest cover. This forest loss is often overestimated in prior studies that assume a complete loss in forest cover occurs with development or use uniform rule-based assumptions on the relationship between urban development and forest loss. For instance, Lawler et al. (2014) provide a comprehensive national assessment for land-use change and ecosystem services; however, the urban containment policies assume a uniform rule that only 10% of the initial forest carbon stock remains after development (implying a 90% loss in forest carbon with development). We anticipate that the combination of micro-level land use decisions and fine-scale panel data on forest cover change used in our study will have future research opportunities in other regions since the North American Forest Dynamics Project provides similar publically available data on historic forest cover at 55 sites located across the United States.

TABLE 2.1. COVARIATE SUMMARY STATISTICS

Variables	Mean	Standard Deviation	Min	Max
Existing Forest Cover Quintile				
Forest Cover 0-20%	0.2218	0.4155	0	1
Forest Cover 20-40%	0.1837	0.3872	0	1
Forest Cover 40-60%	0.1641	0.3704	0	1
Forest Cover 60-80%	0.1589	0.3656	0	1
Forest Cover 80-100%	0.2715	0.4447	0	1
Parcel Characteristics				
Parcel Area (acres)	28.2811	35.4608	5	348.5600
Zoned Capacity	4.3610	7.1924	2	148
Distance to Baltimore City (miles)	19.6115	7.6000	3.2167	37.0040
Distance to Major Road (miles)	0.7206	0.6061	0.0270	3.9589
Riparian Buffer Area (%)	20.2102	19.8844	0	100
Slope (%)	10.9102	4.8903	0	42.9550
Elevation (meters)	15.8409	4.5448	0.1006	26.2322
Prime Ag Land	0.3728	0.2648	0	1
Soil Erosion Potential	34.8567	2.7386	9.5000	45
Existing House	0.3522	0.4777	0	1
Authorized Minor	0.7749	0.4177	0	1
Easement Eligibility	0.2478	0.4317	0	1
Housing Price Indices at Census Tract Level				
Housing Price	1.1102	0.1480	0.6429	1.9366
Housing Price Variance	0.2110	0.0975	0.0423	0.5984
Surrounding Land Use within 500 Meter Buffer				
Residential (%)	19.4592	16.3433	0	95.6246
Non-residential (%)	1.9862	5.5623	0	55.6519
Parks (%)	3.8275	10.6321	0	97.8537
Number of Parcels	3043			
Observations	44,002			

TABLE 2.2. FULL INFORMATION MAXIMUM LIKELIHOOD ESTIMATION RESULTS ON PANEL HECKMAN SELECTION MODEL

Variables	Probability of Development Coefficient	Probability of Development Standard Error	Forest Cover Change Coefficient	Forest Cover Change Standard Error
Forest Cover Quintiles[a]				
Forest Cover 20-40%	-0.09233	0.10069	-6.36171**	2.09959
Forest Cover 40-60%	0.11061	0.09302	-6.24995**	2.00697
Forest Cover 60-80%	0.13283	0.09392	-7.18041**	2.39288
Forest Cover 80-100%	0.13812	0.08810	-3.45483*	1.70715
Post-1993 Forest Cover Quintiles[a]				
Post-1993* Forest Cover 20-40%	0.21831	0.13588	5.53714	3.15922
Post-1993* Forest Cover 40-60%	0.02125	0.13123	8.51852**	3.11322
Post-1993* Forest Cover 60-80%	0.02058	0.13088	0.26920	2.63859
Post-1993* Forest Cover 80-100%	-0.02250	0.11951	-9.40946**	2.58841
Post-1993	-0.00539	0.15072	8.01267*	3.27345
Parcel Characteristics				
Parcel Area	0.00332*	0.00136	-0.04726	0.02512
Parcel Area^2	-4.16×10^{-6}	-4.89×10^{-6}	0.00016*	0.00007
Zoned Capacity	0.00437	0.00225	0.06610	0.03901
Distance to Baltimore City	-0.01272	0.00816	-0.18215	0.19702
Distance to Major Road	0.03766	0.03996	-0.06565	1.01262
Riparian Buffer Area	-0.00640**	0.00135	0.05600	0.04153
Slope	-0.00286	0.00580	0.39383*	0.15958
Elevation	0.00665	0.01058	-0.04729	0.23714
Prime Ag Land	0.00862	0.09595	0.61742	2.80434
Soil Erosion Potential	-0.00169	0.00817	-0.30658	0.24937
Existing House	-0.07424	0.04261	-0.14781	0.96978
Authorized Minor	-0.35698**	0.04900	--	--
Easement Eligibility	-0.08794	0.06143	--	--
Housing Price Indices at Census Tract Level				
Housing Price	-0.03400	0.23138	-3.46215	5.49321
Housing Price Variance	0.56648	0.31636	10.48239	8.52744
Surrounding Land Use within 500 Meter Buffer				
Residential	0.00787**	0.00125	0.10120*	0.04866
Non-residential	0.00022	0.00391	-0.01843	0.10092
Parks	-0.00016	0.00211	0.03876	0.04722
ρ	0.70139**	0.16779	--	--
Annual Time Fixed Effects	Yes		Yes	
Census Tract Fixed Effects	Yes		Yes	
Observations	44,002		413	

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.
[a] Marginal effects are based upon a discrete change from the baseline 0-20% existing forest category.

TABLE 2.3. MARGINAL EFFECT OF COVARIATES ON ANNUAL PROBABILITY OF DEVELOPMENT AND FOREST COVER CHANGE

Variables	Probability of Development		Forest Cover Change	
	Marginal Effect	Standard Error	Marginal Effect	Standard Error
Forest Cover Quintiles[a]				
Forest Cover 20-40%	-0.00160	0.00178	-5.70414**	1.95036
Forest Cover 40-60%	0.00242	0.00202	-7.03405**	1.94555
Forest Cover 60-80%	0.00298	0.00211	-8.12156**	2.29835
Forest Cover 80-100%	0.00311	0.00194	-4.43334**	1.57215
Post-1993 Forest Cover Quintiles[a]				
Post-1993* Forest Cover 20-40%	0.00277	0.00211	-1.71753	2.21690
Post-1993* Forest Cover 40-60%	0.00292	0.00223	1.33408	2.28967
Post-1993* Forest Cover 60-80%	0.00348	0.00232	-7.99792**	1.78568
Post-1993* Forest Cover 80-100%	0.00251	0.00207	-13.68405**	2.23552
Parcel Characteristics				
Parcel Area	0.00007**	0.00002	-0.06029**	0.01977
Zoned Capacity	0.00010	0.00005	0.03515	0.03250
Distance to Baltimore City	-0.00030	0.00019	-0.09209	0.17547
Distance to Major Road	0.00088	0.00093	-0.33229	0.97428
Riparian Buffer Area	-0.00015**	0.00003	0.10129**	0.03477
Slope	-0.00007	0.00013	0.41406**	0.15522
Elevation	0.00015	0.00025	-0.09436	0.22410
Prime Ag Land	0.00020	0.00223	0.55639	2.74729
Soil Erosion Potential	-0.00004	0.00019	-0.29460	0.23886
Existing House	-0.00173	0.00099	0.37786	0.90944
Easement Eligibility	-0.00830**	0.00119	--	--
Authorized Minor	-0.00204	0.00143	--	--
Housing Price Indices at Census Tract Level				
Housing Price	-0.00079	0.00538	-3.22137	5.13131
Housing Price Variance	0.01316	0.00739	6.47129	8.27907
Surrounding Land Use within 500 meter buffer				
Residential	0.00018**	0.00003	0.04547	0.03190
Non-residential	0.00001	0.00009	-0.02001	0.09417
Parks	0.00001	0.00005	0.03989	0.04191

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

[a] Marginal effects are based upon a discrete change from the baseline 0-20% existing forest category.

TABLE 2.4. PERCENT FOREST COVER CHANGE CONDITIONAL ON DEVELOPMENT IN 1985-1992 AND 1993-2000

Forest Cover Quintile	**Forest Cover Change in 1985-1992**	**Forest Cover Change in 1993-2000**	**Difference**
Forest Cover 0-20%	-3.2407	4.8103**	8.0510**
	(2.8917)	(1.3109)	(3.0761)
Forest Cover 20-40%	-8.9439*	3.0914	12.0352**
	(3.5051)	(1.7698)	(3.7318)
Forest Cover 40-60%	-10.2760**	6.1429**	16.4189**
	(3.4151)	(1.9391)	(3.7250)
Forest Cover 60-80%	-11.3638**	-3.1894*	8.1744*
	(4.2193)	(1.2573)	(3.9265)
Forest Cover 80-100%	-7.6756*	-8.8751**	-1.1994
	(3.2067)	(1.7245)	(3.4211)

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

TABLE 2.5. LANDSCAPE-LEVEL PREDICTIONS ON LAND ACREAGE, EXISTING FOREST COVER AND FOREST COVER CHANGE WITH AND WITHOUT FCA

	Subdivisions without FCA			**Subdivisions with FCA**			**Difference**		
Forest Cover Quintile	Land area	Existing forest area	Forest cover change	Land area	Existing forest area	Forest cover change	Land area	Existing forest area	Forest cover change
Forest Cover 0-20%	1395*	175*	-97	1400*	176*	16	5	1	113*
	[518, 2634]	[60, 284]	[-269, 2]	[581, 2123]	[64, 252]	[-38, 84]	[-1423, 810]	[-133, 89]	[19, 246]
Forest Cover 20-40%	1371*	396*	-197*	2216*	639*	-57	845	243	140*
	[564, 3175]	[170, 954]	[-490, -53]	[1325, 3332]	[393, 956]	[-128, 75]	[-446, 1674]	[-133, 489]	[7, 479]
Forest Cover 40-60%	1969*	931*	-273*	2013*	955*	51	44	24	324*
	[866, 3498]	[417, 1686]	[-598, -90]	[1198, 3439]	[565, 1707]	[-54, 178]	[-1281, 1323]	[-618, 635]	[100, 692]
Forest Cover 60-80%	1221*	841*	-164*	1366*	936*	-77*	145	95	87
	[659, 2752]	[441, 1871]	[-488, -54]	[835, 2562]	[557, 1725]	[-161, -22]	[-1130, 908]	[-780, 616]	[-2, 384]
Forest Cover 80-100%	1548*	1400*	-163*	1405*	1263*	-162*	-143	-137	1
	[822, 2929]	[753, 2664]	[-326, -*30]	[889, 2307]	[815, 2119]	[-350, -75]	[-1314, 730]	[-1210, 672]	[-197, 201]
Total	7504*	3743*	-893	8400*	3969*	-229*	896	226	664
	[4928, 13455]	[2587, 6866]	[-1823, -354]	[7270, 11065]	[3401, 5547]	[-389, 1]	[-4137, 3732]	[-2165, 1793]	[153, 1584]

All numbers above reported in acres. Asterisk (*) denotes statistical significance of the bootstrapped 95% confidence interval not containing zero.

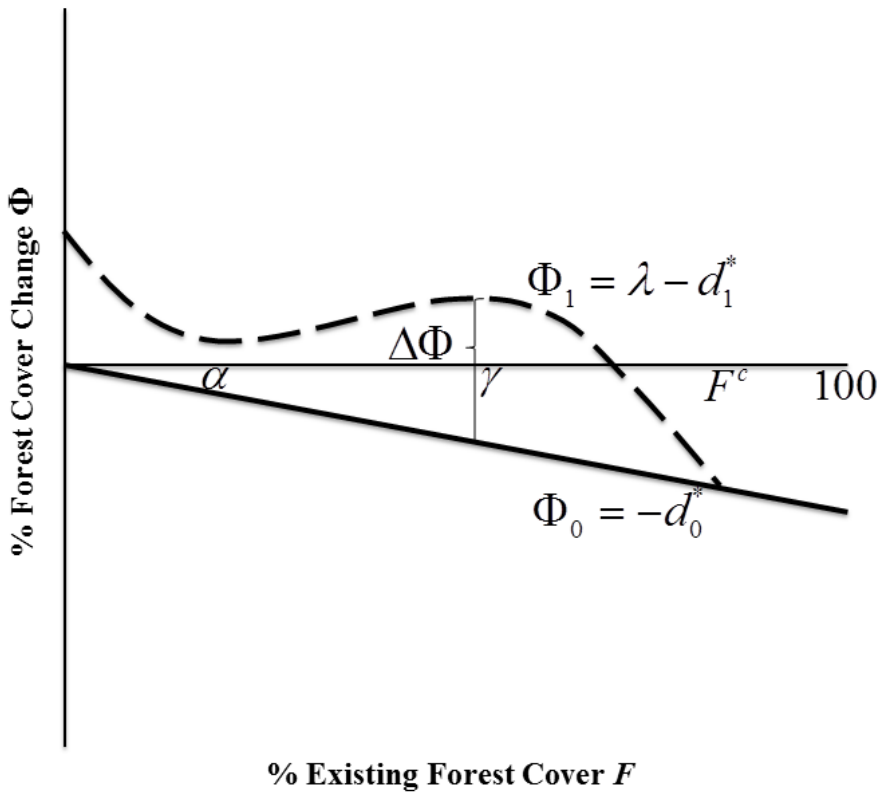


FIGURE 2.1. FOREST COVER CHANGE DUE TO FCA PLANTING AND AVOIDED DEFORESTATION OVER EXISTING FOREST COVER VALUES

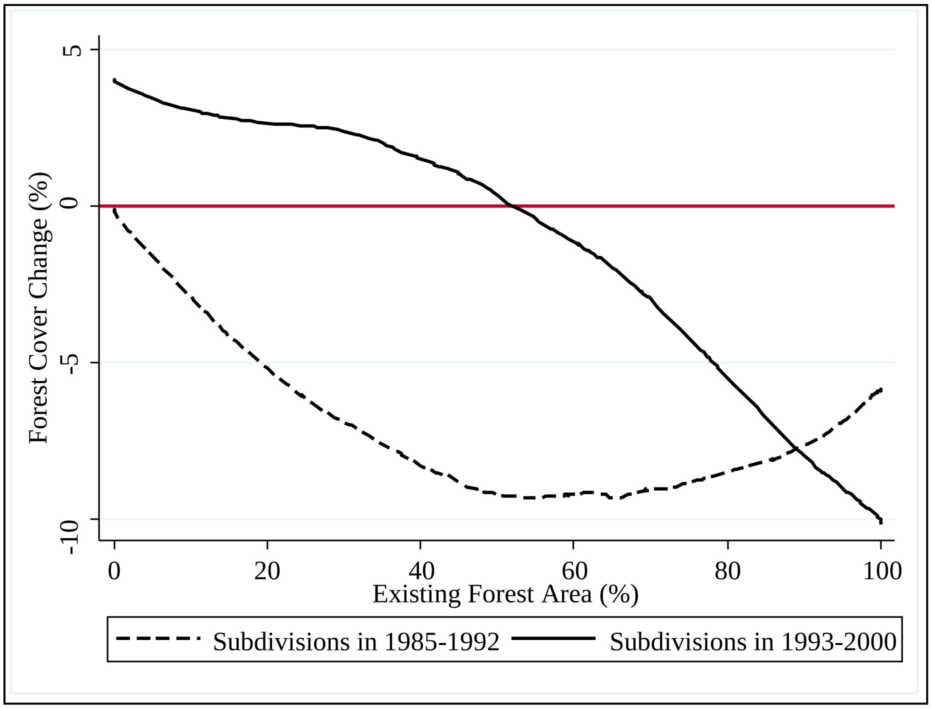


FIGURE 2.2. LOWESS OF AVERAGE FOREST COVER CHANGE FOR SUBDIVISIONS BEFORE FCA (1985-1992) AND AFTER FCA (1993-2000)

Chapter 3: Wildfires, Hazard Disclosure and the effect on Land Development

In the United States, wildfires are among the most destructive natural hazards and endanger valuable natural resources along with human life and property. One challenge to combating wildfires is the growth of developed lands in wildfire prone areas, known as the wildland urban interface (WUI). Currently, at least 44 million homes are located in the WUI and this number is expected to increase by 66% by 2030 (Hammer et al. 2009). Land development in the WUI is known to increase fire suppression costs and may also increase the incidence of wildfire by multiplying the number of residents and potential sources of wildfire ignition (Stein et al. 2013). To help reduce risk from wildfire damage and decrease fire suppression costs, many communities have adopted hazard disclosure requirements to educate new residents about the potential risks of wildfire. In response to recent large and destructive wildfires, in July of 1991, California began publicly publishing wildfire hazards for all state responsibility area (SRA) lands and implemented a new law that requires the seller of any property located in SRA lands to provide a written disclosure regarding the risk posed by wildfire in these areas. In this paper, I study the effect of the hazard disclosure law on land development decisions from a community in the sierra foothills of California.

Previous researchers have used empirically focuses assessments of individual land development decisions to evaluate the effect of land use policy on development patterns (Irwin and Bockstael 2004, Newburn and Berck 2006, Lewis et al. 2009). These studies determine the location and timing of land development based upon individual tax-assessed parcel records. Results of these studies highlight the importance of spatial and temporal heterogeneity of parcel attributes to development decisions and land-use policy effectiveness. However, to date, no studies have examined the effect of wildfire risk and policy on land development decisions.

Prior studies of wildfire risk focused mostly on determining the effect of perceived changes in wildfire risk on housing price. For instance, Loomis (2004) and Mueller et al. (2009) utilized cross-sectional hedonic analyses to determine the effect of large wildfires on nearby home prices. They find that large wildfires may contribute to decreases in home value by between 10-20%. Donovan et al. (2007) studied the effect of the Colorado Springs Fire Department publishing home specific wildfire risk online on local home sales prices. They found that housing price was positively correlated with natural amenities that contribute to increased risk of wildfire prior to wildfire rating being posted online. After wildfire ratings were posted online, housing prices were negatively correlated with these attributes, indicating that home price adjusts due to changes in information regarding the underlying risk of wildfire damage. Champ et al. (2009) conducted a survey of homeowners affected by the change in wildfire rating policy in Colorado Springs and found that even after the policy was adopted, homeowners often perceived wildfire risk as substantially lower than actual risk.

However, among respondents who actually visited the Colorado Springs FDP website, perceptions of risk more closely mirrored actual risk.

A handful of studies have examined the effect of wildfire hazards and hazard reduction incentives on other land use decisions. Busby et al. (2012) developed a stylized game-theoretic model to understand how the spatial configuration of land ownership impacts wildfire risk mitigating behavior. They find that because private landowners are not residual claimants to all the benefits from fire prevention, they have an incentive to under invest in risk mitigating behaviors, relative to the social optimum. Shafran (2008) studied incentives for homeowners to adopt defensible fire spaces around their homes using data from properties near Boulder, Colorado. They found that sub-optimal investment in defensible spaces was likely because homeowners' investment decisions were conditional on their neighbors' level of investment. Kousky and Olmstead (2012) studied the effect of a change in federal wildfire suppression policy in the Yellowstone National Park region on land development trends. Using a panel dataset of land use change derived from Landsat satellite imagery, Kousky and Olmstead (2012) show that federal fire suppression efforts encourage development because homeowners free ride off federal fire suppression expenditure.

The primary purpose of this paper is to study the effect that the introduction of California's hazard disclosure requirement in July of 1991 had on a parcel's probability of development. Wildfire hazard severity rankings, published by the State of California, are grouped into three classes: very high,

high and medium. Under the hypothesis that the hazard disclosure requirement conveyed new information regarding the underlying risk of wildfire, we should expect a larger reduction in probability of development for parcels with very high and high hazard severity than for ones with medium severity. Aside from hazard severity rankings, wildfire events may provide additional information to landowners about their exposure to fire risk. Because large wildfires are a low probability occurrence and fire risk is non-stationary, a wildfire nearby the parcel may update the subjective risk perception of the landowner and impact the timing and location of subsequent land development. This study is based upon a spatially and temporally explicit panel dataset of residential subdivisions from 1985 to 2004 in El Dorado County, California. My analysis includes both a pre-disclosure period (1985-1991) as well as a post-disclosure period (1992-2004). To estimate probability of development, I utilize a linear probability model with parcel based fixed effects. By including fixed effects, I reduce potential bias from time invariant and unobserved parcel attributes and identify coefficients for observed attributes that vary over time. Probability of development is estimated as a function of a number of spatially and temporally varying parcel characteristics, including: post-disclosure hazard severity group, proximity to recent large wildfires, forest area within the parcel and within 500 meters of the parcel, as well as surrounding land use within 500 meters.

Results of my analysis support the hypothesis that the hazard disclosure requirement is effective in reducing probability of development for parcels located in areas with the highest designated wildfire severity in El Dorado

County. Parcels located in very high severity areas are 24% less likely to develop per year than parcels located in medium severity zones. Recent wildfire events also have an effect on development decisions. Parcels located within 1.25 km of recent large wildfires are nearly 1% less likely to develop the following year. However, parcels further removed in time and distance are statistically more likely to develop following large wildfire events. This result suggests a possible misperception of community wildfire risk by landowners akin to the so called "gambler's fallacy," or the mistaken belief that because a low probability event occurred in the recent past, it is less likely to occur in the near future.

This paper makes several contributions to the literature. Relative to previous empirical land use economic studies, I improve upon identification of policy variables by studying a sample of properties observed before and after the hazard disclosure law adoption. Previous studies (e.g., Irwin and Bockstael 2004, Newburn and Berck 2006, Towe et al. 2008, Lewis et al. 2009, Bustic et al. 2011) all study residential land use decisions only after policy adoption and identification of policy effects are based only on spatial variation in policy effectiveness. To the best of my knowledge, this is the first paper to study the impact of either hazard disclosure requirements or recent wildfire events on residential land use decisions. California is currently the only state with a statewide hazard disclosure requirement related to wildfire risk, which could provide guidance to other regions considering similar regulations. However, policy makers could make efforts to better educate residents regarding causes of wildfire and risk updating, particularly in areas near recent wildfire events.

This paper proceeds by presenting an overview of the study and policy setting for this analysis in Section I. In Section II, I discuss the available data and in Section III I present my empirical methodology. Sections IV and V discus the main model findings and various robustness checks. Section VI provides concluding remarks.

I. Study Area and Policy Overview

El Dorado is a fast growing rural county thirty miles from Sacramento and bordered by Lake Tahoe on the East. Between the 1980 Census and the 2000 Census, the population of El Dorado nearly doubled from 86,000 to over 155,000 residents over the span of twenty years (US Census Bureau 2013). This growth of population is driven primarily by an increase in exurban development in the unincorporated areas of the county. Between 1990 and 2000, the population in unincorporated El Dorado County grew by over 20% and accounted for 95% of the total change in population over the ten year period (Center for Economic Development 2011). In these areas, land is converted primarily from agriculture and forestry uses to low-density residential development.

As in many communities in the United States, growth of urban housing density is regulated primarily through minimum lot zoning regulations. In unincorporated El Dorado County, there are a total of five exurban residential zoning categories: medium-density residential (MDR), low-density residential (LDR), rural recreational (RR), agricultural lands (AL) and natural resource (NR). Zoned density ranges between one dwelling per acre on MDR up to one dwelling per 160 acres on NR lands.[25] Figure 3.1 displays a map of El Dorado County along with the location and spatial extent of zone classes. Over 50% of El Dorado County land area is owned and managed by the federal government, which includes two major national forests, the El Dorado National Forest and the Lake Tahoe Basin Management Unit. The majority of government lands reside in areas zoned as NR. County zoning ordinances date back to the 1960s with some amendments made over the years, though zoning in unincorporated El Dorado County remained essentially stable from 1985 to 2004, the sample timeline of my analysis.[26]

Wildfires are a common occurrence in El Dorado County both on federal and private lands. El Dorado County is prone to long dry summers, conditions favorable to wildfire ignition, and the natural wildlife is adapted to periodic wildfire occurrence (Stephens 1997). Between 1985 and 2004, 128 wildfires occurred in El Dorado County that were larger than ten acres in size. The mean size of fire in this sample was approximately 732 acres, though this estimate is influenced by a handful of exceptionally large wildfires including the 1992 Cleveland wildfire that was over 22,000 acres in size.[27] The main contributors to wildfire risk in El Dorado County include: weather, fuel level (e.g. quantity of timber), and terrain. Aside from natural landscape attributes, land development in fire prone regions may contribute to growth in wildfire risk as well as increased

[25] For parcels with elevation below 3,000 ft zoned density is 1 Du/40 Ac on NR lands, parcels above 3,000 ft in elevationhave a zoned density of 1 Du/160 Ac

[26] Confirmed through personal contact with El Dorado County Planner Tom Purciel

[27] For comparison, the median fire size was approximately 35 acres

costs for wildfire suppression. Previous studies have linked the presence of humans in wildfire prone areas to an increase in fire incidence and spread (Hammer, 2007, Blonski et al. 2010). Several studies have also found that the quantity and value of developed land near large wildfires are among the greatest predictors of fire suppression expenditure (Liang et al. 2008, Gebert et al. 2007).

To help control the risk of wildfire and reduce costs of fire suppression, the State of California and El Dorado County adopted a variety of hazard mitigation policies to regulate land development and other landowner behavior. El Dorado established a hazard removal requirement in 1985 that requires the owner of any structure in the county to maintain a defensible space of cleared land and to remove any vegetation or other debris from the structure's roof. Defensible spaces must extend at least 30 feet from the structure. In 2005 this threshold was extended out to 100 feet from the structure.[28] In addition, in response to recent large wildfires, including the 49er fire of 1988 which destroyed over 300 structures, the State of California passed a hazard disclosure law[29] in 1989 (Assembly Bill 1812, 1989). This regulation impacts any parcel located in a state responsibility area (SRA), which include any areas where the State has a financial responsibility for wildland fire protection. Under this policy, after July of 1991, any seller of a property located in SRA lands must disclose that the property is located in a wildland area that may contain substantial wildfire risk. To coincide

[28] http://www.eldoradocountyfire.com/prevention/defensiblespace.html

[29] The State of California hazard disclosure law is detailed in sections 4125 and 4136 of the California Public Resource Code: http://www.leginfo.ca.gov/cgi-bin/displaycode?section=prc&group=04001-05000&file=4125-4137

with the adoption of the new disclosure law, the State of California began publishing publicly available hazard severity maps for each county which detail the hazard severity in SRA lands in July of 1991. Figure 3.2 displays a map of wildfire hazard severity zones in El Dorado County, with data collected from the California Department of Forestry and Fire Protection. Fire hazard is divided into three classes: very high, high and medium. Areas outside this designation are either under the protection of local municipalities, which include the incorporated cities of Placerville and South Lake Tahoe, or are federally owned and managed lands.

The El Dorado County Council also adopted an additional hazard disclosure law in November of 1992. This ordinance was designed to complement the State's hazard disclosure law and must be completed before the sale of any property located in SRA lands in El Dorado County. The hazard disclosure form required by El Dorado County law is reported in Appendix D. The language of this hazard disclosure law mirrors the state requirement but it further clarifies the local fire department's responsibilities for fire protection and advises the prospective buyer of behaviors which may reduce risks from wildfire damage. This policy also advises buyers and sellers to seek professional guidance and inspection to more accurately assess the local risk of wildfire risk in the vicinity of the property.

II. Econometric Model

The landowner is assumed to be a utility maximizing agent who makes a discrete choice in each period to convert a parcel from undeveloped to developed land use. Let U_{it} be landowner $i's$ utility from development in period t, net the return from his outside option of remaining undeveloped for an additional period. Let $U_{it} = V_{it} + \varepsilon_{it}$, where V_{it} is a function of observable parcel attributes expected to influence land conversion and ε_{it} is independently and identically distributed and clustered at the parcel level. Conditional upon a parcel being undeveloped in the current period, landowner i will develop if $V_{it} + \varepsilon_{it} > 0$.

Landowner development decisions are assumed to be a function of both time variant and time invariant parcel attributes. Let H_{it} be a vector of hazard severity, divided into medium (the baseline), high and very high classes. The variable τ is a dummy variable that takes on a value of one for all years after the hazard disclosure law was introduced. F_{it} is a vector of dummy variables that capture whether a recent large wildfire occurred near the parcel in the recent past.[30] Let X_{it} be a vector of time varying parcel attributes (e.g. parcel level forest area and surrounding land use), Z_{it} be a vector of observable, time invariant parcel attributes (e.g. zoning and parcel area). T_t is a set of yearly dummy variables and μ_i is a parcel specific intercept. Equation 1 represents the econometric specification for my model

[30] Please refer to section 4 for more information about construction of the fire proximity variables

(1) $$U_{it} = H_{it}\beta_1 + \tau H_{it}\beta_2 + \beta_3\tau + F_{it}\beta_4 + X_{it}\beta_5 + Z_{it}\beta_6 + T_i\beta_7 + \mu_i + \varepsilon_{it}\ .$$

Assuming that $E\left[\mu_i\right] = 0$, Equation 1 may be estimated through, for example, a random effects probit, or logit model. However, if for some set of observations, $E\left[\mu_i\right] \neq 0$, random effects models may yield inconsistent coefficient estimates. Wildfire hazard severity is determined based upon a number of risk factors, such as nearby fuel stock, weather, and wind patterns, some of which are observed and some unobserved. Therefore, to overcome bias from unobserved time invariant parcel attributes potentially correlated with hazard severity class, in the primary specification of my model, I estimate a linear probability model of land development decisions with parcel based fixed effects. Equation 2 represents the simplified linear probability model estimated in my primary specification

(2) $$U_{it} = \tau H_{it}\beta_2 + \beta_3\tau + F_{it}\beta_4 + X_{it}\beta_5 + T_t\beta_7 + \mu_i + \varepsilon_{it},$$

$$\varepsilon_{it} \sim N\left(0, \sigma_i^2\right)\ .$$

By including fixed effects in Equation 2, I estimate coefficients only for covariates that vary over time and parameters are identified based upon within parcel variation in covariate values. Unlike a non-linear model, coefficients from Equation 2 may be interpreted directly as the average marginal effect of covariates on the likelihood of development. In addition, because the marginal effects of a linear probability model are not conditional upon the estimates of other parameters and covariates, interpreting the magnitude and significance of interaction terms, such as β_2, is straightforward. In non-linear models, structural parameters of the model need not have either the same sign[31] or significance as marginal effects, confounding standard hypothesis testing procedures (Ai and Norton 2003).

Linear probability models do have some important draw backs. Estimating a linear probability model will introduce heteroskedasticity to parameter estimates by imposing a continuous distribution to an inherently binary process. In practice, heteroskedasticity may be overcome by estimating models with cluster-robust standard errors. In addition, linear probability models may estimate predicted probabilities that lie outside the unit interval. This issue poses a more serious problem, particularly when researchers are interested in interpreting outcomes far from the average covariate values, and may imply inconsistent or biased parameter estimates (Horrace and Oaxaca 2006). However, so long as covariates are all discrete and completely saturated, the conditional expectation function can be linearly parameterized and a linear probability model will yield consistent parameter estimates (Angrist 2001). Even if all covariates are not fully saturated, as Wooldridge (2010) notes, to the extent that we are interested in the marginal effects of independent variables on the response probability for the average observation, the fact that some predicted vales are outside the unit interval may not be very important.

In Equations 1 and 2, the effect of the hazard disclosure law on land development decisions is captured by the vector of parameters β_2. A negative and significant estimate for these parameters would indicate a reduction in probability

[31] In a difference-in-differences (DID) model, Puhani (2012) showed that the sign of the interaction term should at least be the same as the marginal effect

of development due to the hazard disclosure law relative to the baseline medium severity category. This result would suggest that the hazard disclosure law effectively conveyed new information regarding the underlying risks of wildfire, correspondingly reducing the rate of development for parcels with greater hazard severity. The effect of proximity to large wildfires is captured by the vector of coefficients β_4. A negative and significant coefficient estimate would indicate that proximity to a recent large wildfire tends to reduce probability of land development. Conversely, a positive coefficient estimate would indicate that parcels are more likely to develop after large wildfires occur. Because large wildfires occur with low probability, when a wildfire occurs nearby, some landowners may perceive this as a signal that their actual wildfire risk is now lower than before the fire. In reality, although large wildfires in close proximity to the parcel may provide some short term protection from fire damage by exhausting nearby fuel, over the medium to long term, the underlying risk of wildfire is unchanged by the occurrence of individual wildfire events.

Estimates of the treatment effect of the hazard disclosure law in Equation 2 are robust to sources of both spatial and temporal heterogeneity but rely upon the assumption of parallel time trends between treatment and control groups for purposes of identification. In robustness checks included in the Results section, I conduct a temporal falsification test using data only from the pre-hazard disclosure period (1985-1991), with false treatment occurring in 1988, to test for baseline differences in development patterns between severity classes. In addition, to reduce bias from unobserved spatial and temporal heterogeneity, I estimate a model that includes only parcels within a two-kilometer spatial buffer of the border with medium hazard severity lands. Both probit and logit model specifications face problems with incidental parameters when estimated with fixed effects[32] but, for sake of comparison, I also report results of a random effect probit model of land development decisions, which are estimated based upon Equation 1, above.

III. Available Data

The sample used for this analysis consists of all subdivisions and undeveloped parcels zoned for less than one dwelling per acre between the years 1985 and 2004 in El Dorado County. The El Dorado County Geographic Information System (GIS) Program Office provided current parcel boundaries, zoning, and parcel attribute data. Undeveloped parcels include any property zoned for at least two authorized lots as of 1985, and with no more than one structure already built on the property. For subdivisions, the parcel boundary prior to development (the parent parcel) is determined based upon common attribute information stored in the legal description of each parcel. Subdivisions are identified as any parent parcel that produced two or more residential lots following land development. The year of development is based upon the year of construction for the first residential lot built. However, if more than ten years separate construction year for the first lot and successive lots, the date of construction for the second lot is treated as the

[32] Probit models cannot be consistently estimated with fixed effects and logit models can only be estimated for observations with variation in the dependent variable (i.e. developed parcels in my sample) .

year of development and the subdivision is recorded as having an existing house. In El Dorado County, major developments are considered any subdivision with more than five buildable lots and minor developments have five or fewer lots. In my sample, the vast majority, 96% of subdivisions, are considered minor developments. The final sample for my analysis includes 5,921 parcels, 1,117 (19%) of which subdivided.

The dependent variable for my analysis is a binary indicator of development. All parcels begin as undeveloped at year start in 1985 and once a parcel develops, it exits the sample permanently. Land development decisions are modeled as a function of spatially and temporally varying parcel attributes described in the remainder of this section. The primary model specification used for this analysis consists of a linear probability model of land development decisions with parcel based specific effects. By running a fixed effects model, I eliminate bias from any unobserved parcel attributes held constant over the sample timeline but also require that included explanatory variables temporally vary for purposes of identification. In robustness checks, I present an alternative random effects probit model and include other temporally invariant parcel attributes in this model. Table 3.1 provides summary statistics for included explanatory variables, including covariate means with standard deviations listed in parenthesis.

For each parcel in my sample I determine wildfire risk based upon fire hazard severity data provided by the California Department of Forestry and Fire Protection (Cal FIRE). The spatial extent of Cal FIRE, hazard severity data is reported in Figure 3.2. Hazard severity is mapped for all SRA lands in El Dorado. A total of 64 parcels were dropped from my analysis because they were located outside Cal FIRE data coverage. Hazard severity is divided into three classes: medium (the baseline), high and very high. Approximately 34% of sample properties reside in medium hazard severity zones, 26% in high severity zones and 41% in very high severity zones.

The primary purpose of this analysis is to determine the effect that the introduction of the California wildfire hazard disclosure law had on land development patterns in El Dorado County. This policy was approved in 1989 and adopted in July 1991 and I therefore treat 1992 as the start of the post-disclosure, treatment period for purposes of my analysis. Thus, my sample includes both a pre-disclosure period (1985-1991) and a post-disclosure period (1992-2004). To test the hypothesis that the introduction of the hazard disclosure requirement caused a reduction in development for parcels with higher hazard severity, I interact a parcels hazard severity with a dummy variable equal to one for years greater than or equal to 1992.

I determine the proximity of each parcel to several large wildfires that occurred in and around El Dorado County from a sample of mapped wildfires produced by Cal FIRE. Cal FIRE works jointly with the US Forest Service, the Bureau of Land Management and the National Park Service to develop a comprehensive GIS database of fire perimeters on public and private lands throughout California.[33] Cal FIRE maps fire perimeters for timber fires larger than

[33] For more information regarding Cal FIRE, fire perimeter data see: http://frap.cdf.ca.gov/projects/fire_data/fire_perimeters/methods.php

ten acres, brush fires larger than fifty acres and grass fires three hundred acres or more from 1950 to the present day. In El Dorado County, mixed-oak and pine forests are the primary vegetation types (US Forest Service 2013) and thus, for most intents and purposes, Cal FIRE data contains fire perimeters for fires larger than ten acres. The current fire perimeter data represents the most comprehensive digital record of fire perimeters in the state of California. Fire perimeters for fires mapped by Cal FIRE between the years 1980 and 2004 near El Dorado County are reported in figure 3.3, along with the location of all the subdivisions included in my sample.

Although wildfires are common in El Dorado County, the actual probability of a large wildfire occurring near a given parcel in a particular year is relatively small. In my sample, in each year, on average only 6% of parcels were within 7.5km of a wildfire. Thus, a parcel may update their subjective risk assessment even if not immediately threatened by the wildfire event. For each parcel in my sample and in each year, I create a set of dummy variables to indicate if a large wildfire occurred in the year prior within 1.25 km, 1.25-5 km and 5-7.5 km buffer. I also determine if a wildfire occurred in the two to five years prior over an identical set of distance thresholds. Under the hypothesis that the presence of a nearby large wildfire in the recent past generally delays development by conveying new information about the actual risk of wildfire, we should expect a negative coefficient for these fire proximity variables. However, a positive and significant coefficient for fire proximity may indicate a possible misperception regarding fire risk updating.

Historical forest cover is derived from the North American Carbon Project (NACP): Forest Disturbance data (Goward et al. 2012). NACP maintains detailed GIS raster databases of forest change for 55 selected locations across the United States at 30 square-meter resolution. For each study location, Landsat satellite imagery is collected starting in year 1984 and re-sampled every two to three years to create panel based observations of forest vegetation. Using this panel satellite data, the NACP apply their proprietary Vegetation Change Tracker (VCT) algorithm to determine timing and location of forest change (Huang et al. 2010). Results may be used to predict timing and distribution of deforestation, reforestation and afforestation events, based upon the date of first and last disturbance of each observation cell. For each parcel in my sample, I calculate the percent of parcel area covered by forest as well as the percent of the area within 500 meters covered by forest. Each parcel is assigned forest values from the previous year. I expect a negative coefficient for the effect of forest area within parcel on probability of development. Parcels with larger forest area require more costly forest clearing to produce cleared land, ready for the construction of dwellings and defensible spaces. Previous empirical research by Bockstael (1996) found that forest clearing costs negatively affect probability of development. However, previous hedonic research has also shown that adjacent forest area tends to increase home values (Garrod and Willis 1992, Thorsnes 2002). To the extent that forests provide amenities valued by future homeowners, forest area within 500 meters may have a positive effect on probability of development.

Surrounding land use (SLU) within five hundred meters was estimated for each parcel, in each year, based upon parcel plat data provided by the El Dorado GIS Program Office. Land use is divided up into four categories: undeveloped, developed, non-residential and government lands. Undeveloped lands are considered the baseline land use in my models. The developed area surrounding each parcel updates each year as new structures are built and parcels are converted from undeveloped land uses to developed uses. For each parcel in my sample, I calculate the percent of area within a five hundred meter buffer identified as developed, non-residential, government, or undeveloped land uses. Of all the land use designations, only developed and undeveloped surrounding land use percentages update over time. Developed and non-residential surrounding land use both have ambiguous signs and may attract, or repel additional development relative to undeveloped land uses. I expect government surrounding land use to have a positive effect on development because government land includes large tracts of protected open space which may provide local amenities to homeowners.

I calculate several time invariant parcel attributes included in robustness checks using a random effects probit model of land development. I calculate parcel area, existing house and zoning based upon data provided by The El Dorado County Geographic Information System (GIS) Program Office. I expect parcel area to have a positive effect on a parcel's probability of development and existing house to have a negative effect. Zoning is calculated as a categorical variable with five potential values: MDR (1 du/1-5 acre), LDR (1 du/5-10 acre), RR (1 du/10 acre), AL (1 du/20 acre) and NR (1 du/40-160 acre). MDR is treated as the baseline zoning category. Assuming that zoning laws are binding in El Dorado, we should expect a negative sign for the coefficients of the other zone classes. Distance to Sacramento and distance to major road are calculated as the linear distance, in kilometers from parcel centroid to Sacramento city boundary and closest major road. Both of these variables are measures of parcel accessibility and I expect parcels further away from Sacramento and further from major roads to have a lower probability of development. Mean parcel elevation, in meters, and slope, in degrees, are calculated using 10-meter resolution US Geological Survey (USGS) National Elevation Dataset. I expect a positive sign for elevation because parcels at higher elevation tend to have better views, which are valued by prospective homebuyers. Slope should have a negative effect, however, because parcels with more variable terrain are also more costly to develop. Using hydrography data provided by CalFish, I calculate the total length of intermittent streams, perennial streams and rivers and scale this measure by parcel area to determine parcel level stream density, measured in feet per acre. Stream density is expected to negatively affect probability of development by increasing construction costs and limiting lot configuration options.

IV. Results

Results of a fixed effect linear probability model of land development decisions are reported in in table 3.2. Table 3.2 is estimated between the years 1985 and 2004, with the hazard disclosure requirement beginning in 1992. By including parcel fixed effects, table 3.2 excludes all time invariant observed and unobserved parcel attributes from the estimation. In table 3.2, estimated coefficients are displayed in column 2 with cluster-robust standard errors in parenthesis.

Coefficient estimates for forest variables included in table 3.2 are in line with expectation. Existing forest area within the parcel decreases probability of development on average and is statistically significant at below the one percent level. This result is consistent with the interpretation that larger forest area on the parcel contributes to higher forest clearing cost necessary to construct structures and defensible spaces. Forest area within 500 meters does have a slight positive effect on probability of development, which may imply that nearby forests may provide some amenity to homeowners, though this effect is not statistically significant. Percent developed land within 500 meters has a positive and statistically significant effect on probability of development. This implies that residential land development in rural El Dorado County tends to attract more neighboring development. Isolated clusters of developed infrastructure tend to be more difficult to defend against wildfire damage than more densely populated areas (Syphard et al. 2012). Given the high risk of fire damage in this area, residents have a strong incentive to locate homes closer to existing developed infrastructure to maximize their benefit from community wildfire protection and reduce risk of damage from catastrophic wildfire.

I account for the impact of the 1992 hazard disclosure law introduction based upon a fixed average change in the rate of development in the post disclosure period and a relative change in consumption of parcels based upon hazard severity. The sign of the coefficient for τ is negative, which indicates that after 1992, all parcels were on average slightly less likely to develop. This effect is statistically insignificant and not robust to changes in other temporally varying market conditions. However, relative to parcels located in medium hazard severity zones, both very high and high severity parcels are less likely to develop after hazard disclosure law introduction in 1992. Relative to medium severity parcels, on an annual basis, probability of development for very high hazard severity parcels after 1992 is approximately -0.28% lower, a result significant at below the five percent level. Probability of development is reduced on high severity parcels by an average -0.01% per year though this result is not statistically significant. These results support the hypothesis that the hazard disclosure requirement caused a reduction in development for parcels with higher State designated wildfire risk.

In table 3.3, I report average annualized probability of development by hazard severity class during the post-disclosure period (1992-2004). In addition, I also report the average percent change in probability of development for high and very high severity parcels relative to medium severity parcels, based upon a non-linear test of hypothesis. On average, approximately 1% of all parcels are developed each year. However, relative to the baseline medium severity group, high and very high severity parcels report a decrease in probability of development of approximately 13% and 24%, respectively. The latter decrease is significant at below the five percent level. In the thirteen year period after the disclosure law was adopted (1992-2004), 145 parcels were developed in high severity areas and 202 parcels were developed in very high severity areas.

Without the hazard disclosure policy introduction, results from table 3.3 imply an expected increase of 20 and 60 developed parcels on high and very high severity lands.

Table 3.2 does not permit a direct understanding of the level of community knowledge of fire risk prior to the introduction of the hazard disclosure requirement. Any baseline effect of hazard severity would be absorbed by the parcel fixed effects. However, the negative and significant coefficient for very high hazard post 1992 suggests that prior to policy introduction, the community was either under-informed or asymmetrically informed. Anecdotal evidence from California legislative history suggests little prior landowner knowledge of underlying wildfire risk. In 1992, the California Association of Realtors petitioned the California Legislator to amend the existing hazard disclosure requirement to explicitly state that responsibility for hazard disclosure is solely that of the property owner (Assembly Bill 2428, 1992). Although this responsibility was already the sellers, few landowners had direct knowledge of their property's location in SRA lands or susceptibility to wildfire and thus the realtor was generally requested to research the required information. Evidenced by this legislative action, the market's prior failure to account for underlying wildfire risk may have been due, in part, to poor information delineation to landowners.

Proximity to large wildfires also has a significant effect on probability of development. When a large fire occurs, parcels close to the fire tend to delay land development plans the following year. Parcels are nearly 1% less likely to develop the year following large wildfires that occurred within 1.25 kilometers, a result significant below the five percent level. Landowners may delay development plans because the visible damage to the surrounding landscape reduces subdivision profitability. Alternatively, the occurrence of the wildfire may increase the community or landowner's perception of future risk posed by wildfires which would tend to delay subsequent development. Interestingly, any negative shock to probability of development dissipates the further removed a parcel is in time or distance from the wildfire. Between two and five years after fire, no parcels within 7.5 kilometers are statistically less likely to develop than if a fire had not occurred. In fact, parcels between 1.25 and 7.5 kilometers away from wildfire are actually more likely to develop in the following years. For instance, parcels between 5 and 7.5 kilometers are on average 0.7% more likely to develop the year following wildfire and 0.5% more likely to develop two to five years after wildfire. Both of these estimates are significant at below the one percent level. These results are somewhat paradoxical, as we would generally expect wildfires in the vicinity of the parcel to delay development plans. However, these results could be evidence of possible misperception of wildfire risk updating.

Because of cognitive limitations, humans have difficulty evaluating risk associated with low probability events. Individuals tend to have an optimistic bias towards disasters and systematically underestimate their true exposure to risk (Camerer and Kunreuther 1989). When a large wildfire occurs, a nearby landowner may believe that because a low probability event occurred in the recent past, it is less likely to occur in the future. Such a conclusion is similar to the "gambler's fallacy," and has been observed in individual perceptions of risk posed by other natural disasters such as flooding (Pielke 1999). In the case of wildfire, individuals may believe that a large fire consumes nearby combustible fuel and nearby wildfires are therefore less likely to occur again in the near future. While large wildfires may lower future probability of wildfire over the short term, wildfire events do not substantial impact long term fire risk. In fact, Hurteau and North (2010) find that following controlled burn and understory thinning in Southern California, local forest carbon stock returned to normal in as little as seven years following fuel treatment. The authors also note that because small, understory trees are more fire prone than older stocks, fire hazard may recover at a faster rate than forest carbon. Other researchers have found that hazard reduction benefits from prescribed burning dissipate in as little as 2-4 years (Fernandez and Betelho 2003). The spatial benefits from natural and prescribed wildfires extend approximately as far as the maximum fire spotting distance[34] from burn perimeter, typically less than one mile (Finney et al 1997). For parcels located as much as 7.5km from the leading edge of a wildfire, there is little reason to believe that even an exceptionally large fire event could provide any substantial protection from future wildfire incidence.

[34] Fire spotting refers to the spread of wildfire to neighboring fuel sources from ignitable firebrand embers.

A. Robustness Checks

In this section, I test robustness of previous results to a variety of alternative specifications. The estimated effect of the hazard disclosure law may be confounded if very high, high and medium severity parcels have non-parallel baseline time trends. To test robustness of my results to unobserved market time trends, I conduct a temporal falsification test using data from the pre-disclosure period (1985-1991), with hypothetical treatment beginning in 1988. These results are presented in table D1, located in Appendix D. Coefficients for post-1988 hazard severity treatment are all insignificant at the five percent level, indicating no significant baseline differences in rate of development by hazard severity class during the pre-disclosure period. In addition, in unreported results I also try interacting hazard severity with a linear time trend, and find no change in conclusions. These alternative results are available upon request.

The hazard disclosure law was passed in 1989 and officially enacted in July of 1991. I therefore treat the year 1992 as the start date for this policy in my primary model. Given the delay between hazard disclosure law approval and enactment, policy preemption by landowners is a possibility. In addition, because the date of development in my sample is based upon the year of lot construction and not the date of subdivision approval, some parcels that were developed after 1992 may be exempt from the hazard disclosure requirement, which would imply attenuation in the effect of the hazard disclosure law. To control for potential policy preemption and attenuation, in alternative results presented in table D2, I estimate a model dropping the years just before and after hazard policy enactment

(1991 and 1992). Results of this model are essentially unchanged from those of table 2, though the coefficient very high hazard severity is slightly larger, in absolute value, and more significant. In unreported results, I also estimate a model dropping the years 1990 to 1993, with coefficient for very high hazard severity negative and significant at below the one percent level. Overall, these results imply that attenuation in my estimates of the effect of the post-1992 hazard disclosure law is likely. Assuming this hypothesis is true; coefficient estimates for hazard severity variables in table 2 would be under-estimates of the true average marginal effect.

In table D3, I restrict the sample exclusively to parcels located within a two-kilometer buffer of the border with medium severity lands to reduce potential bias from other unobserved sources of market level heterogeneity. In this model, I include high and very high severity parcels within two-kilometers of medium severity areas and medium severity parcels within two-kilometers of high or very high severity areas. Parcel based fixed effects may reduce bias from time-invariant and unobserved parcel attributes but limiting the analysis to parcels within a boundary of medium severity lands may reduce bias from unobserved local amenities that vary over time, such as the construction of a new fire station or variation in wildfire home insurance rates. Previous research by Dempsey and Plantinga (2013), Cunningham (2006), Black (1999) and Holms (1998), estimated models restricting their sample to parcels in the vicinity of a jurisdictional boundary to reduce bias from unobserved geographic and economic conditions. In table D3, the effect of the hazard disclosure law is substantially larger for high and very high severity parcels relative to results reported in table 3.2. Coefficients for the treatment effect of the introduction of the hazard disclosure law on high and very high severity parcels are negative and significant at below the five percent level and one percent level, respectively. These results suggest that estimates from table 3.2 may be a lower bound for the true effect of the hazard disclosure law on probability of development

I report a set of random effects probit models of parcel level probability of development in table D4. The first model includes the full sample used for table 3.2 and the second model limits the population to parcels within a two-kilometer buffer of medium severity lands, as is the case in table D3. In these models, the probability of development is estimated as a function of all temporally varying parcel attributes included in table 3.2, along with temporally invariant parcel attributes including: natural log of parcel area, presence of an existing house, distance to Sacramento, distance to the closest major road, elevation, slope, stream density, as well as non-residential and government land use within 500 meters of the parcel. In unreported results, I also estimate random effects logit models and linear probability models with no significant differences in model performance. In table D4, the effect of the hazard disclosure requirement is identified based upon a difference in differences (DID) variation in policy effectiveness between hazard severity classes. Coefficients in non-linear models need not have the same sign or significance as marginal effects in models with interactions terms, therefore, marginal effects for the DID effect of the hazard disclosure law are calculated based upon the method proposed by Puhani (2012) and are reported in table D5.

In contrast to table 3.2, marginal effects for post-1992 hazard disclosure are positive but insignificant for very high and high hazard severity parcels in the unrestricted sample. For the sample of parcels within two-kilometers of the medium severity border, marginal effects for high and very high severity parcels are negative but statistically insignificant at the five percent level. These results are opposite expectation and suggest little to no effect of the hazard disclosure law on probability of development. However, estimates from DID models are not robust to the presence of unobserved, time invariant variables that's effects covary jointly with the treatment and dependent variable. By including fixed effects in table 3.2, I reduce bias from unobserved heterogeneity in stationary parcel attributes and therefore treat this as my primary specification to test hypotheses related to the impact of the hazard disclosure law. Coefficients for fire proximity variables are of the same sign and similar significance to those of table 3.2. The effects of other parcel attributes included in table D4 are in keeping with expectation. Parcel area, elevation, and more government lands within 500 meters all positively impact a parcels probability of development. Whereas, the presence of an existing house, higher stream density and more non-residential land near the parcel negatively affect probability of development. Coefficients for zoning categories are by in large insignificant, which suggests that zoning regulations in El Dorado County do not significantly curtail residential development decisions.

In unreported results, I estimate several models with differing specifications of the effect of nearby wildfires on land development. These include models with more finely delineated distance thresholds for nearby wildfires[35] and additional intercepts if a wildfire occurred on the parcel or within 10 kilometers of the parcel. Results from these alternative models all support the conclusions from table 2 and are available upon request. I also estimate a fully saturated linear probability model by dividing up the three continuous variables from table 2 (parcel forest area, forest area within 500 meters and developed land within 500 meters) into quintiles or deciles. Conclusions from these models are unchanged from table 3.2 and are also available upon request.

V. Conclusion

Wildfires are a common occurrence in many communities across the United States and may become more common in the future as climate change permanently alters temperature and precipitation patterns across the globe. Land development in at risk areas may contribute to higher expected damages from wildfire as well as more costly fire suppression efforts. Evidence from El Dorado County California suggests that hazard disclosure requirements are at least moderately effectively in curtailing development on parcels located in the highest fire risk areas of the county. In other communities facing similar fire risk, hazard disclosure requirements, coupled with detailed risk mapping may provide a viable

[35] I include separate dummy variables by 1.25km bands (i.e. within 0-1.25km, 1.25-2.5km, etc.)

option to limit land development in areas most threatened by wildfire. Hazard disclosure requirements may have the added advantage of being less politically contentious than other land use regulations such as taxation or zoning policy. However, it is currently unknown what the optimal rate of land development should be in these communities. Future research could reveal what policy, or mix of policies most optimally balances the costs and benefits associated with land development and growing wildfire risk.

This research also highlights the importance of recent wildfires events to land development decisions in El Dorado County. Parcels close to wildfire perimeters (less than 1.25km) tend to delay land development the year following a fire event. However, parcels further removed in time or distance are more likely to develop following wildfire events. Residents may believe that because a large wildfire occurred in recent memory near their house, they face less risk of wildfire damage in the future. Although wildfires confer some short-term protection from future risk by consuming available fuel, long term fire risk is unaffected by individual fire events. This result is similar to the “gambler’s fallacy,” or the mistaken belief that because an outcome recently occurred, it is less likely to occur in the future, which has been observed by individuals in response to other natural hazards, such as flooding. To correct this problem, policy makers could make efforts to educate residents regarding the determinants of wildfire risk, particularly in the areas surrounding recent wildfire events. Depending upon the severity of wildfire risk in these areas, direct policy intervention may be necessary to prevent growth of housing in areas with critically high fire risk.

TABLE 3.1: COVARIATE SUMMARY STATISTICS (MEANS WITH STANDARD DEVIATIONS IN PARENTHESIS)

Variables	Pre-1992 Data Undeveloped Parcels	Pre-1992 Data Developed Parcels	Post-1992 Data Undeveloped Parcels	Post-1992 Data Developed Parcels
Hazard Severity Class				
Medium Severity	0.3313	0.3752	0.3311	0.3327
	(0.4707)	(0.4846)	(0.4706)	(0.4716)
High Severity	0.2582	0.2379	0.256	0.2788
	(0.4377)	(0.4261)	(0.4364)	(0.4489)
Very High Severity	0.4105	0.3869	0.4129	0.3885
	(0.4919)	(0.4875)	(0.4924)	(0.4879)
Fire Event 1 Year Prior				
Fire within 0-1.25km	0.0022	0.005	0.0049	0.0019
	(0.0466)	(0.0708)	(0.0695)	(0.0439)
Fire within 1.25-5km	0.0184	0.0235	0.034	0.0769
	(0.1345)	(0.1515)	(0.1813)	(0.2667)
Fire within 5-7.5km	0.0145	0.0436	0.0392	0.0962
	(0.1195)	(0.2043)	(0.1941)	(0.2951)
Fire Event 2-5 Year Prior				
Fire within 0-1.25km	0.0084	0.0201	0.0116	0.0154
	(0.0911)	(0.1405)	(0.1069)	(0.1232)
Fire within 1.25-5km	0.0579	0.0988	0.0773	0.15
	(0.2335)	(0.2987)	(0.267)	(0.3574)
Fire within 5-7.5km	0.0466	0.1139	0.096	0.1942
	(0.2108)	(0.318)	(0.2945)	(0.396)
Time Varying Attributes				
Forest Area (%)	49.387	47.5254	48.4998	49.4701
	(36.7782)	(33.8888)	(36.6942)	(34.2389)
Forest within 500m (%)	48.8861	50.355	47.2877	54.6756
	(33.461)	(30.8857)	(33.3798)	(29.2798)
Developed within 500m (%)	13.4406	27.7591	17.1765	37.5638
	(14.7164)	(14.4823)	(18.5648)	(17.76)
Undeveloped within 500m (%)	66.7344	61.7309	62.0587	51.2929
	(19.0819)	(15.5549)	(21.4577)	(17.2666)
Stationary Attributes				
ln(Parcel Area)	2.6284	2.6486	2.6017	2.8748
	(1.2416)	(0.9734)	(1.2679)	(0.931)
Existing House	0.4308	0.3233	0.4033	0.6846
	(0.4952)	(0.4681)	(0.4906)	(0.4651)
Distance to Sacramento (km)	48.5038	50.6784	48.0906	52.3226
	(12.0147)	(10.6851)	(12.1102)	(10.3484)

Distance to Major Road (km)	0.673	0.6097	0.6761	0.6444
	(0.7357)	(0.5647)	(0.7461)	(0.6307)
Elevation (m)	593.2375	639.1453	585.0004	669.3511
	(263.4741)	(224.2451)	(265.4422)	(231.243)
Slope (°)	9.8522	9.5163	9.8745	9.6464
	(4.7024)	(4.195)	(4.7562)	(4.1713)
Stream Density (ft/acre)	25.3404	23.5648	25.2848	25.8538
	(40.0699)	(37.71)	(40.4804)	(36.0846)
Non-residential within 500m (%)	10.3005	3.4001	11.08	3.0994
	(11.1206)	(7.7321)	(11.1675)	(7.5245)
Government within 500m (%)	9.5407	7.1099	9.7027	8.0439
	(12.9534)	(10.382)	(13.0933)	(11.4838)
Zoning				
MDR	0.3919	0.33	0.4125	0.2019
	(0.4882)	(0.4706)	(0.4923)	(0.4018)
LDR	0.2832	0.2831	0.2789	0.3231
	(0.4506)	(0.4509)	(0.4485)	(0.4681)
RR	0.2633	0.3417	0.2489	0.3962
	(0.4404)	(0.4747)	(0.4324)	(0.4896)
AL	0.0314	0.0218	0.0293	0.05
	(0.1743)	(0.1461)	(0.1688)	(0.2182)
NR	0.0302	0.0235	0.0304	0.0288
	(0.1712)	(0.1515)	(0.1716)	(0.1675)
Parcel Count	5325	597	4805	520

TABLE 3.2: TABLE 2, LINEAR PROBABILITY MODEL OF DEVELOPMENT WITH PARCEL FIXED EFFECTS (1985-2004)

VARIABLES	Probability of Development
Post-1992 Hazard Severity Class	
Post-1992 * High Severity	-0.00146
	(0.00144)
Post-1992 * Very High Severity	-0.00275*
	(0.00129)
Post-1992	-0.00026
	(0.00196)
Fire Event 1 Year Prior	
Fire within 0-1.25km	-0.00988*
	(0.00452)
Fire within 1.25-5km	0.00266
	(0.00237)
Fire within 5-7.5km	0.00735**
	(0.00262)
Fire Event 2-5 Year Prior	
Fire within 0-1.25km	0.00180
	(0.00374)
Fire within 1.25-5km	0.00274
	(0.00168)
Fire within 5-7.5km	0.00488**
	(0.00171)
Time Varying Parcel Attributes	
Forest Area (%)	-0.00052**
	(0.00016)
Forest within 500m (%)	0.00011
	(0.00010)
Developed within 500m (%)	0.00214**
	(0.00012)
Constant	0.00377
	(0.00793)
Fixed Effects	
Year	Yes
Parcel	Yes
Observations	105,912
Number of Parcels	5,921

Cluster-Robust standard errors in parentheses
** p<0.01, * p<0.05

TABLE 3.3: ANNUALIZED PROBABILITY OF DEVELOPMENT AND PERCENT CHANGE BY HAZARD SEVERITY CLASS DURING POST-DISCLOSURE PERIOD (1992-2004)

	Probability of Development		Percent Reduction+	
Hazard Severity	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Medium	0.01139**	0.00102	--	--
High	0.00993**	0.00113	-12.81	11.91
Very High	0.00864**	0.00098	-24.18*	10.04

+Percent reduction relative to baseline medium severity parcels
**p<0.01, *p<0.05

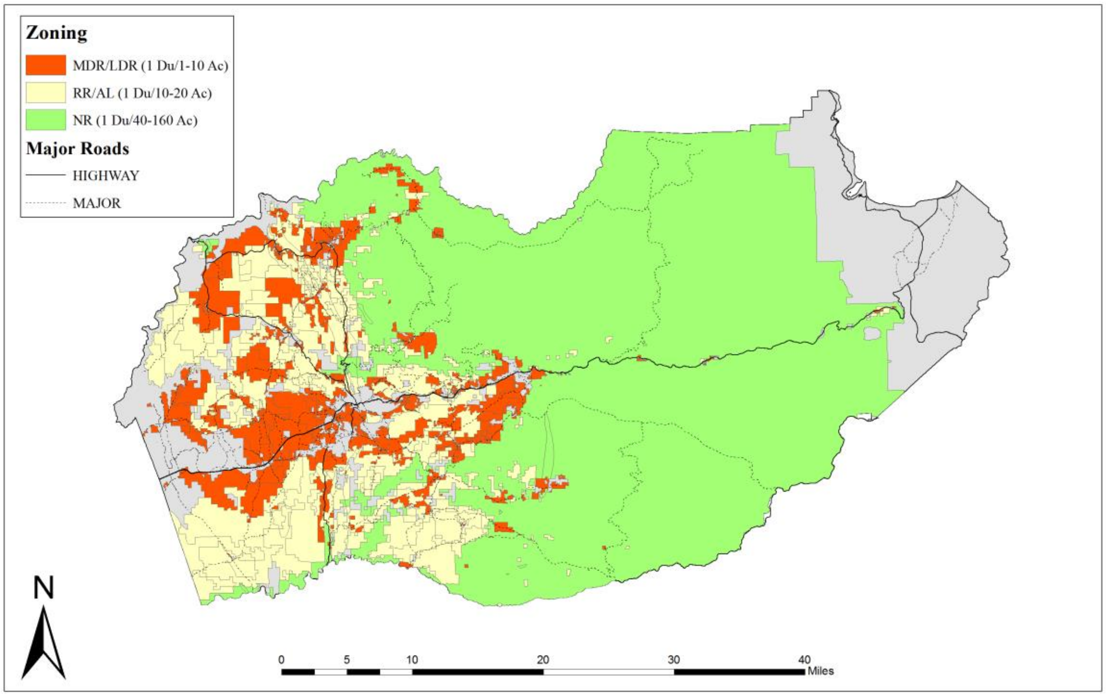


FIGURE 3.1: EL DORADO COUNTY ZONING LOCATIONS

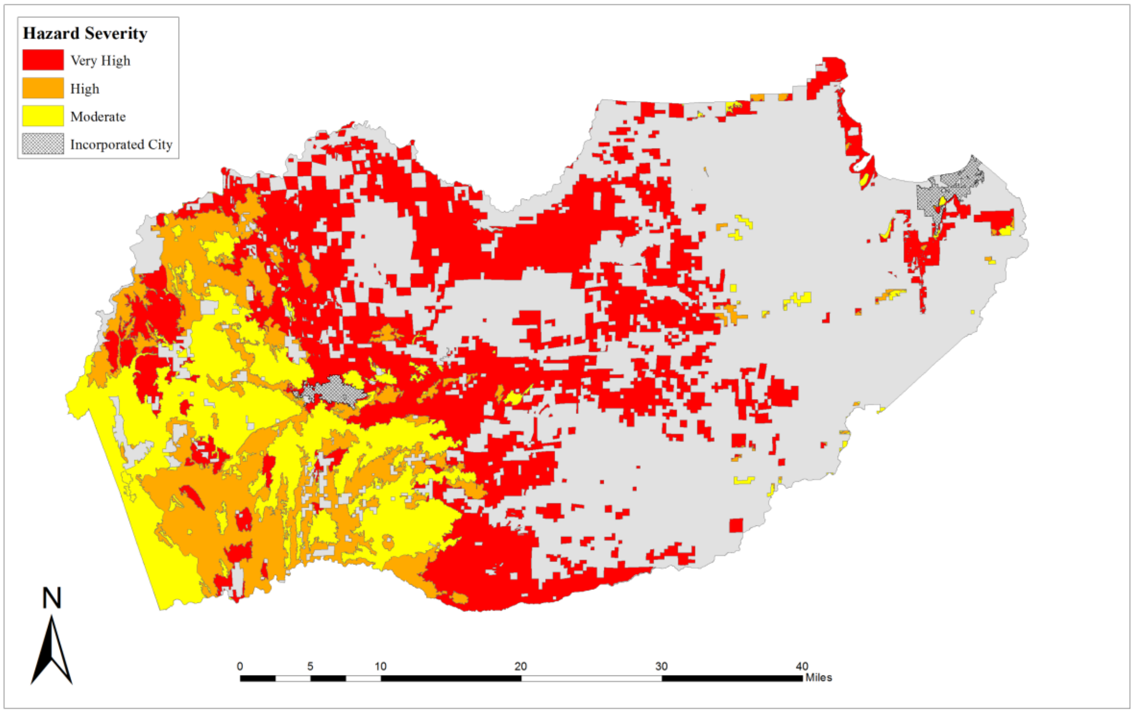


FIGURE 3.2: EL DORADO FIRE HAZARD SEVERITY ZONES (CAL FIRE, 2007)

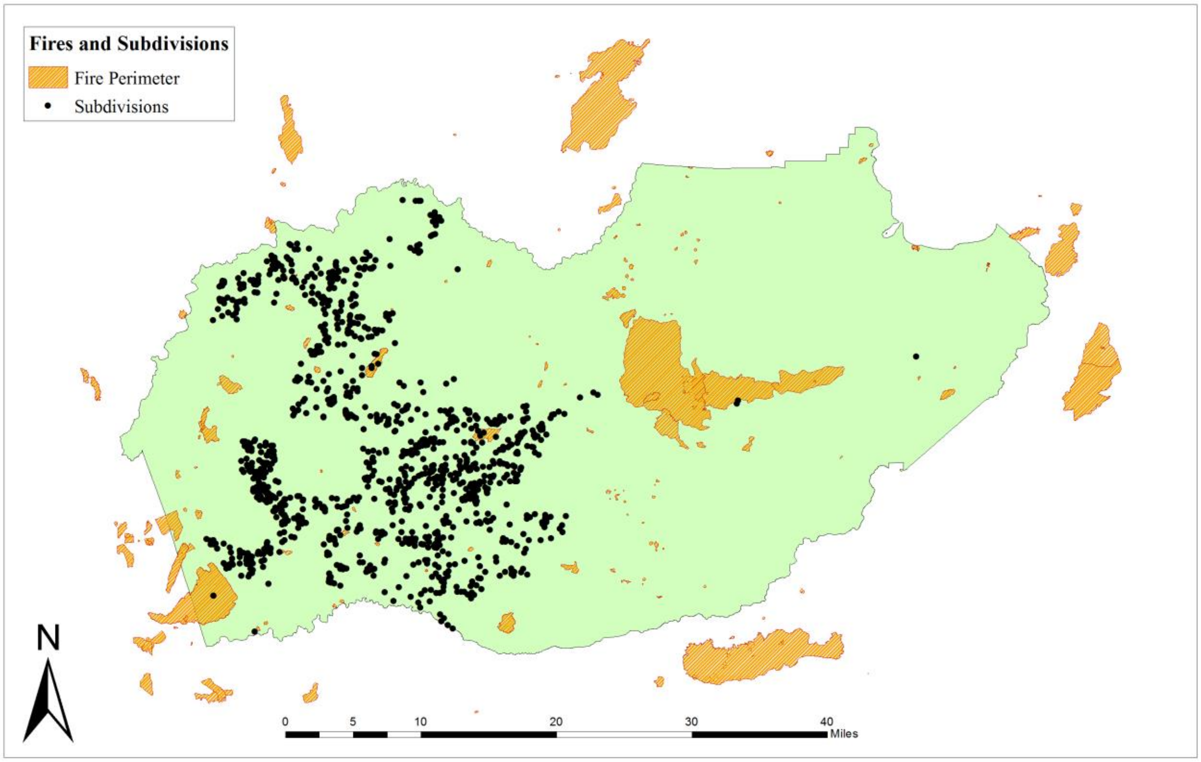


FIGURE 3.3: FIRE PERIMETERS MAPPED BY CAL FIRE (1980-2004) NEAR EL DORADO COUNTY AND SUBDIVISIONS (1985-2004)

Appendix A

Table A1. Covariate Marginal Effects for Temporal Falsification Test Using Pre-WEA (July, 2011 – June, 2012) Observations with False Treatment Beginning in January, 2012

Variables	Coefficient	Standard Error
WEA Period x Warning County		
WEA Period	-0.8009	0.7264
Warning County	1.7260***	0.4427
WEA Period x Warning County	0.3850	0.7273
Alert Time of Day[a]		
4am - 8am	0.7040*	0.3731
8am - 12pm	0.1453	0.3770
12pm - 4pm	0.7594*	0.4369
4pm - 8pm	0.6941	0.5569
8pm - 12am	-0.7854	0.8072
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-2.2378***	0.7279
Warning County x 8am - 12pm	-1.1683	0.8863
Warning County x 12pm - 4pm	-1.0728	0.8198
Warning County x 4pm - 8pm	-0.6589	0.8782
Warning County x 8pm - 12am	0.2362	0.9357
Day of Week		
Monday	0.8330***	0.2169
Tuesday	1.7767***	0.5210
Wednesday	1.3676***	0.4124
Thursday	0.9683***	0.1788
Friday	1.5759***	0.4547
Saturday	0.8063**	0.3403

Weather Controls		
Precipitation (mm)	0.0005	0.0050
Wind Speed (m/s)	0.0785	0.0759
Fixed Effects		
County	Yes	
Month x Year	Yes	
Observations	746	
Number of Dates	62	

***Significant at the 1 percent level

**Significance at the 5 percent level

*Significance at the 10 percent level

[a]Baseline time category of 12am-4am

Table A2. Temporal Falsification Test, Change in Car Accident Count Conditional on Flash Flood Warning in Post-WEA Period (Standard Errors in Parentheses)

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	4.988***	4.603***	0.385	0.462	8.363
	(0.345)	(0.667)	(0.727)	(0.889)	(16.88)

***Significant at the 1 percent level

**Significance at the 5 percent level

*Significance at the 10 percent level

Table A3. Covariate Marginal Effects for Spatial Falsification Test

Variables	Coefficient	Standard Error
WEA Period x Warning County		
WEA Period	-0.8200	1.1101
Warning County	-0.0500	0.2932
WEA Period x Warning County	0.1570	0.2408
Alert Time of Day[a]		
4am - 8am	-0.3312	0.2847
8am - 12pm	-0.4230	0.2894
12pm - 4pm	-0.1470	0.3280
4pm - 8pm	-0.3615	0.3111
8pm - 12am	-0.8826*	0.5098
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	0.2650	0.3816
Warning County x 8am - 12pm	0.1390	0.4431
Warning County x 12pm - 4pm	-0.2818	0.4963
Warning County x 4pm - 8pm	-0.0577	0.3522
Warning County x 8pm - 12am	0.4171	0.4564
Day of Week		
Monday	0.3223	0.2065
Tuesday	0.8619***	0.2440
Wednesday	0.5620**	0.2552
Thursday	0.4392**	0.2155
Friday	0.8546***	0.2270
Saturday	0.4067**	0.2016
Weather Controls		
Precipitation (mm)	0.0084***	0.0022
Wind Speed (m/s)	0.1077**	0.0482

Fixed Effects	
County	Yes
Month x Year	Yes
Observations	1516
Number of Dates	133

***Significant at the 1 percent level

**Significance at the 5 percent level

*Significance at the 10 percent level

[a]Baseline time category of 12am-4am

Table A4. Spatial Falsification Test, Change in Car Accident Count Conditional on Flash Flood Warning in Post-WEA Period (Standard Errors in Parentheses)

Warning	With WEA	Without WEA	DD Treatment Effect	Per 100,000 Licensed Drivers	Percent Change
Flash Flood	2.348***	2.191***	0.157	0.429	7.166
	(0.087)	(0.234)	(0.241)	(0.659)	(28.321)

***Significant at the 1 percent level

**Significance at the 5 percent level

*Significance at the 10 percent level

Table A5. Difference-in-Differences (DD) Poisson Model for Daily Count of Car Accidents with Fixed Effects by County (Incident Rate Ratios Reported)

Variables	Incident Rate Ratio	Standard Error
WEA Period x Warning County		
WEA Period	1.0509	0.2339
Warning County	1.3392***	0.1284
WEA Period x Warning County	0.8267***	0.0545
Alert Time of Day[a]		
4am - 8am	1.1508	0.1018
8am - 12pm	0.9925	0.1050
12pm - 4pm	1.0182	0.0928
4pm - 8pm	1.0199	0.0905
8pm - 12am	1.0337	0.1543
Warning County x Alert Time of Day[a]	0.6439***	0.1245
Warning County x 4am - 8am	1.1135	0.3692
Warning County x 8am - 12pm	1.0723	0.1314
Warning County x 12pm - 4pm	1.0629	0.1334
Warning County x 4pm - 8pm	0.8269	0.1524
Warning County x 8pm - 12am	0.6439***	0.1245
Day of Week		
Monday	1.5077***	0.1103
Tuesday	1.7638***	0.0921
Wednesday	1.5509***	0.0812
Thursday	1.5562***	0.0817
Friday	1.6568***	0.0959
Saturday	1.5000***	0.1393
Weather Controls		
Precipitation (mm)	1.0014	0.0009

Wind Speed (m/s)	0.9717	0.0186
Fixed Effects		
County	Yes	
Month x Year	Yes	
Observations	1820	
Number of Counties	130	

***Significant at the 1 percent level

**Significance at the 5 percent level

*Significance at the 10 percent level

[a]Baseline time category of 12am-4am

Table A6. Linear Model of Daily Count of Car Accidents, Two-way Clustered at Date and County Level

Variables	Coefficient	Standard Error
WEA Period x Warning County		
WEA Period	0.2517	0.8631
Warning County	0.2757	0.5959
WEA Period x Warning County	-0.8559***	0.3161
Alert Time of Day[a]		
4am - 8am	-0.3841	0.6057
8am - 12pm	-0.9494	0.8839
12pm - 4pm	-0.7520	0.6922
4pm - 8pm	-0.6245	0.6229
8pm - 12am	-0.7047	0.8244
Warning County x Alert Time of Day[a]		
Warning County x 4am - 8am	-0.6569	0.7576

Warning County x 8am - 12pm	1.1666	1.0404
Warning County x 12pm - 4pm	1.4834	0.9190
Warning County x 4pm - 8pm	1.1119	0.9172
Warning County x 8pm - 12am	0.1548	0.8276
Day of Week		
Monday	1.1998***	0.3441
Tuesday	1.4258***	0.3732
Wednesday	1.3992***	0.4438
Thursday	1.2477***	0.3053
Friday	1.4933***	0.4776
Saturday	1.1796***	0.2197
Weather Controls		
Precipitation (mm)	0.0039*	0.0023
Wind Speed (m/s)	-0.0072	0.0942
Fixed Effects		
County	Yes	
Month x Year	Yes	
Observations	1850	
Number of Counties	134	
Number of Dates	133	

***Significant at the 1 percent level

**Significance at the 5 percent level

*Significance at the 10 percent level

[a]Baseline time category of 12am-4am

Table A7. Regression Discontinuity Models of Impact of Pre-WEA and Post-WEA Flash Flood Warnings on Traffic Volume by Alert Time of Day (Bootstrapped Standard Errors Listed in Parentheses)

	12am-6am	6am-12pm	12pm-6pm	6pm-12am
Pre-WEA	8.83	8.86	21.99**	11.74
	(7.79)	(7.21)	(9.25)	(7.12)
Post-WEA	-29.02***	-30.5***	-27.46***	-22.7**
	(8.91)	(8.76)	(10.43)	(9.65)
Difference	-37.85***	-39.35***	-49.45***	-34.45***
	(11.21)	(10.92)	(13.51)	(11.05)
Station-Day FE	Yes	Yes	Yes	Yes
Stations	51	256	190	258
Observations	1534	11516	13062	8657

***Significant at the 1% level; **Significant at the 5% percent level; *Significant at the 10% level

Based upon 1,000 bootstrapped replications

Figure A1. Frequency of WEA messages by Virginia county

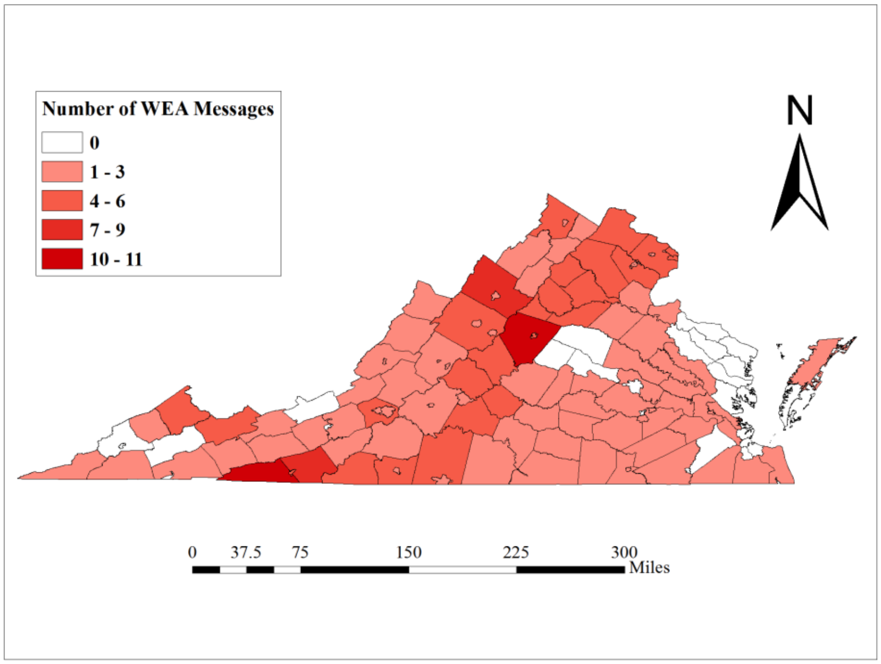


Figure A2. Continuous traffic monitoring station locations in the State of Virginia

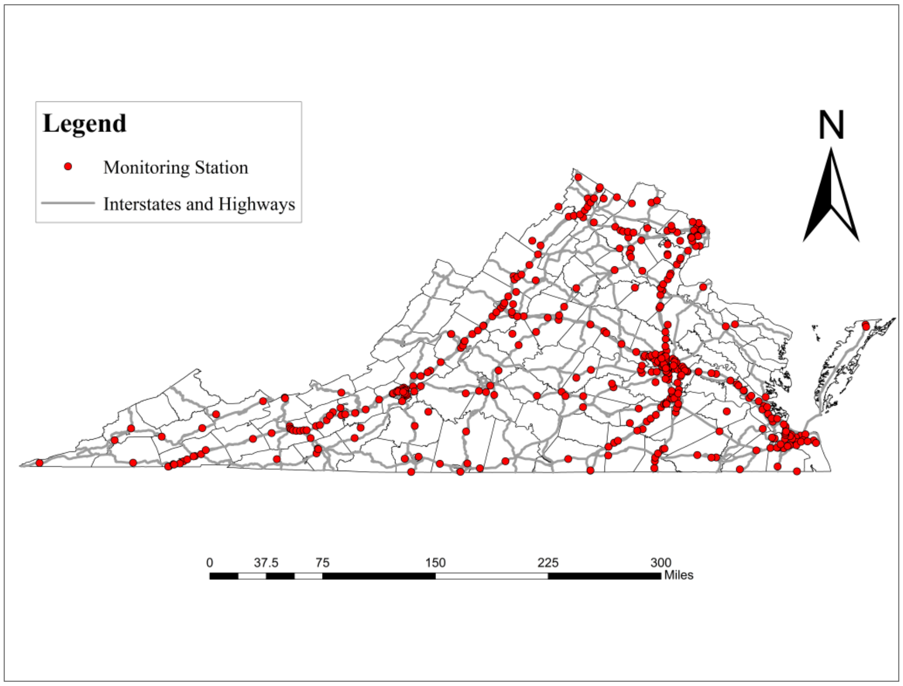
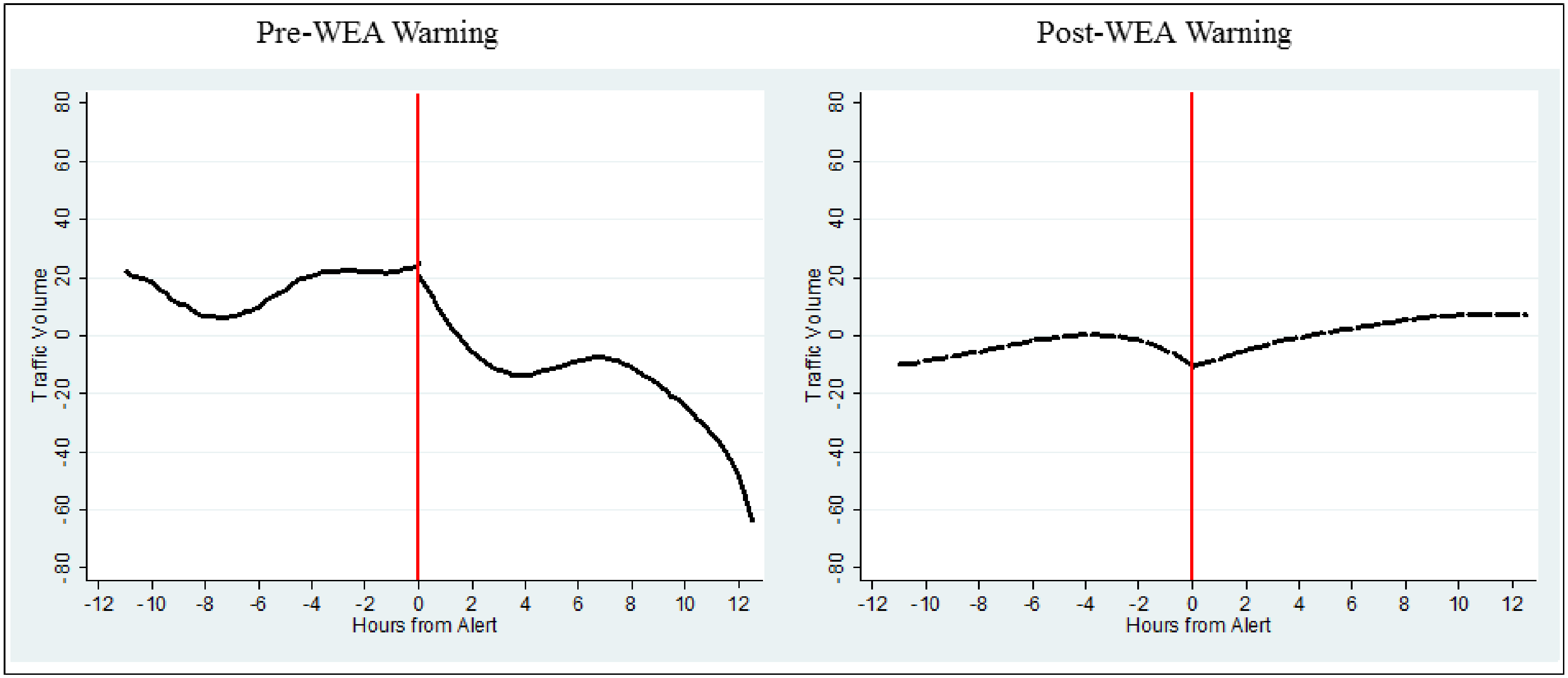
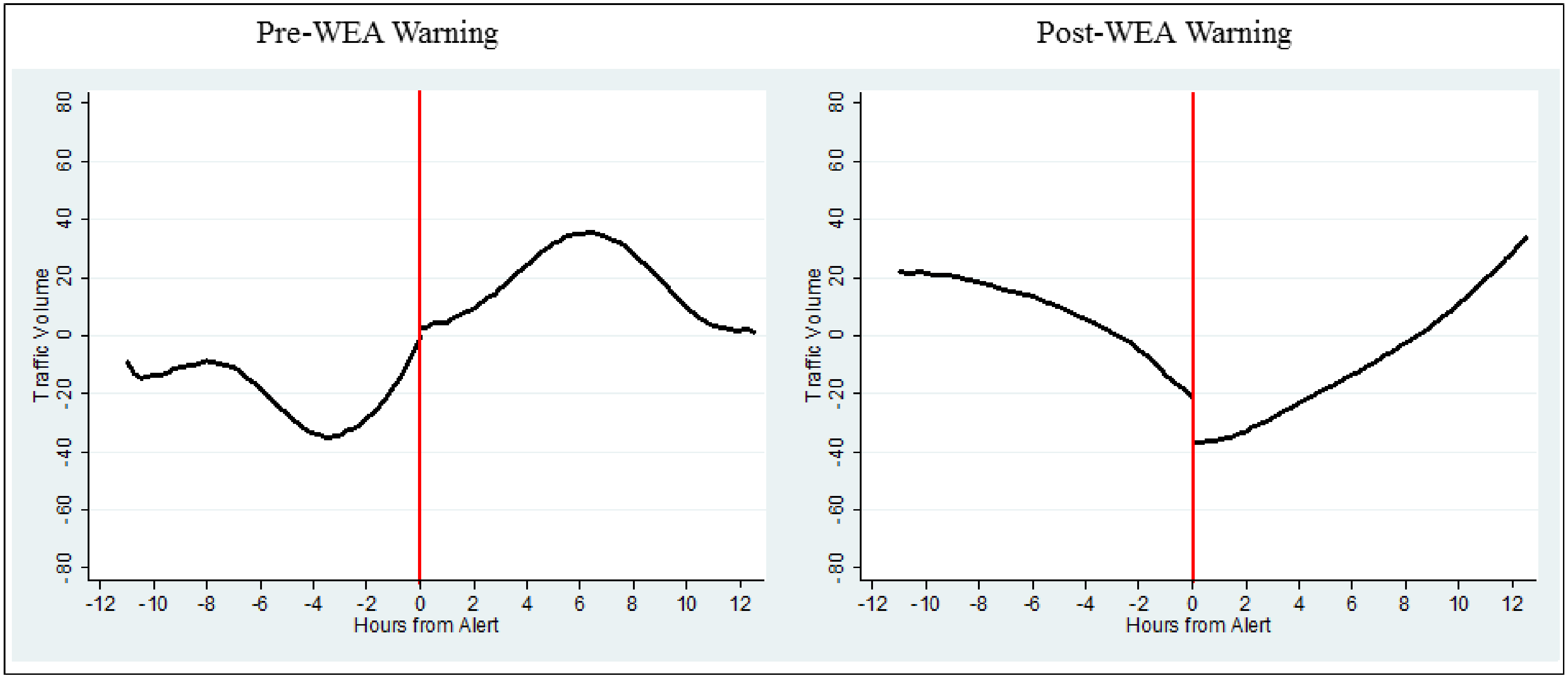

Legend
Monitoring Station
Interstates and Highways
N
0
37.5
75
150
225
300
Miles

Figure A3. Local linear regression of hours from alert on traffic volume from day prior to alert (Model 3)



Notes: Controlling for hourly trends by quarter-station and station by day fixed effects

Figure A6. Local linear regression of hours from alert on traffic volume from counties neighboring flash flood warning counties (Model 4)



Notes: Controlling for hourly trends by quarter-station and station by day fixed effects

Appendix B

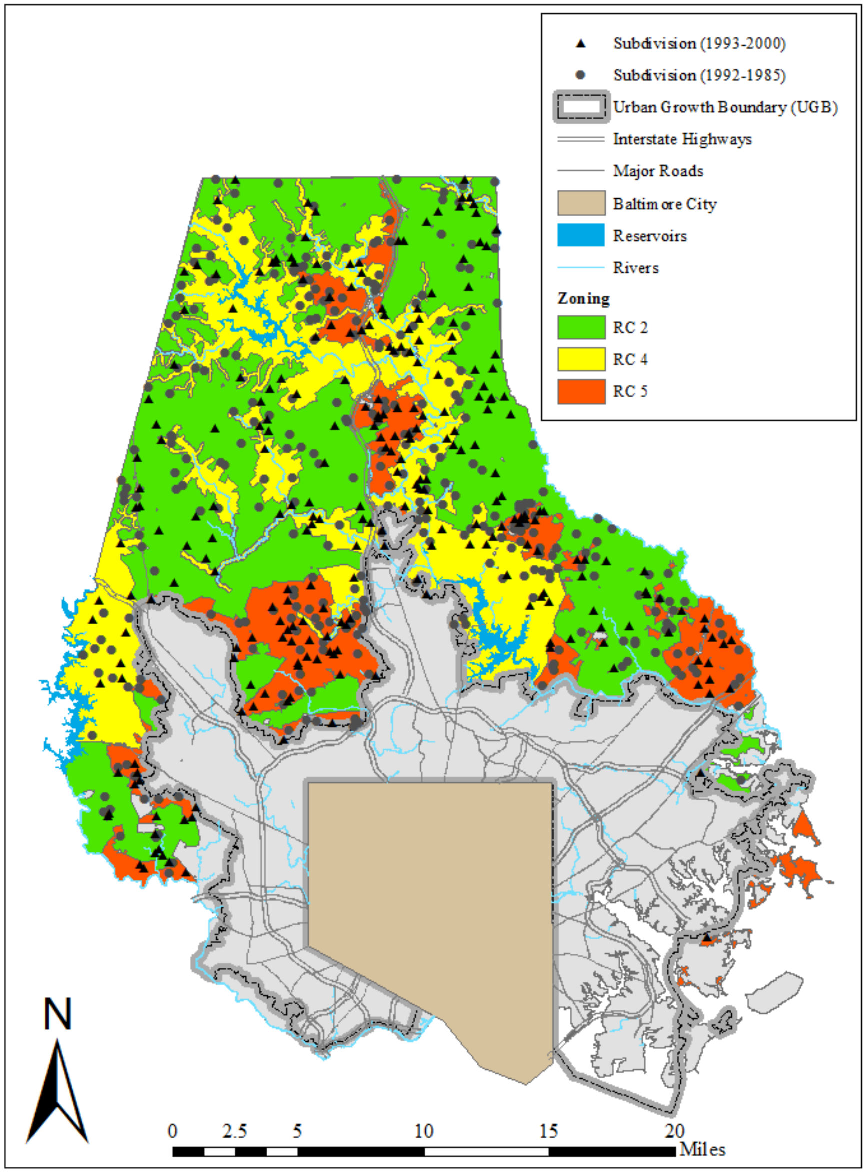


Figure B1. Residential subdivisions in 1985-2000 in rural Baltimore County

Table B1. Temporal Falsification Test on Percent Forest Cover Change Conditional on Development in 1993-1996 and 1997-2000 (False Regulatory Event=1997)

Forest Cover Quintile	Forest Cover Change in 1993-1996	Forest Cover Change in 1997-2000	Difference
Forest Cover 0-20%	8.1711*	7.5559**	-0.6151
	(3.6325)	(2.4141)	(3.8344)
Forest Cover 20-40%	7.7132*	3.7127	-4.0005
	(3.6792)	(3.002)	(4.5581)
Forest Cover 40-60%	5.2248	8.8514**	3.6266
	(3.5153)	(2.6696)	(4.25)
Forest Cover 60-80%	-0.0414	-2.5983	-2.5568
	(3.2973)	(2.0821)	(3.485)
Forest Cover 80-100%	-8.486*	-7.1626**	1.3234
	(3.7806)	(2.5944)	(4.4135)

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

Table B2. Temporal Falsification Test on Percent Forest Cover Change Conditional on Development in 1985-1988 and 1989-1992 (False Regulatory Event=1989)

Forest Cover Quintile	Forest Cover Change in 1985-1988	Forest Cover Change in 1989-1992	Difference
Forest Cover 0-20%	-0.0803	0.4633	0.5436
	(3.1825)	(1.2571)	(3.0198)
Forest Cover 20-40%	-5.4528	-5.7471**	-0.2944
	(3.7697)	(1.5829)	(4.378)
Forest Cover 40-60%	-8.9164*	-3.8089**	5.1075
	(3.8481)	(1.2609)	(3.9863)
Forest Cover 60-80%	-7.8195**	-8.2477**	-0.4281
	(2.7497)	(2.952)	(4.9285)
Forest Cover 80-100%	-4.6040	-4.1951**	0.4089
	(2.6429)	(1.1967)	(2.7736)

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

Table B3. Marginal Effect of Covariates on Annual Probability of Development and Forest Cover Change (1988-1997)

Variables	Probability of Development Marginal Effect	Probability of Development Standard Error	Forest Cover Change Marginal Effect	Forest Cover Change Standard Error
Forest Cover Quintiles[a]				
Forest Cover 20-40%	-0.00061	0.00229	-3.66954	2.02522
Forest Cover 40-60%	0.00065	0.00238	-3.28292	1.73414
Forest Cover 60-80%	0.00110	0.00256	-7.32801*	3.02690
Forest Cover 80-100%	0.00135	0.00236	-3.23078	1.65573
Post-1993 Forest Cover Quintiles[a]				
Post-1993* Forest Cover 20-40%	0.00035	0.00279	0.96027	2.51787
Post-1993* Forest Cover 40-60%	0.00060	0.00288	0.12311	2.63140
Post-1993* Forest Cover 60-80%	0.00292	0.00320	-5.41213**	1.93637
Post-1993* Forest Cover 80-100%	0.00119	0.00276	-12.14439**	2.68034
Parcel Characteristics				
Parcel Area	0.00008**	0.00003	-0.09476**	0.02425
Zoned Capacity	0.00007	0.00007	0.03650	0.04119
Distance to Baltimore City	-0.00042	0.00024	-0.07736	0.18007
Distance to Major Road	0.00083	0.00118	-0.70108	1.15396
Riparian Buffer Area	-0.00012**	0.00004	0.11048*	0.04429
Slope	-0.00002	0.00017	0.28380	0.14507
Elevation	0.00011	0.00032	-0.15133	0.23185
Prime Ag Land	0.00105	0.00275	0.23597	2.88823
Soil Erosion Potential	0.00002	0.00023	-0.48981	0.29864
Existing House	-0.00173	0.00099	0.37786	0.90944
Easement Eligibility	-0.00870**	0.00151	--	--
Authorized Minor	-0.00612**	0.00225	--	--
Housing Price Indices at Census Tract Level				
Housing Price	0.00349	0.00707	-5.57392	5.98297
Housing Price Variance	0.01627	0.00994	7.20897	11.39436
Surrounding Land Use within 500 Meter Buffer				
Residential	0.00016**	0.00004	-0.00280	0.03850
Non-residential	-0.00004	0.00012	-0.03573	0.12573
Parks	-0.00004	0.00007	0.04786	0.05549

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

[a] Marginal effects are based upon a discrete change from the baseline 0-20% existing forest category.

Table B4. Percent Forest Cover Change Conditional on Development in 1988-1992 and 1993-1997

Forest Cover Quintile	Forest Cover Change in 1988-1992	Forest Cover Change in 1993-1997	Difference
Forest Cover 0-20%	-2.8146	1.1447	3.9593
	(2.8061)	(1.0585)	(2.9505)
Forest Cover 20-40%	-9.2385**	-1.9391	7.2994*
	(3.3935)	(1.3585)	(3.55)
Forest Cover 40-60%	-10.1855**	0.7941	10.9796**
	(3.3587)	(1.5095)	(3.5285)
Forest Cover 60-80%	-11.0173**	-5.0917**	5.9257
	(4.1305)	(1.3125)	(3.8417)
Forest Cover 80-100%	-7.0294*	-9.2351**	-2.2057
	(3.0912)	(1.6703)	(3.2881)

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

Table B5. Marginal Effect of Covariates on Annual Probability of Development and Forest Cover Change Using Existing Forest Cover Deciles (1985-2000)

Variables	Probability of Development Marginal Effect	Probability of Development Standard Error	Forest Cover Change Marginal Effect	Forest Cover Change Standard Error
Forest Cover Deciles[a]				
Forest Cover 10-20%	0.00154	0.00265	-0.24484	2.05101
Forest Cover 20-30%	0.00090	0.00258	-5.23324*	2.38447
Forest Cover 30-40%	-0.00260	0.00218	-7.17858*	3.23449
Forest Cover 40-50%	0.00428	0.00282	-7.83797**	2.55761
Forest Cover 50-60%	0.00192	0.00269	-6.55699*	2.74452
Forest Cover 60-70%	0.00393	0.00284	-5.85405*	2.33180
Forest Cover 70-80%	0.00353	0.00285	-10.70781**	3.49479
Forest Cover 80-90%	0.00250	0.00270	-5.51554*	2.49724
Forest Cover 90-100%	0.00450	0.00248	-4.25257*	2.05497
Post-1993 Forest Cover Deciles[a]				
Post-1993*Forest Cover 10-20%	-0.00065	0.00252	-4.21941	2.25090
Post-1993*Forest Cover 20-30%	0.00301	0.00296	-2.95215	2.66580
Post-1993*Forest Cover 30-40%	0.00194	0.00284	-4.17179	3.37044
Post-1993*Forest Cover 40-50%	0.00147	0.00285	0.08732	3.34962
Post-1993*Forest Cover 50-60%	0.00422	0.00339	-1.41646	2.95707
Post-1993*Forest Cover 60-70%	0.00412	0.00309	-10.93418**	2.19783
Post-1993*Forest Cover 70-80%	0.00216	0.00327	-8.13439**	2.67318
Post-1993*Forest Cover 80-90%	0.00126	0.00303	-16.78175**	3.57278
Post-1993*Forest Cover 90-100%	0.00275	0.00267	-15.19892**	2.74415
Parcel Characteristics				
Parcel Area	0.00007**	0.00002	-0.05379**	0.02071
Zoned Capacity	0.00011*	0.00005	0.02788	0.03454
Distance to Baltimore City	-0.00028	0.00019	-0.09545	0.18090
Distance to Major Road	0.00087	0.00093	-0.39872	0.98109
Riparian Buffer Area	-0.00015**	0.00003	0.09942**	0.03486
Slope	-0.00007	0.00014	0.44192**	0.15611
Elevation	0.00015	0.00025	-0.06986	0.22277
Prime Ag Land	0.00018	0.00222	0.08806	2.75346
Soil Erosion Potential	-0.00004	0.00019	-0.30814	0.24144
Existing House	-0.00174	0.00099	0.37154	0.93229
Easement Eligibility	-0.00831**	0.00119	--	--
Authorized Minor	-0.00195	0.00143	--	--
Housing Price Indices at Census Tract Level				
Housing Price	-0.00094	0.00538	-3.40132	5.04824

Housing Price Variance	0.01338	0.00740	8.11707	8.52739
Surrounding Land Use within 500 Meter Buffer				
Residential	0.00018**	0.00003	0.04874	0.03220
Non-residential	0.00001	0.00009	0.00841	0.09522
	0.00001	0.00005	0.03749	0.04421

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

[a] Marginal effects are based upon a discrete change from the baseline 0-10% existing forest category.

Table B6. Percent Forest Cover Change Conditional on Development in 1985-1992 and 1993-2000 Using Existing Forest Cover Deciles

Forest Cover Decile	Forest Cover Change in 1985-1992	Forest Cover Change in 1993-2000	Difference
Forest Cover 0-10%	-3.6581	6.6227**	10.2808**
	(3.1139)	(1.6895)	(3.4561)
Forest Cover 10-20%	-3.9039	2.4036	6.3075
	(3.006)	(1.6996)	(3.324)
Forest Cover 20-30%	-8.8919*	3.6690	12.5609**
	(3.5638)	(2.0952)	(4.0235)
Forest Cover 30-40%	-10.8349**	2.4499	13.2847**
	(4.2014)	(2.8505)	(4.7376)
Forest Cover 40-50%	-11.4984**	6.7092*	18.2076**
	(3.7459)	(2.9328)	(4.5894)
Forest Cover 50-60%	-10.2162**	5.2041*	15.4204**
	(3.5773)	(2.3636)	(4.1259)
Forest Cover 60-70%	-9.5143**	-4.3135**	5.2007
	(3.5528)	(1.4184)	(3.3937)
Forest Cover 70-80%	-14.3678**	-1.5129	12.8550*
	(5.0514)	(2.0604)	(5.0731)
Forest Cover 80-90%	-9.1751**	-10.1598**	-0.9847
	(3.5043)	(3.2272)	(4.5571)
Forest Cover 90-100%	-7.9131*	-8.5777**	-0.6646
	(3.1818)	(2.0077)	(3.5726)

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

Table B7. Full Information Maximum Likelihood Estimation Results on Panel Heckman Selection Model with Quadratic Existing Forest Cover

	Probability of Development		Forest Cover Change	
Variables	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Continuous Forest Variables				
Existing Forest Cover	0.00136	0.00378	-0.31985**	0.08622
Existing Forest Cover^2	0.00001	0.00003	0.00276**	0.00076
Post-1993*Existing Forest Cover	0.00285	0.00527	0.41090**	0.12195
Post-1993*Existing Forest Cover^2	-0.00004	0.00005	-0.00518**	0.00119
Post-1993	0.01630	0.16661	6.15036	3.51653
Parcel Characteristics				
Parcel Area	0.00325*	0.00135	-0.04058	0.02615
Parcel Area^2	$3.80\text{x}10^{-6}$	$4.90\text{x}10^{-6}$	0.00014*	0.00007
Zoned Capacity	0.00462*	0.00225	0.06926	0.04134
Distance to Baltimore City	-0.01292	0.00816	-0.20419	0.20150
Distance to Major Road	0.03752	0.03999	-0.00031	0.99061
Riparian Buffer Area	-0.00636**	0.00135	0.05533	0.04208
Slope	-0.00266	0.00586	0.37276*	0.16151
Elevation	0.00689	0.01058	-0.04718	0.24311
Prime Ag Land	0.00402	0.09553	-0.01639	2.80915
Soil Erosion Potential	-0.00149	0.00815	-0.20780	0.24977
Existing House	-0.07058	0.04241	-0.06763	0.98056
Authorized Minor	-0.35751**	0.04957	--	--
Easement Eligibility	-0.09180	0.06134	--	--
Housing Price Indices at Census Tract Level				
Housing Price	-0.03867	0.23170	-3.35442	5.56555
Housing Price Variance	0.55620	0.31584	10.54182	8.29223
Surrounding Land Use within 500 Meter Buffer				
Residential	0.00784**	0.00125	0.10179*	0.04970
Non-residential	0.00013	0.00391	-0.02535	0.10592
Parks	-0.00009	0.00210	0.02490	0.04372
Constant	-2.44338**	0.49822	-20.41032	15.81169
ρ	0.72761**	0.15623	--	--
Annual Time Fixed Effects	Yes		Yes	
Census Tract Fixed Effects	Yes		Yes	
Observations	44,002		413	

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.
[a] Marginal effects are based upon a discrete change from the baseline 0-20% existing forest category.

Table B8. Marginal Effect of Covariates on Annual Probability of Development and Forest Cover Change with Quadratic Existing Forest Cover

Variables	Probability of Development Marginal Effect	Probability of Development Standard Error	Forest Cover Change Marginal Effect	Forest Cover Change Standard Error
Forest Cover Quintiles[a]				
Forest Cover 30%	0.00061	0.00095	-4.42910**	1.11009
Forest Cover 50%	0.00137	0.00152	-6.68036**	1.68057
Forest Cover 70%	0.00229	0.00170	-6.75361**	1.76972
Forest Cover 90%	0.00341	0.00175	-4.64863**	1.59013
Post-1993 Forest Cover Quintiles[a]				
Post-1993* Forest Cover 20-40%	0.00132	0.00108	-0.57473	1.14663
Post-1993* Forest Cover 40-60%	0.00218	0.00173	-2.89737	1.65347
Post-1993* Forest Cover 60-80%	0.00247	0.00188	-6.96888**	1.70210
Post-1993* Forest Cover 80-100%	0.00213	0.00191	-12.78956**	1.91877
Parcel Characteristics				
Parcel Area	0.00007**	0.00002	-0.05616**	0.02044
Zoned Capacity	0.00011*	0.00005	0.03387	0.03349
Distance to Baltimore City	-0.00030	0.00019	-0.10511	0.17926
Distance to Major Road	0.00087	0.00093	-0.28804	0.95016
Riparian Buffer Area	-0.00015**	0.00003	0.10409**	0.03562
Slope	-0.00006	0.00014	0.39313*	0.15551
Elevation	0.00016	0.00025	-0.10002	0.22530
Prime Ag Land	0.00009	0.00222	-0.04720	2.73416
Erosion k-factor	-0.00003	0.00019	-0.19636	0.23791
Existing House	-0.00164	0.00099	0.47368	0.91872
Easement Eligibility	-0.00832**	0.00120	--	--
Authorized Minor	-0.00214	0.00143	--	--
Housing Price Indices at Census Tract Level				
Housing Price	-0.00090	0.00539	-3.05790	5.17774
Housing Price Variance	0.01294	0.00738	6.27628	7.90262
Surrounding Land Use within 500 Meter Buffer				
Residential	0.00018**	0.00003	0.04162	0.03232
Non-residential	0.00001	0.00009	-0.02633	0.09855
Parks	0.00001	0.00005	0.02558	0.03848

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

[a] Marginal effects are based upon a discrete change from the baseline 10% existing forest category.

Table B9. Percent Forest Cover Change Conditional on Development with Quadratic Existing Forest Cover

Forest Cover Quintile	Forest Cover Change in 1985-1992	Forest Cover Change in 1993-2000	Difference
Forest Cover 0-20%	-4.0947	5.3284**	9.4231**
	(2.9132)	(1.193)	(3.0512)
Forest Cover 20-40%	-8.5242*	4.753**	13.2771**
	(3.3782)	(1.1214)	(3.2804)
Forest Cover 40-60%	-10.7758**	2.4299	13.2058**
	(3.703)	(1.2921)	(3.5127)
Forest Cover 60-80%	-10.8496**	-1.6417	9.2078**
	(3.7073)	(1.1399)	(3.4463)
Forest Cover 80-100%	-8.7451*	-7.4623**	1.2829
	(3.4468)	(1.4226)	(3.4346)

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

Table B10. Marginal Effect of Covariates Using Indpendent Model with Separately Estimated Equations for Development and Forest Cover Change ($\rho = 0$)

Variables	Probability of Development Marginal Effect	Probability of Development Standard Errors	Forest Cover Change Marginal Effect	Forest Cover Change Standard Errors
Forest Cover Quintiles[a]				
Forest Cover 20-40%	-0.00163	0.00178	-5.39091**	1.89326
Forest Cover 40-60%	0.00235	0.00201	-6.67588**	1.87579
Forest Cover 60-80%	0.00292	0.00210	-7.71678**	2.23698
Forest Cover 80-100%	0.00312	0.00194	-4.22618**	1.52334
Post-1993 Forest Cover Quintiles[a]				
Post-1993* Forest Cover 20-40%	0.00274	0.00213	-1.49220	2.27253
Post-1993* Forest Cover 40-60%	0.00276	0.00221	1.71401	2.53415
Post-1993* Forest Cover 60-80%	0.00357	0.00236	-8.11151**	1.79947
Post-1993* Forest Cover 80-100%	0.00251	0.00210	-13.62128**	2.24654
Parcel Characteristics				
Parcel Area	0.00007**	0.00002	-0.06686**	0.01905
Zoned Capacity	0.00011*	0.00005	0.01627	0.03154
Distance to Baltimore City	-0.00029	0.00019	-0.08784	0.17378
Distance to Major Road	0.00086	0.00093	-0.29554	0.95713
Riparian Buffer Area	-0.00015**	0.00003	0.08580*	0.03657
Slope	-0.00006	0.00013	0.35782*	0.15066
Elevation	0.00015	0.00025	-0.10177	0.23124
Prime Ag Land	0.00020	0.00224	0.43416	2.71821
Soil Erosion Potential	-0.00004	0.00019	-0.26262	0.23943
Existing House	-0.00175	0.00099	0.62027	0.94043
Easement Eligibility	-0.00815**	0.00123	--	--
Authorized Minor	-0.00187	0.00148	--	--
Housing Price Indices at Census Tract Level				
Housing Price	-0.00080	0.00539	-2.66288	5.04415
Housing Price Variance	0.01330	0.00739	7.09213	8.21542
Surrounding Land Use within 500 Meter Buffer				
Residential	0.00018**	0.00003	0.03372	0.03115
Non-residential	0.00001	0.00009	-0.03407	0.09256
Parks	0.00000	0.00005	0.02535	0.04188

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

[a] Marginal effects are based upon a discrete change from the baseline 0-20% existing forest category.

Table B11. Percent Forest Cover Change Conditional on Development in 1985-1992 and 1993-2000 Using Independent Model with Separately Estimated Equations for Development and Forest Cover Change ($\rho = 0$)

Forest Cover Quintile	Forest Cover Change in 1985-1992	Forest Cover Change in 1993-2000	Difference
Forest Cover 0-20%	-3.7115	4.1557**	7.8672*
	(2.8367)	(1.3621)	(3.1466)
Forest Cover 20-40%	-9.1024**	2.6635	11.7659**
	(3.4453)	(1.7756)	(3.6905)
Forest Cover 40-60%	-10.3874**	5.8697**	16.2571**
	(3.3595)	(2.0492)	(3.6595)
Forest Cover 60-80%	-11.4283**	-3.9558**	7.4725
	(4.1345)	(1.2163)	(3.9333)
Forest Cover 80-100%	-7.9377*	-9.4656**	-1.5279
	(3.1387)	(1.7574)	(3.429)

Double and single asterisks (*, **) denote statistical significance at the five and one percent level, respectively.

Table B12. Landscape-Level Predictions on Land Acreage, Existing Forest Cover and Forest Cover Change With and Without FCA (Bootstrapped 90% Confidence Intervals)

	Subdivisions without FCA			Subdivisions with FCA			Difference		
Forest Cover Quintile	Land area	Existing forest area	Forest cover change	Land area	Existing forest area	Forest cover change	Land area	Existing forest area	Forest cover change
Forest Cover 0-20%	1395*	175*	-97*	1400*	176*	16	5	1	113*
	[678, 2342]	[63, 260]	[-213, -17]	[754, 2007]	[86, 244]	[-23, 55]	[-994, 616]	[-105, 77]	[27, 224]
Forest Cover 20-40%	1371*	396*	-197*	2216*	639*	-57	845	243	140*
	[726, 2647]	[214, 794]	[-377, -60]	[1571, 3059]	[445, 887]	[-91, 59]	[-230, 1577]	[-70, 468]	[34, 353]
Forest Cover 40-60%	1969*	931*	-273*	2013*	955*	51	44	24	324*
	[1046, 3333]	[494, 1609]	[-558, -99]	[1226, 3090]	[591, 1487]	[-37, 163]	[-1074, 1160]	[-521, 566]	[148, 668]
Forest Cover 60-80%	1221*	841*	-164*	1366*	936*	-77*	145	95	87*
	[800, 2674]	[549, 1823]	[-451, -71]	[992, 2453]	[685, 1667]	[-146, -28]	[-913, 660]	[-610, 428]	[3, 340]
Forest Cover 80-100%	1548*	1400*	-163*	1405*	1263*	-162*	-143	-137	1
	[880, 2858]	[791, 2617]	[-305, -48]	[962, 2293]	[881, 2066]	[-285, -88]	[-1054, 601]	[-960, 565]	[-146, 152]
Total	7504*	3743*	-893*	8400*	3969*	-229*	896	226	664*
	[5198, 12540]	[2738, 6473]	[-1661, -378]	[7424, 10518]	[3557, 5419]	[-337, -37]	[-3070, 3563]	[-1893, 1505]	[218, 1542]

All numbers above reported in acres. Asterisk (*) denotes statistical significance of the bootstrapped 90% confidence interval not containing zero.

Table B13. Landscape-Level Predictions on Land Acreage, Existing Forest Cover and Forest Cover Change With and Without FCA (Bootstrapped 80% Confidence Intervals)

	Subdivisions without FCA			**Subdivisions with FCA**			**Difference**		
Forest Cover Quintile	Land area	Existing forest area	Forest cover change	Land area	Existing forest area	Forest cover change	Land area	Existing forest area	Forest cover change
Forest Cover 0-20%	1395*	175*	-97*	1400*	176*	16	5	1	113*
	[757, 2154]	[84, 239]	[-169, -31]	[880, 1815]	[94, 206]	[-18, 46]	[-685, 506]	[-76, 61]	[34, 188]
Forest Cover 20-40%	1371*	396*	-197*	2216*	639*	-57	845	243	140*
	[860, 2295]	[248, 663]	[-292, -71]	[1595, 2780]	[467, 838]	[-68, 49]	[-7, 1309]	[-1, 422]	[53, 308]
Forest Cover 40-60%	1969*	931*	-273*	2013*	955*	51	44	24	324*
	[1169, 2976]	[541, 1469]	[-453, -129]	[1317, 2787]	[630, 1368]	[-16, 133]	[-761, 726]	[-379, 347]	[190, 531]
Forest Cover 60-80%	1221*	841*	-164*	1366*	936*	-77*	145	95	87*
	[1077, 2502]	[714, 1684]	[-392, -98]	[1118, 2193]	[752, 1498]	[-123, -38]	[-671, 550]	[-470, 382]	[18, 289]
Forest Cover 80-100%	1548*	1400*	-163*	1405*	1263*	-162*	-143	-137	1
	[1037, 2546]	[957, 2340]	[-285, -59]	[1104, 2174]	[1019, 1983]	[-237, -102]	[-735, 441]	[-704, 404]	[-98, 122]
Total	7504*	3743*	-893*	8400*	3969*	-229*	896	226	664*
	[5887, 11413]	[3076, 5759]	[-1439, -465]	[7639, 10051]	[3668, 5120]	[-309, -73]	[-1949, 2826]	[-1198, 1317]	[260, 1372]

All numbers above reported in acres. Asterisk (*) denotes statistical significance of the bootstrapped 80% confidence interval not containing zero.

Appendix C: Creation of Housing Price Variables

In this appendix, we describe the methodology used to create census tract-level variables for both the price for housing services and variance of housing prices. To construct our housing price indices, we use arm's length housing transaction data between 1985 and 2000 in Baltimore County compiled from the Maryland Property View (MDPV) database. Next, we combine the MDPV housing transactions with tax assessment data for the study region, which contains additional structural and property specific attributes for each house. Finally, we exclude observations with housing prices in the top and bottom 1% of the sample to reduce the potential influence of outliers. The final data set on housing transactions includes 9,030 arm's length housing sales between 1985 and 2000 in Baltimore County.

Based upon the method described in Sieg et al. (2002), we proceed by running a series of hedonic regressions for each year to distinguish the pure price of housing services, at the neighborhood level, from the quantity index of structural and lot-specific characteristics of the house. The dependent variable for our analysis is the real transaction price of housing P_{ij} for house i in census tract j converted into 2000 dollars using the CPI for the Baltimore metro region. The vector X_{ij} represents the structural and lot-specific characteristics from tax assessment records for each house, such as building square footage, number of floors, lot acreage, etc. For each year between 1985 and 2000, we estimate a separate hedonic price equation represented in Equation C.1

(C.1) $$P_{ij} = \rho_j e^{X_{ij}\beta + \varepsilon_{ij}} \ .$$

Taking the natural log of each side yields the price function

(C.2) $$\ln P_{ij} = \ln \rho_j + X_{ij}\beta + \varepsilon_{ij} \ .$$

The coefficient $\beta_k \in \beta$ represents the average marginal effect of the structural characteristic, k, on the natural log of housing price and ε_{ij} is the housing price residual. After controlling for the structural and lot-specific attributes of the house, the vector of fixed effects, ρ_j, represents the price for housing services for each census tract for the given year of the hedonic model (Sieg et al. 2002). By combining the vector of fixed effects for all the hedonic models estimated between 1985 and 2000, we construct the index variable on housing price that varies spatially and temporally by census tract and by year, respectively. Higher housing prices are expected to increase the probability of development by increasing the expected returns from subdivision development.

In addition, we use predictions from Equation C.2 to construct a measure of housing price variability. Capozza and Li (1994, 2002) show theoretically that an increase in housing price uncertainty raises the expected return needed to justify development. Based on this conceptual framework, Cunningham (2006, 2007) finds empirical evidence that an increase in housing price uncertainty tends to delay development (reduce probability of development). Following the related approach in Towe, Nickerson and Bockstael (2008), the measure for housing price variance for census tract j for each year is represented by Equation C.3

(C.3) $$Var_j\left(\hat{v}_{ij}\right)=\frac{\sum_{i\in j}\left[\exp\left(\ln\hat{P}_{ij}+0.5\left[\hat{\varepsilon}_{ij}^2/\left(l_{ij}-k\right)\right]\right)-P_{ij}\right]^2}{l_{ij}}\ .$$

Here, $\ln\hat{P}_{ij}$ represents the predicted natural log of housing price predicted from Equation C.2, l_{ij} is the number of observations in census tract j, k is the number of regressors and $\hat{v}_{ij}$ is the deviation in the untransformed housing price from the predicted level. However, we are primarily interested in the relative level of housing price variability and we therefore standardize price variance by taking the square root and dividing by the average housing price in each census tract, represented in Equation C.4

(A.4) $$\bar{E}_j=\frac{\sqrt{Var\left(\hat{v}_j\right)}}{\bar{P}_j}\ .$$

The empirical measure for the variance in housing price also varies spatially and temporally by census tract and by year.

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Sieg, H., V.K. Smith, H.S. Banzhaf, and R. Walsh. 2002. Interjurisdictional Housing Prices in Locational Equilibrium. *Journal of urban Economics* 52(1): 131-153.

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Appendix D

REAL ESTATE TRANSFER DISCLOSURE STATEMENT

THIS DISCLOSURE STATEMENT CONCERNS THE REAL PROPERTY SITUATED IN THE COUNTY OF EL DORADO, STATE OF CALIFORNIA, DESCRIBED AS

____

THIS STATEMENT IS A DISCLOSURE OF THE CONDITION OF THE ABOVE DESCRIBED PROPERTY IN COMPLIANCE WITH ORDINANCE NO. _________________ OR COUNTY CODE AS OF ________________, 19__. IT IS NOT A WARRANTY OF ANY KIND BY THE SELLER(S) OR ANY AGENT(S) REPRESENTING ANY PRINCIPAL(S) IN THIS TRANSACTION, AND IS NOT A SUBSTITUTE FOR ANY INSPECTION OR WARRANTIES THE PRINCIPAL(S) MAY WISH TO OBTAIN SELLERS INFORMATION.

The seller hereby discloses the following information with the knowledge that even though this is not a warranty, prospective buyers may rely on this information in deciding whether, and on what terms, to purchase the subject property. Seller hereby authorizes any agent(s) representing any principal(s) in this transaction to provide a copy of this statement to any person or entity in connection with any actual or anticipated sale of the property.
THE FOLLOWING ARE REPRESENTATIONS MADE BY THE SELLER(S) AS REQUIRED
BY THE COUNTY OF EL DORADO AND ARE NOT THE REPRESENTATION OF THE AGENT(S), IF ANY. THIS INFORMATION IS A DISCLOSURE AND IS NOT INTENDED TO BE PART OF ANY CONTRACT BETWEEN BUYER AND SELLER.

1. Buyer is advised that this property is within an area of state responsibility for fire protection and is within a wildland area which may contain substantial forest or wildfire risks and hazards, subject to the fire prevention measures of Public Resources Code section 4291. Further, that it is not the state's responsibility to provide fire protection services to any building or structure located therein; which is therefore the responsibility of the local fire department.
2. Understanding and cooperation of property owners is essential to provide adequate fire protection services. The buyer or new homeowner can help by providing a defensible space around structures, reducing flammable vegetation on roads and driveways, widening of narrow roadways or driveways, and providing proper road signs and number signs which meet fire safe requirements for existing properties. Your local fire agency (local fire district, California Department of Forestry, or United States Forest Service) may provide additional information regarding risks and hazards of forest fires and wildland fires for specific properties.

To be filled out by seller:

_________________________ _________________________

(Local Fire District) (Telephone Number)

____

____

(Local Fire District Office Address)

C.D.F., 2840 Mount Danaher Road, Camino, California 95709 (916) 644-2345

U.S.F.S., 100 Forni Road, Placerville, California 95667 (916) 622-5061

Seller certifies that the information herein is true and correct to the best of the seller's knowledge
as of the date signed by the seller.

(Seller) (Date)

(Seller) (Date)

BUYER(S) AND SELLER(S) MAY WISH TO OBTAIN PROFESSIONAL ADVICE AND/OR INSPECTIONS OF THE PROPERTY AND TO PROVIDE FOR APPROPRIATE PROVISIONS IN A CONTRACT BETWEEN BUYER AND SELLER(S) WITH RESPECT TO ANY ADVICE/INSPECTION DEFECTS.

I/WE ACKNOWLEDGE RECEIPT OF A COPY OF THIS STATEMENT.(Date)

_______________ ______________________________

(Seller) (Date) (Buyer) (Date)

________________ __________ _____________ ________

(Seller) (Date) (Buyer) (Date)

Agent (Broker
Representing Seller) __________ By ______________ _______

(Signature) (Date)

Agent (Broker
Obtaining Offer) __________ By ______________ _______

(Signature) (Date)

A REAL ESTATE BROKER IS QUALIFIED TO ADVISE ON REAL ESTATE. IF YOU
DESIRE LEGAL ADVICE, CONSULT AN ATTORNEY.

Table D1: Falsification Test of Hazard Disclosure Treatment in Pre-Disclosure Period (1985-1991)

VARIABLES	Probability of Development
Post-1988 Hazard Severity Class	
Post-1988 * High Severity	-0.00118
	(0.00289)
Post-1988 * Very High Severity	0.00183
	(0.00262)
Post-1988	0.01325
	(0.00258)
Fire Event 1 Year Prior	
Fire within 0-1.25km	-0.00331
	(0.01727)
Fire within 1.25-5km	-0.00160
	(0.00467)
Fire within 5-7.5km	0.01514
	(0.00813)
Fire Event 2-5 Year Prior	
Fire within 0-1.25km	0.02234*
	(0.01117)
Fire within 1.25-5km	0.00827
	(0.00454)
Fire within 5-7.5km	0.01756**
	(0.00547)
Time Varying Parcel Attributes	
Forest Area (%)	-0.00113
	(0.00099)
Forest within 500m (%)	-0.00014
	(0.00010)
Developed within 500m (%)	0.00466**
	(0.00040)
Constant	0.05777
	(0.07232)
Fixed Effects	
Year	Yes
Parcel	Yes
Observations	39,730
Number of Parcels	5,921

Cluster-Robust standard errors in parentheses
** p<0.01, * p<0.05

Table D2: Linear Probability Model of Development with Parcel Fixed Effects
(1985-1990, 1993-2004)

VARIABLES	Probability of Development
Post-1992 Hazard Severity Class	
Post-1992 * High Severity	-0.00039
	(0.00152)
Post-1992 * Very High Severity	-0.00320*
	(0.00131)
Post-1992	-0.00319
	(0.00195)
Fire Event 1 Year Prior	
Fire within 0-1.25km	-0.00992*
	(0.00454)
Fire within 1.25-5km	0.00315
	(0.00238)
Fire within 5-7.5km	0.00734**
	(0.00265)
Fire Event 2-5 Year Prior	
Fire within 0-1.25km	0.00203
	(0.00383)
Fire within 1.25-5km	0.00164
	(0.00166)
Fire within 5-7.5km	0.00472**
	(0.00176)
Time Varying Parcel Attributes	
Forest Area (%)	-0.00057**
	(0.00017)
Forest within 500m (%)	0.00012
	(0.00011)
Developed within 500m (%)	0.00198**
	(0.00011)
Constant	0.00377
	(0.00793)
Fixed Effects	
Year	Yes
Parcel	Yes
Observations	95,180
Number of Parcels	5,921

Cluster-Robust standard errors in parentheses
** $p<0.01$, * $p<0.05$

Table D3: Linear Probability Model of Development with Parcel Fixed Effects, Parcels within 2km of Medium Severity Border (1985-2004)

VARIABLES	**Probability of Development**
Post-1992 Hazard Severity Class	
Post-1992 * High Severity	-0.00355*
	(0.00170)
Post-1992 * Very High Severity	-0.00554**
	(0.00174)
Post-1992	-0.00454
	(0.00276)
Fire Event 1 Year Prior	
Fire within 0-1.25km	-0.00520
	(0.00516)
Fire within 1.25-5km	0.00263
	(0.00305)
Fire within 5-7.5km	0.00310
	(0.00341)
Fire Event 2-5 Year Prior	
Fire within 0-1.25km	-0.00060
	(0.00469)
Fire within 1.25-5km	0.00257
	(0.00220)
Fire within 5-7.5km	0.00473*
	(0.00236)
Time Varying Parcel Attributes	
Forest Area (%)	-0.00086*
	(0.00037)
Forest within 500m (%)	-0.00031
	(0.00033)
Developed within 500m (%)	0.00200**
	(0.00015)
Constant	0.02917
	(0.01917)
Fixed Effects	
Year	Yes
Parcel	Yes
Observations	53,491
Number of Parcels	2,972

Cluster-Robust standard errors in parentheses
** p<0.01, * p<0.05

Table D4: Random Effects Probit Model of Development (1985-2004)

VARIABLES	(1)	(2)
Hazard Severity Class		
High Severity	0.01469	-0.00749
	(0.04748)	(0.06394)
Very High Severity	-0.03079	-0.00287
	(0.04593)	(0.06724)
Post-1992 Hazard Severity Class		
Post-1992 * High Severity	0.06675	-0.00135
	(0.06607)	(0.08683)
Post-1992 * Very High Severity	0.05652	-0.08194
	(0.05869)	(0.09130)
Post-1992	-0.36377**	-0.49165**
	(0.08591)	(0.12375)
Fire Event 1 Year Prior		
Fire within 0-1.25km	-0.07706	-0.36080
	(0.19670)	(0.38968)
Fire within 1.25-5km	0.15513*	0.12766
	(0.06434)	(0.09682)
Fire within 5-7.5km	0.29223**	0.24247**
	(0.05644)	(0.08389)
Fire Event 2-5 Year Prior		
Fire within 0-1.25km	0.23572*	-0.08959
	(0.09805)	(0.18988)
Fire within 1.25-5km	0.19465**	0.14558*
	(0.04099)	(0.06129)
Fire within 5-7.5km	0.25365**	0.26085**
	(0.03826)	(0.05413)
Parcel Attributes		
ln(Parcel Area)	0.16949**	0.13983**
	(0.02186)	(0.03195)
Existing House	-0.25369**	-0.24292**
	(0.02814)	(0.04178)
Distance to Sacramento (km)	0.00307	0.00559
	(0.00343)	(0.00498)
Distance to Major Road (km)	-0.01544	0.03531
	(0.02212)	(0.03772)
Elevation	0.00037*	0.00011
	(0.00016)	(0.00024)
Slope	-0.00513	-0.01076*

	(0.00344)	(0.00518)
Stream Density (ft/acre)	-0.00104**	-0.00075
	(0.00035)	(0.00056)
Forest Area (%)	-0.00259**	-0.00207**
	(0.00050)	(0.00070)
Forest within 500m (%)	0.00126*	0.00005
	(0.00058)	(0.00080)
Developed SLU within 500m (%)	0.01946**	0.01851**
	(0.00081)	(0.00115)
Non-residential within 500m (%)	-0.04581**	-4.79891**
	(0.00258)	(0.37817)
Government within 500m (%)	0.00396**	0.00364
	(0.00119)	(0.00192)
Zoning		
LDR	-0.00604	0.11224
	(0.04252)	(0.06244)
RR	0.06465	0.13797
	(0.05195)	(0.07922)
AL	-0.13417	0.06925
	(0.08970)	(0.12682)
NR	0.14810	0.58826**
	(0.10350)	(0.15257)
Constant	-2.95231**	-2.76480**
	(0.10939)	(0.15403)
Fixed Effects		
Year	Yes	Yes
Parcel	No	No
Observations	105,912	53,491
Number of Parcels	5,921	2,972

Notes: (1) Includes the unrestricted sample from Table 2,
(2) Includes only parcels within 2km of medium severity border
Cluster-Robust standard errors in parentheses
** $p<0.01$, * $p<0.05$

Table D5: Difference in Differences (DID) Hazard Severity Treatment Effect on Probability of Development

	Full Sample		
Hazard Severity	**With Disclosure Law**	**Without Disclosure Law**	**DID Treatment Effect**
High	0.01232**	0.01057**	0.00175
	(0.00119)	(0.00103)	(0.00174)
Very High	0.01084**	0.00951**	0.00134
	(0.00096)	(0.00081)	(0.00139)

**p<0.01, *p<0.05

	Parcels within 2km of Medium Severity Border		
Hazard Severity	**With Disclosure Law**	**Without Disclosure Law**	**DID Treatment Effect**
High	0.01006**	0.01009**	-0.00003
	(0.00131)	(0.00135)	(0.00202)
Very High	0.00842**	0.0102**	-0.00178
	(0.00127)	(0.00141)	(0.00198)

**p<0.01, *p<0.05

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End Notes