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Analysis

Cannabis legalization by states reduces illegal growing on US national forests

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ABSTRACT

Ten US states and the District of Columbia have legalized cannabis as of November 2018, and have adopted other policies regarding production, consumption, and the penalties associated with it. These policy changes may have affected illegal growing operations on national forests of the United States. Using data on the number of cannabis grow sites reported on 111 national forests between 2004 and 2016 together with information about state cannabis laws and when they were implemented, we find that recreational cannabis legalization is associated with decreased reports of illegal grow operations on national forests. Laws mandating minimum sentences for illegal cannabis possession or sales are associated with fewer reported grows, as is strict regulation of cannabinoid products. Taxes on sales have positive impacts on illegal growing, while law enforcement presence has a negative effect. Counterfactual simulations for 2016 quantify the magnitudes of these policy effects.

1. Introduction

The legal landscape of cannabis production and consumption in the United States has shifted markedly in the past decade. Since 2012, ten states (Colorado, Oregon, Washington, Alaska, California, Nevada, Maine, Massachusetts, Vermont, and, in November 2018, by popular referendum, Michigan) and the District of Columbia have legalized recreational cannabis consumption and, except for the District of Columbia and Vermont, acted to implement legislation that also legalizes commercial production. By 2016, 23 states had legalized medical cannabis. Additionally, a number of states, as far back as the 1960s, have decriminalized the possession of small quantities of cannabis for personal use (e.g., Sacco and Finklea, 2013). In states where commercial production is legal, it is subject to strict regulation, including requirements for chain of custody, reporting, and licensing with associated fees (Bryant, 2017). Typically, legal retail purchases of recreational cannabis are taxed at the point of sale at rates higher than for other (non-food) products (ad valorem equivalent taxes ranging up to 45%), although medical cannabis is usually taxed less or not at all. For example, cannabis sales yielded $315 million (m) in taxes and $4 m in licensing fees for the state of Washington in its fiscal year 2017 (July 2016–June 2017) (Washington State Liquor and Cannabis Board, 2018), $234 m in taxes and $13 m in licensing fees for Colorado in calendar year 2017 (Colorado Department of Revenue, 2018), and $63 m in state taxes and $10 m in local taxes for Oregon in calendar year 2016 (Oregon Department of Revenue, 2018). Commercial production and retail operations are further limited by federal laws classifying cannabis as a Schedule I drug (US Drug Enforcement Administration, 2018), which prohibits banks from handling revenues or issuing loans to assist in cannabis production, transport, processing, or sales (pursuant to the Comprehensive Drug Abuse Prevention and Control Act of 1970[1] and the Controlled Substances Act of 1971). Federal tax regulations, including US Code 26 Section 280E (Legal Information Institute, 2018), also place financial burdens on cannabis operations. Such restrictions likely slow expansion of state-legalized production and retail operations.

The combination of persistent cannabis demand (e.g., Merline et al., 2011; Wall et al., 2004; Azofeifa et al., 2016) and historical restrictions on legal commercial production for recreational purposes, in all states prior to 2012 and in most states since 2012, has sustained an economic and policy environment in which illegal production is widespread in the United States. Although precise numbers on the size of the illegal market are elusive, Yakowicz (2017) estimated that illegal cannabis sales in North America exceeded $46 billion (b) in 2016, representing

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[1] Public Law 91–513 (www.gpo.gov/fdsys/pkg/STATUTE-84/pdf/STATUTE-84-Pg1236.pdf)

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87% of all sales that year. In the United States, annual cannabis sales, both legal and illegal, were estimated at $50b in 2018, with legal sales accounting for just over $10b (Corbett, 2018; Reisinger, 2018). According to the US Department of Justice (2017a), the two main source states for domestic marijuana are Colorado and (especially) California, which by itself may supply as much as 70% of the cannabis consumed nationwide (Carah et al., 2015). Most of California's production is exported illegally to other states; indeed, < 20% of the cannabis grown in California is consumed there (Fuller, 2019a). Smuggling that surplus – which is thirteen times the size of Colorado's total production – to the eastern United States can be particularly lucrative since cannabis prices are commonly three times as high as in California (Fuller, 2019b). Although Mexico is the most significant foreign source, the total weight of cannabis seized along the US-Mexico border declined almost 47% between 2011 and 2016 (US Department of Justice, 2017a). With respect to demand, the Substance Abuse and Mental Health Services Administration (2018) reported survey results showing that, in 2017, 9.6% of the US population 12 years of age and older had used cannabis in the month prior to the survey interview, an increase from the 7.5% reported for 2013 (Azofeifa et al., 2016). Generally, cannabis usage is highest in states that have (legal) personal use laws. Thus, demand is expected to continue to increase as more states decriminalize cannabis usage,[2] along with illegal cultivation and transport, especially to states where medical and recreational cannabis production are still illegal (US Department of Justice, 2017a). In short, the illegal cannabis market in the United States is likely to remain robust, for at least the near term, despite the expanding legal market.

This market environment has encouraged a variety of production methods that are largely hidden from public view. The US Department of Justice (2011) reported that the rate of outdoor grown plant seizures nationwide increased > 200% from 2005 to 2010, fueled especially by apparent demand growth and profit-earning opportunities for domestic producers. The report stated that producers face low average costs, at $75 per pound, and sell their product on the street in typically smaller quantities (e.g., an ounce) that translates into per-pound sales as high as $7000. The Department of Justice also reported that cannabis eradicated from federal lands, especially national forests, comprised 44% of all outdoor grown plants seized in 2010. According to Koch et al. (2016), illegal growing was prevalent on national forests through 2012, especially in California, Oregon, and Washington, three states that have recently legalized recreational cannabis. These operations threaten the people who visit and manage such forests and create environmental damages (Eth, 2008; Carah et al., 2015; Thompson et al., 2017) (Table 1). The Office of National Drug Control Policy (2014) stated that illegal outdoor grows negatively affect natural resources through their use of a variety of chemicals (e.g., fertilizers, pesticides), terracing, and the poaching of wildlife by grow site workers. Interdiction operations strain Forest Service law enforcement resources, whose sworn officers number fewer than 1000 nationwide (Bouchard, 2007; Koch et al., 2016).

Data on reported grow operations, which are illegal on all federal lands, including the national forests of the United States,[3] confirm that illegal production continues despite circumstances where recreational and medical cannabis are legal to produce. Grows continue to be reported in states that have legalized as well as in states that have mandatory sentencing rules for convicted producers and traffickers and that have strict regulations (though varying across states in specifics) on cannabidiol (CBD), which is used in medical applications, and similar cannabinoid products. New national forest grows also continue to be found in states with legalized cannabis in spite of potentially increased law enforcement funding designated to combat illegal production. For example, Colorado dedicates 35% of cannabis tax revenue for state and local law enforcement (Bryant, 2017).

In spite of data documenting grows on national forests, no empirical research has been published that tests whether cannabis-related policies, including enhanced law enforcement efforts, affect illegal production on national forests. In an era of ongoing and anticipated loosening of cannabis restrictions across the United States, such research could help land management and law enforcement agencies design more effective means of managing both illegal and legal production and consumption of cannabis. This research may be especially pertinent to the USDA Forest Service, which has both land management and law enforcement responsibilities on national forests. In states with legal recreational and medical cannabis, state governments need to understand how or whether sales taxes on legal cannabis boost production of illegal cannabis, potentially cutting into tax takes from legal cannabis sales. These governmental bodies also could benefit from an assessment of the practical effects of deployment of law enforcement resources on the amount of illegal production, given that such production likely dampens legal sales and generates environmental damages.

The objective of our research was to assess whether policies have affected the number of illegal grow operations on national forests of the United States. We believe this is the first study to scientifically assess the effects of policies on illegal outdoor grows in the United States and on national forests. The modeling also quantifies the effects of neighboring states' policies, recognizing the potential importance of interstate trafficking, in addition to the policies of the state (or states, since some national forests cross state lines) containing each national forest. Furthermore, our analysis addresses the difficulty of inference and the model biases and inconsistencies associated with response-based sampling, in which the existence of an observation in the dataset is partially determined by variables that affect reporting.

2. Methods

2.1. Conceptual model

Recent research (Koch et al., 2016) identified factors affecting decisions by growers to establish cannabis operations on national forests in California, Oregon, and Washington. First, grows are favored in places where productivity is highest: near water sources for irrigation, on south-facing slopes, in warmer climates, and at lower elevations. Second, grows are more prevalent in times and places where law enforcement levels are low, cannabis street prices are high, and difficult economic conditions exist in the surrounding communities. Taken together, and consistent with analyses by Bouchard et al. (2013) for British Columbia, Koch et al. (2016) found that growers respond rationally to economic incentives and the risk of being caught.

Regardless of changes in state and federal cannabis policies, either now or in the future, production on national forests and other public lands will almost certainly remain illegal. Nevertheless, how the legalization and decriminalization processes develop in states and with respect to federal law enforcement actions will determine how much growing will occur on these lands.

The relationships between legal and illegal markets for any given state (i.e., ignoring, for compactness, explicit recognition of out-of-state cannabis markets) can be formalized in aggregate mathematical terms:

[2] Decriminalization removes criminal penalties; for cannabis, decriminalization pertains especially to possession of small amounts for personal use. However, individuals caught with small amounts are still subject to civil penalties, such as fines. Decriminalization also means that possession is still illegal, and so state laws decriminalizing possession are still consistent with federal laws, including the Controlled Substances Act.

[3] The National Forest System Drug Control Act of 1986 (P. L. 99–570, Title XV) (16 U.S.C. 559b – 559 g) authorizes the Secretary of Agriculture "…to take actions necessary in connection with the administration and use of the National Forest System to prevent the manufacture, distribution or dispensing of marijuana and other controlled substances…." (See, for example, www.law.cornell.edu/uscode/text/16/559b).

Table 1
Human impacts and environmental damages from cannabis growing operations that have been noted by public lands managers.

Impact or damage	Source
Injury of tourists/visitors and public employees from booby traps and weapons	Eth (2008)
Garbage dumping	Office of National Drug Control Policy (2014)
Fertilizer contamination of soils and water	Denver Post (2014), Office of National Drug Control Policy (2014)
Pesticide contamination of soils and water	Denver Post (2014), Office of National Drug Control Policy (2014)
Wildlife poisoning from chemicals	Abraham (2013), Office of National Drug Control Policy (2014)
Vegetation and natural landform damages from terracing	Houston (2014), Office of National Drug Control Policy (2014)
Tree cutting	Office of National Drug Control Policy (2014)
Wildlife poaching	Abraham (2013), Office of National Drug Control Policy (2014)
Human waste deposition	Office of National Drug Control Policy (2014)
Plastic tubing dumping	Office of National Drug Control Policy (2014)

$$\begin{aligned} Q_I^S &= f_1(P_I^R, \mathbf{r}, \mathbf{o}, \mathbf{z}) \\ Q_{LR}^S &= f_1(P_L^R, \mathbf{r}, \mathbf{o}, \mathbf{z}) \\ Q_{LM}^S &= f_1(P_L^M, \mathbf{r}, \mathbf{o}, \mathbf{z}) \\ Q_{LR}^D &= f_1(P_L^M, P_L^R, P_I^R, P_{IF}^R, Y, \mathbf{o}) \\ Q_{LM}^D &= f_1(P_L^M, P_L^R, P_I^R, P_{IF}^R, Y, \mathbf{o}) \\ Q_I^D &= f_1(P_L^M, P_L^R, P_I^R, P_{IF}^R, Y, \mathbf{o}) \end{aligned} \tag{1}$$

where $Q_I{}^S$, $Q_{LR}{}^S$, $Q_{LM}{}^S$, $Q_{LR}{}^D$, $Q_{LM}{}^D$, $Q_I{}^D$ are the quantity of illegal cannabis supplied, quantity of legal recreational cannabis supplied, quantity of legal medical cannabis supplied, quantity of legal recreational cannabis demanded, quantity of legal medical cannabis demanded, and the quantity of illegal cannabis demanded, respectively; $P_I{}^R$, $P_L{}^R$, $P_M{}^R$, and $P_{IF}{}^R$ are prices of illegal, legal recreational, legal medical, and imported illegal cannabis (i.e., from outside the state); $\mathbf{r}$ is a vector of production inputs, $\mathbf{o}$ is a vector of cannabis-relevant policies, $\mathbf{z}$ is a vector of exogenous environmental factors affecting the productivity of cannabis grow operations, and Y is aggregate income. Primarily, we are interested in modeling the first of the six equations in (1), $Q_I{}^S$.

Recognizing that the price of imported illegal cannabis is a function of out-of-state policies, $\mathbf{o}_F$, we can specify a reduced-form price equation for illegal recreational cannabis:

$$P_I^R = f_1(\mathbf{r}, \mathbf{o}, \mathbf{o}_F, \mathbf{z}, Y) \tag{2}$$

In an econometric estimation of the structural supply equation for illegal cannabis, (2) would describe exogenous price determinants that could be used in instrumenting price to avoid endogeneity bias.

The effects of changes in prices and the exogenous determinants of illegal cannabis supply are partially informed by comparative statics:

$$\begin{aligned} &\frac{\partial Q_I^S}{\partial P_I^R} > 0 \\ &\frac{\partial Q_I^S}{\partial \mathbf{r}} < 0 \\ &\frac{\partial Q_I^S}{\partial z_k} \lesseqgtr 0 \\ &\frac{\partial Q_I^S}{\partial o_j} \lesseqgtr 0 \\ &\frac{\partial Q_I^S}{\partial o_{F,\mathbf{j}}} \lesseqgtr 0 \end{aligned} \tag{3}$$

What (3) shows is that, while illegal cannabis producers respond predictably to illegal own-prices (positively), legal own-prices (positively, perhaps even implying perfect substitution), and input prices (negatively), responses to variables contained in $\mathbf{z}$, $\mathbf{o}$, and $\mathbf{o}_F$ require further elaboration of their contents. Amlung et al. (2018) performed an empirical analysis of some of the own-price and cross-price relationships laid out in Eq. (3).

Eqs. (1)–(3) characterize the overall market conditions experienced by illegal producers. In this study, we are concerned only with the production decisions of cannabis growers on national forests. An empirical model of cannabis production on national forests conforms to rational choice theory (Becker, 1968; Cornish and Clarke, 1986, 1987; Akers, 1990). Fundamentally, growers decide where to establish operations based on productivity factors that are composites of characteristics of the landscape (e.g., Hirschi, 1986; Weisburd and Piquero, 2008) and the legal risks inherent in grow site establishment. The general model of a grow decision is described as (Becker, 1968):

$$EU(C) = [1 - \pi(\mathbf{e})]u(B) - \pi(\mathbf{e})u(A) - c(C), \tag{4}$$

where EU is expected utility, C is a criminal action, π is the perceived (by the criminal) probability of suffering a criminal sanction, $\mathbf{e}$ is a vector of exogenous variables affecting the probability, $u(B)$ is the utility gain from committing the crime, $u(A)$ is the utility loss from being caught (including the pecuniary and non-pecuniary costs associated with imprisonment), and $c(C)$ are the direct costs of committing (e.g., costs of carrying out) the crime. The vector $\mathbf{e}$ may also include variables describing the presence of police or other capable guardians. The benefits of committing a crime depend on the size of the reward. In the case of a crime such as cannabis cultivation for sale to distributors, the benefits could be connected to the quantity, which is affected by the productivity of a grow site, and the subsequent value of the cannabis produced, which is governed by cannabis market prices. The direct (pecuniary) costs of crime commission could include the opportunity cost of engaging in another activity (e.g., wage labor) and the costs of supplies.

In seeking scientific inferences on the effects of the variables governing the rate of occurrences of crimes committed in a landscape or in a population, the analyst must recognize that the existence of a reported occurrence in an analytical data set is a function of efforts to discover the occurrence: not all occurrences are discovered and reported and, therefore, not all make it into the data set. If the share of crime incidents reported relative to the crime incidents that occur is constant across space and time, then with the exception of the intercept term, under-reporting will not impact parameter bias or consistency. Constancy is, in fact, a common assumption in most quantitative criminology research, although the issue has been addressed econometrically in some studies (e.g., MacDonald, 2001; Fajnzylber et al., 2002). In our analyses, however, we relax this assumption by including a set of variables in our statistical models intended to control for possible reporting-to-occurrence share changes over time and across space by including a vector explaining the likelihood of reporting, $\mathbf{d}$. One formal method for controlling for reporting likelihood is to include a single logarithmic exposure, or offset, variable, constrained to have a coefficient equal to 1. To implement that approach, the analyst identifies a single variable from among the elements $\mathbf{d}$ to serve as an offset variable (e.g., Goodwin and Piggott, 2009). An additional approach is to model reported grows with a statistical framework accounting for unobserved cross-sectional random effects.

An empirical model of the supply of illegal cannabis from national forests is the sum of individual decisions on grow site establishment. The sum of individual producer decisions in favor of establishing individual grows can be indexed by the count of reported grow sites, N.

Regardless, a "grow" is not the same as a quantity supplied, so the sum of those grow decisions is not identical to the quantity of cannabis produced in the national forests. However, the number of actual grow sites and the number reported are likely to be positively correlated with the quantity of cannabis produced.[4] As with any supply function, the number of (reported) grows is a function of variables affecting the prices of production inputs (**r**), environmental factors affecting the quantity produced (**z**), the overall likelihood that the operation is reported (**d**), policies affecting arrest risk (**e**), and the price of illegal cannabis (P_I^R). Thus, the empirical model for N can be generally described, for any location i and year t, as

$$N_{i,t} = f(\mathbf{r}_{i,t}, \mathbf{z}_{i,t}, \mathbf{d}_{i,t}, \mathbf{e}_{i,t}, P_{Ii,t}^R) + \omega_{i,t}, \tag{5}$$

where $\omega_{i,t}$ is a random error. Note that variables in **d** could be among those also found in **e**. This overlap may be expected if law enforcement resources can both discover existing grows and, by their presence and interdiction success, deter future grows.

Eq. (2) showed that P_I^R, the (in-state) price for illegal cannabis, is itself a function of production input prices (**r**) and productivity variables (**z**), which directly affect illegal supply decisions. Eq. (2) also showed that P_I^R is additionally a function of in-state (**o**) and out-of-state ($\mathbf{o}_F$) policies for legal and illegal cannabis, which both affect illegal supply decisions indirectly, due to prospective or actual cross-state arbitrage related product movements, through the in-state illegal market price. If the analyst has in hand only a national street price for cannabis, P^R, then P_I^R is unobserved, compelling inclusion of proxy variables that capture the state-level effects.[5] In our empirical specification of Eq. (5), we therefore include **o** and $\mathbf{o}_F$:

$$N_{i,t} = f(\mathbf{r}_{i,t}, \mathbf{z}_{i,t}, \mathbf{d}_{i,t}, \mathbf{e}_{i,t}, P_t^R, \mathbf{o}_{i,t}, \mathbf{o}_{F,i,t}) + \omega_{i,t}, \tag{6}$$

The variables in **o** and $\mathbf{o}_F$ include those associated with enforcement of historical prohibitions against cannabis production and consumption as well as with incentives to purchase legal cannabis products. In our analysis, we identify six such policies as indicator variables, $\mathbf{o} = (o_1, \ldots, o_6)$: legalization of recreational cannabis production and consumption (o_1), so that $\frac{\partial N_i}{\partial o_1} \lesseqgtr 0$ because legalization positively affects demand for, and creates a new supply of, legal cannabis; legalization of medical cannabis production and consumption (o_2), so that $\frac{\partial N_i}{\partial o_2} \lesseqgtr 0$ because legalization has the same effect as in the case of recreational cannabis, under the assumption that some legal medical cannabis sales may be diverted to recreational uses (e.g., Wall et al., 2011; Cerdá et al., 2012; Chu, 2015); decriminalization of cannabis possession (o_3), where $\frac{\partial N_i}{\partial o_3} > 0$ because decriminalization reduces the penalties for being caught with small amounts of cannabis for personal use; mandatory minimum sentencing laws for possession or production of illegal cannabis (o_4), for which $\frac{\partial N_i}{\partial o_4} < 0$ due to an expected higher overall penalty for being caught producing illegal cannabis; and regulations affecting the production and consumption of CBD- and tetrahydrocannabidiol (THC)-containing products for medical or recreational uses (o_5), so that $\frac{\partial N_i}{\partial o_5} < 0$ because of a more limited market for cannabis extracts. Finally, many states that have legalized medical and recreational cannabis apply taxes, o_6, on the wholesale and/or retail sales of legally produced cannabis products, so that $\frac{\partial N_i}{\partial o_6} > 0$ because taxes increase the price of legal cannabis, P_L^R and P_M^R, as well as the price of illegal cannabis, thereby incentivizing illegal production. We note here, however, that $o_6 = (T_1, T_2)$, where T_1 are recreational cannabis taxes and T_2 are medical cannabis taxes.

Some of the listed policies are the basis for six simulations that we conduct using our empirical models. These simulations quantify six counterfactual policy environments, each applied to our models of reported grows for the last year of our data, 2016:

(A) revocation of existing laws that allow for legal recreational cannabis production and consumption, which, consistent with the hypothesized effect of o_1 on cannabis, would have an ambiguous impact, depending on how much legal demand would shift to the illegal market;

(B) revocation of existing laws that allow for both legal recreational and legal medical cannabis production and consumption, with the same ambiguous effect as in simulation (A), because the effect of medical cannabis legalization (o_2) is also ambiguous;

(C) implementation of recreational cannabis legalization policies in the states that approved such policies by statewide vote in November 2016 (California, Maine, Massachusetts, Nevada), an effect similar but opposite in sign to simulation (A);

(D) expansion of legal recreational cannabis to include all states that had implemented or passed (but not yet implemented) legal medical cannabis production and consumption by November 2016, an effect similar to simulation (C);

(E) elimination of wholesale and retail sales taxes on legal recreational and legal medical cannabis sales in states ($i = 1, \ldots I$) where such sales are legal (i.e., setting $T_{1i,\ t}, T_{2i,\ t} = 0$ for states with legal recreational and/or medical cannabis in year t), with an expected effect of decreasing the number of grows, consistent with the positive effect of o_6 on grows (though an untested assumption here is that producers facing lower prices due to elimination of taxes might invest fewer resources into hiding their production, increasing their likelihood of being discovered and reported, and we do not model that reaction directly); and

(F) an increase (by 20%) in the number of Forest Service sworn law enforcement officers, which would be expected to decrease the number of grows due to heightened risk of being caught and fined for illegal production. This last effect emerges from our specification of variables affecting risk of discovery contained in **e** (Table 2) in Eq. (6) as $\mathbf{e} = (e_1, e_2, \mathbf{e}_o)$, where e_1 = the budget for law enforcement, such that $\frac{\partial N_i}{\partial \mathbf{e}_1} > 0$; e_2 = the number of law enforcement officers in the field, such that $\frac{\partial N_i}{\partial e_2} < 0$; and $\frac{\partial N_i}{\nabla \mathbf{e}_o} \lesseqgtr 0$

Note that simulations (A) and (B) do not model changes in decriminalization policies in any state, while simulations (C) and (D) assume that cannabis decriminalization laws are newly implemented (or remain in place) in states with simulated newly legal recreational and medical cannabis.

Policy indicators (**o**, $\mathbf{o}_F$) used in this study are imputed as the indicator for a state multiplied by the share of the national forest in each state that comprises it; briefly, the share of national forest i in state s, $H_{i,s} = [0,1]$, so that $\Sigma_s H_{i,\ s} = 1$ ($s = 1, \ldots, S$), is multiplied by the dummy variable policy indicator in each state s in year t, $D_{s,t} = 1$ if the policy is in effect in the state in year t, 0 otherwise. Hence, the policy indicator is $o_{i,\ t} = \Sigma_{s=1}^{S} H_{i,\ s} D_{s,\ t}$. For $\mathbf{o}_F$, $o_{Fi,\ t} = \Sigma_{s=1}^{S} H_{i,\ s} D_{s,\ t} b_s$ where $b_s = 1$ for states bordering state i, 0 otherwise. We note that all of the states that approved legalization of either recreational or medical cannabis in 2016 had $D_{s,\ t} = 0$, because they did not have in place implementing legislation that same year.

[4] Although the quantity of plants in each reported grow varies, there is a positive correlation between the number of grows and the cumulative number of plants for those grows where counts of such plants are recorded. For example, for grows reported in California national forests, 2004–2016, the annual number of grows reported on national forests in California is positively correlated with the total number of plants discovered on those grows, $r = 0.94$. Modeling the total number of plants, however, would not be feasible, as many reported grows have missing entries in the number of plants because sometimes grows are discovered subsequent to plant harvest or because the plant counts were not reported by law enforcement.

[5] Hoffman (2018) documented the apparent strong market integration in cannabis in the United States by observing highly correlated price changes across states, from January 2014 through July 2015. It is important to note that supply from illegal production from non-neighboring states and imported illegally can be summarized in the national average price.

Table 2
Variables used and their definitions in modeling the number of reported cannabis grow operations on national forests, 2004–2016.

Variable category	Variable name	Variable definition	Symbol used in equations	Data source
Enforcement policies (own and neighboring states)	Indicator of recreational cannabis legalization	=1 in years where legalization has been implemented and in effect, 0 otherwise, weighted by the area of the national forest contained in each state	$o_{1i,\ t}$ (in-state), $o_{1Fi,\ t}$ (neighboring state) $o_{1i,\ t}^{T}$ (in-state, tax-adjusted), $o_{F1i,\ t}^{T}$ (neighboring state, tax-adjusted)	The Cannabist (2017)
	Indicator of medical cannabis legalization	=1 in years where legalization has been implemented and in effect, 0 otherwise, weighted by the area of the national forest contained in each state	$o_{2i,\ t}$ (in-state), $o_{2Fi,\ t}$ (neighboring state), $o_{2i,\ t}^{T}$ (in-state, tax-adjusted), $o_{F2i,\ t}^{T}$ (neighboring state, tax-adjusted)	
	Indicator of decriminalized cannabis possession	=1 in years where decriminalization has been implemented and in effect, 0 otherwise, weighted by the area of the national forest contained in each state	$o_{3i,\ t}$ (in-state), $o_{3Fi,\ t}$ (neighboring state)	
	Indicator of mandatory minimum sentences for cannabis production or possession of significant quantities	=1 in states with minimum sentencing guidelines, 0 otherwise, weighted by the area of the national forest contained in each state	$o_{4i,\ t}$ (in-state), $o_{4Fi,\ t}$ (neighboring state)	
	Indicator of law(s) regulating cannabidiol (CBD) oil and similar cannabinoid products	=1 in years where decriminalization has been implemented and in effect, 0 otherwise, weighted by the area of the national forest contained in each state	$o_{5i,\ t}$ (in-state), $o_{5Fi,\ t}$ (neighboring state)	
	Taxes on cannabis sales	Sum of wholesale and retail taxes on the purchase of legal cannabis, weighted by the area of the national forest contained in each state	$T_{1i,\ t}$, $T_{2i,\ t}$	Loughead and Scarboro (2017)
Arrest and punishment risk	Annual total of Forest Service law enforcement officers per capita	Total number of law enforcement officers in the Forest Service divided by total population of the counties containing the national forest, adjusted by the share of the county in the national forest	e_{2t}	US Department of Justice (2017b)
Cannabis demand	Real dollar gross state product	Nominal gross state product adjusted by the gross domestic product deflator, chained dollars (adjusted to 2016 dollars)	Y_t	US Department of Commerce (2017)
	Taxes on cannabis sales	Sum of wholesale and retail taxes on the purchase of legal cannabis	$T_{1i,\ t}$, $T_{2i,\ t}$	Loughead and Scarboro (2017)
Cannabis supply	Cannabis annual percent price change	Composite index of annual cannabis price changes, nationwide	$P_{.t}^{\cdot}$	Western States Information Network (2004, 2006, 2008, 2010, 2012), Price of Weed (2015), High Times (2018), Kilmer et al. (2014)
	Real dollar retail wage rate ($/week)	Nominal wages adjusted by the consumer price index for all urban consumers	$r_{1,\ t}$	US Department of Labor (2017)
	Unemployment rate for all adults (percent)		$r_{2,\ t}$	US Department of Labor (2017)
	Forest area	Area of the national forest in square kilometers	$z_{1,\ t}$	USDA Forest Service (2012)
	Tree canopy cover percent	Percent of the national forest's area that is covered by tree canopy	$z_{2,\ t}$	US Geological Survey (2014, 2015)
	Elevation	Average elevation of the national forest, in meters above sea level	$z_{3,\ t}$	PRISM Climate Group (2017), US Geological Survey (1996)
	Precipitation, average annual	Mean of the average water-equivalent precipitation in the national forest	$z_{4,\ t}$	PRISM Climate Group (2017), Gibson (2009c)
	Temperature, average annual minimum	Minimum daily temperature, in degrees centigrade, for the national forest	$z_{5,\ t}$	PRISM Climate Group (2017), Gibson (2009b)
	Temperature, average annual maximum	Minimum daily temperature, in degrees centigrade, for the national forest	$z_{6,\ t}$	PRISM Climate Group (2017), Gibson (2009a)
	Waterway density	Total length of waterways (km) in the national forest divided by the area of the national forest, in km^2	$z_{7,\ t}$	US Geological Survey (2017)
Exposure variables	Road density	Total length of roads (km) in the national forest divided by the area of the national forest, in km^2	d_{1t}	US Census Bureau (2016)
	Population	Total population of the counties containing the national adjusted by the proportion of the national forest in each county	d_{2t}	US Department of Justice (2017)
	Poverty rate for all individuals (percent)	Percent of all individuals living in poverty in the county, weighted by the share of each county in the national forest	d_{3t}	US Census Bureau (2017)
	Night-time lights density	Mean nighttime lights within a 50-km buffer zone surrounding the national forest	d_{4t}	NOAA National Geophysical Data Center (2017)

(*continued on next page*)

Table 2 (*continued*)

Variable category	Variable name	Variable definition	Symbol used in equations	Data source
	Percent slope	Average percent slope of the land contained in the national forest	d_{5t}	PRISM Climate Group (2017), US Geological Survey (1996); derived from digital elevation data
	Annual real dollar budget of the USDA Forest Service Law Enforcement and Investigation division	Nominal budget adjusted by the gross domestic product deflator, chained dollars (adjusted to 2016 dollars)	e_{1t}	USDA Forest Service-Law Enforcement and Investigations (2018)
Additional instruments of Prices and Forest Service Law Enforcement	Sworn law enforcement officers, state	Count of sworn law enforcement officers, by state containing a national forest; data processed from US Department of Justice (2017)	e_{3t}	ICPSR (2017)

The case of sales taxes motivated us to estimate two versions of Eq. (6). One version used what we refer to as the tax-ignorant legalization indicators for recreational and medical cannabis, $o_{1i,t}$ and $o_{2i,t}$. This version is "ignorant" to the extent that the legalization indicators effectively assume that recreational cannabis is taxed identically across all states with legal recreational cannabis, and that medical cannabis is taxed identically across all states with legal medical cannabis. Although taxes (Table 3) are similar in range for recreational cannabis (ranging from 19 to 45% range for states with legislation in place by January of 2016), they are much more variable for medical cannabis (0 to 99% for states with legal medical cannabis). So the other version modeled the effect of the sales tax more directly by multiplying the legalization indicator for each state by $(1 + T_{1s,\ t})^{-1}$ for legal recreational cannabis and $(1 + T_{2s,\ t})^{-1}$ for legal medical cannabis, where $T_{1s,\ t}$ is the decimal tax rate for legal recreational cannabis and $T_{2s,\ t}$ is the analogous rate for legal medical cannabis in state s in year t. The tax-adjusted effect on legal recreational cannabis is calculated as $o_{1i,\ t}^{T} = \Sigma_{s=1}^{S} H_{i,\ s} D_{s,\ t}(1 + T_{1s,\ t})^{-1}$ for the recreational indicator and $o_{2i,\ t}^{T} = \Sigma_{s=1}^{S} H_{i,\ s} D_{s,\ t}(1 + T_{2s,\ t})^{-1}$ for the medical indicator and $s \neq t$. For tax-adjusted indicators of bordering states, these were $o_{1Fi,\ t}^{T} = \Sigma_{s=1}^{S} H_{i,\ s} D_{s,\ t} b_s (1 + T_{1,\ s,\ t}^{min})^{-1}$ and $o_{2Fi,\ t}^{T} = \Sigma_{s=1}^{S} H_{i,\ s} D_{s,\ t} b_s (1 + T_{2,\ s,\ t}^{min})^{-1}$, $s \neq t$, and $T_{\cdot,\ s,\ t}^{min}$ is the minimum tax rate for all states s bordering state t. We refer to this adjusted set of indicators for recreational and medical cannabis as the tax-adjusted legalization indicators. In simulating the effect of eliminating taxes (simulation (E)) on the number of illegal grows on national forests, we set $T_{1s,\ t}$, $T_{2s,\ t} = 0$ for all states with legal recreational and medical cannabis.

Eq. (6) has many possible specifications, and we follow Leamer's (1983) suggestion that when assumptions about the data generation process plausibly can be disputed, hypotheses should be tested under several alternative model empirical specifications. When $N_{i,t}$ is often zero or close to zero, as in our case, Eq. (6) can be specified as a Poisson or negative binomial model, the latter allowing for an increasing ratio of the expected count $E(N_{i,t})$ to the variance of $e_{i,t}$ (i.e., overdispersion). Theoretically, both model types can be specified with fixed or random effects. Fixed effects models were not possible in our case, given that many states (and hence national forests, the spatial unit of observation) had policy variables (and several biophysical variables affecting productivity of cannabis operations) that were constant 2004–2016, thereby preventing their identification in fixed-effects or cross-sectional dummy variable specifications. We therefore estimated several versions of negative binomial models that allowed either dispersion or variance to vary across units. For example, in the random effects negative binomial model, the dispersion of the expected count is assumed to vary randomly across cross-sections—in this case, national forests, capturing unobserved national forest-level effects that might arise from differences in each forest's average rates of systematic underreporting of cannabis grows. For the random effects application, Eq. (6), was elaborated as:

$$E(N_{i,t} \mid \mathbf{X}_{i,t} = \mathbf{x}_{i,t}, u_i, \epsilon_{i,t}) = \alpha_i \lambda_{i,t} = exp(\mathbf{x}'_{i,t}\boldsymbol{\beta} + u_i + \epsilon_{i,t})$$
$$\mathbf{x}_{i,t} = (\mathbf{r}_{i,t}, \mathbf{z}_{i,t}, \mathbf{d}_{i,t}, \mathbf{e}_{i,t}, P_t^R, \mathbf{o}_{i,t}, \mathbf{o}_{F,i,t}) \quad (7)$$

where E is the expectations operator, *exp* is the exponential operator, $u_i = \ln(\alpha_i)$ is the random effect for spatial unit i and where $\epsilon_{i,\ t}$ is a zero-centered random error. In estimation, we also allowed for generalized heteroscedastic error distribution for $\epsilon_{i,\ t}$. Maximum likelihood estimation of Eq. (7) for both the tax-ignorant and tax-adjusted indicator models was done in Stata (version 13.1). Recognizing that other potential data generation processes are plausible, we report the effects sizes of our six policy simulations for three additional negative binomial specifications: a pooled negative binomial model with cluster-based (national forest-level) heteroscedasticity, a random effects negative binomial model with the lagged law enforcement budget as a single offset variable (i.e., the coefficient of the natural logarithm of lagged spending is constrained to 1), and a zero-inflated negative binomial

Table 3
Recreational and medical cannabis tax rates assumed, by state, for states with legal recreational and/or medical cannabis.

	Recreational	Medical	Recreational	Medical	Notes
	Ad Valorem Tax or Equivalent (%)	Ad Valorem Tax or Equivalent (%)	Specific Tax ($/oz.)	Specific Tax ($/oz.)	
Alaska	18.65	0.00	50	0	
Arizona		9.10			
Arkansas		4.00			
California	19.90	0.00	9.25		State specific tax on flowers is $9.25/oz.; leaf tax of $2.75/oz. not included in the equivalent rate
Colorado	29.80	2.90			
Connecticut		37.20		99.225	
Delaware		0.00			
District of Columbia	0.00	0.00			
Hawaii		8.50			4% excise tax, 4.5% tax on Oahu
Illinois		8.00			1% on pharmaceuticals and 7% on cultivators/dispensaries
Maine	10.00	0.00			A $1.30/pound processed cannabis tax not included
Massachusetts	20.00	0.00			
Michigan		3.00			
Minnesota		36.50		99.225	
Montana		4.00			
Nevada	25.00	2.00			Sum of 15% excise tax on wholesale, 10% retail
New Hampshire		0.00			
New Jersey		7.00			
New Mexico		0.00			
New York		7.00			
North Dakota		0.00			
Ohio		7.75			State and local taxes combined
Oregon	20.00	0.00			State 17% sales tax, and 3% local option
Pennsylvania		5.00			Wholesale tax
Rhode Island		3.28			Medical tax specified as $25/plant. Based on an estimate of 3 oz of dried flowers per plant, this would be $8.33/oz.
Vermont	0.00	0.00			
Washington	45.00	37.00			Includes 8% state tax and 37% excise tax
West Virginia		10.00			Includes a 0% medical sales tax, 10% excise tax

Source: Rough (2017).
Note: Ad valorem-equivalent tax rates for states with specific taxes are based on statewide average prices for medium quality cannabis reported for the first half of 2015 (data by special request to priceofweed.com, August 20, 2015).

model with national forest-level heteroscedasticity with a logit link to model zeroes. Equation estimates for these additional functional forms are available in an online supplement.

2.2. Data and variable definitions

Variables used to estimate Eq. (7) for the tax-ignorant and tax-adjusted models are shown in Table 2. Observations were annual, 2004–2016 inclusive, based on calendar years. We included data from 111 national forests and similar land units managed by the USDA Forest Service[6] in the 48 coterminous states plus Alaska. National forests of several states were combined due to their administrative consolidation: Alabama, Florida, Mississippi, North Carolina, and Texas. To enable geospatial analyses, including calculation of forest area, we developed a national forest data layer (consisting of polygon features) from three Forest Service data sets: ranger district boundaries, administrative forest boundaries, and proclaimed national forest and grassland boundaries (USDA Forest Service, 2017). Although the ranger district boundary data set was our primary source, we used the other two data sets to edit and relabel some features so they conformed to the national forests as defined during the timeframe of the grow site data. All dollar prices and values were adjusted from nominal to real (2016) dollar values, with gross state products adjusted using the chained gross domestic product deflator (US Department of Commerce, 2017) and other prices and values with the consumer price index for all urban consumers (US Department of Labor, 2017). National forest values for economic and demographic variables were area-weighted averages of reported values for the counties or states containing the national forest.

Price data were based on an unweighted national average of prices obtained from several sources, converted to 2016 dollars using the consumer price index (US Department of Commerce, 2017), and translated into an index, with the 2004 average national price set at 100. Because the 2013 price was missing from this series, it was estimated as the average of the 2012 and 2014 prices. The variable entering our models was the change in the price index from year *t*-1 to *t*. In instrumenting this variable, we used the control function approach (e.g., Wooldridge, 2015). The approach entails estimating an instrumental equation including all regressors from the structural equation (random effects negative binomial model of counts of reported grows on national forests, either with the tax-ignorant or tax-adjusted legalization indicator) and additional variables that serve as instruments (shifters of the endogenous variable that are exogenous to grow establishment decisions). The residuals of this control function equation, specified as linear in parameters, are then introduced as additional regressors in the structural equation, effectively capturing the endogeneity. In addition to this instrumental equation for the change in the national cannabis price index in the current year, we estimated a second instrumental equation for Forest Service law enforcement per capita (national law enforcement officer full-time equivalents, divided by area-weighted share of the populations of the counties containing the national forest) in the current year. In both of these equations, we included shifters of cannabis demand and Forest Service law

[6] Including two grasslands (Dakota Prairie Grassland, Midewin National Tallgrass Prairie), one national scenic area (Columbia River Gorge), one national recreation area (Land Between the Lakes), and the Lake Tahoe Basin Management Unit. Except for Dakota Prairie, all had years with at least one grow discovered. One grow fell in Dakota Prairie, according to the provided GPS coordinates, but was labeled as occurring in the Chequamegon-Nicolet National Forest.

Table 4
Price and law enforcement per capita control function estimates and random-effects negative binomial model estimate of the number of reported cannabis grows on national forests of the United States, 2004–2016, with tax-adjusted legalization indicators.

	Price change equation	LEI FTE per capita equation	Count model
Legal Recreational$_t$	0.172***	−6.32e-06	−0.736**
	(0.0389)	(6.61e-06)	(0.335)
Legal Medical$_t$	0.00619	1.38e-06	−0.282*
	(0.0200)	(3.40e-06)	(0.161)
Decriminalized$_t$	−0.0554***	−1.30e-06	−0.0356
	(0.0187)	(3.18e-06)	(0.198)
Cannabidiol Law$_t$	0.0663**	2.58e-06	−0.546**
	(0.0318)	(5.40e-06)	(0.214)
Mandatory Sentence$_t$			−0.519**
			(0.224)
Mandatory Sentence$_{t-1}$	0.000621	1.41e-07	
	(0.0202)	(3.43e-06)	
LEI Budget$_{t-1}$	−0.00263***	3.92e-07***	0.00811***
	(0.000350)	(5.95e-08)	(0.00216)
Gross State Product$_t$	−1.160***	4.67e-05	
	(0.239)	(4.06e-05)	
Gross State Product$_{t-1}$	1.702***	−3.91e-05	
	(0.247)	(4.19e-05)	
LEI FTE Per Capita$_{t-1}$	−10.58	0.980***	
	(27.40)	(0.00465)	
State LEO Per Capita $_{t-1}$	−32.86***	0.00251	
	(12.11)	(0.00206)	
Legal Recreational, Neighbor$_t$	0.122***	−8.76e-06*	−0.463***
	(0.0268)	(4.56e-06)	(0.147)
Legal Medical, Neighbor$_t$	−0.0139	−6.76e-07	0.490***
	(0.0182)	(3.09e-06)	(0.145)
Decriminalized, Neighbor$_t$	−0.0342**	−1.80e-06	0.0314
	(0.0147)	(2.50e-06)	(0.152)
Cannabidiol Law, Neighbor$_t$	0.0301	−1.28e-05***	0.0344
	(0.0204)	(3.46e-06)	(0.132)
Mandatory Sentence, Neighbor$_t$	−0.0128	−1.59e-06	−0.379
	(0.0271)	(4.61e-06)	(0.297)
Retail Weekly Wage$_t$	2.36e-05	−2.74e-08**	−0.000227
	(7.26e-05)	(1.23e-08)	(0.000799)
Unemployment Rate Percent$_t$	0.0117***	−1.54e-06***	0.0547***
	(0.00294)	(5.00e-07)	(0.0155)
Poverty Rate Percent$_t$	−0.00655***	−3.82e-07	−0.0207
	(0.00193)	(3.27e-07)	(0.0154)
National Forest Area$_t$	0.241	−1.11e-05	47.90***
	(0.951)	(0.000161)	(12.45)
Tree Canopy Cover Percent, Average$_t$	0.000614	−5.41e-08	0.0245***
	(0.000421)	(7.15e-08)	(0.00553)
Elevation, Average$_t$	−4.68e-06	−3.21e-09	3.08e-05
	(2.03e-05)	(3.44e-09)	(0.000240)
Percent Slope, Average$_t$	−0.00101	3.11e-07	0.0529**
	(0.00216)	(3.67e-07)	(0.0257)
Waterway Density, Average$_t$	−0.00509	−3.35e-06	0.563
	(0.0352)	(5.98e-06)	(0.401)
Road Density, Average$_t$	−0.00252	−1.21e-06	−0.127
	(0.0150)	(2.54e-06)	(0.181)
Precipitation, Annual Average$_t$	−1.53e-05	−3.46e-10	−0.000718***
	(1.71e-05)	(2.91e-09)	(0.000224)
Daily Minimum Temperature,	−0.00668	−7.21e-09	0.00141
Annual Average$_t$	(0.00867)	(1.47e-06)	(0.0981)
Daily Maximum Temperature,	0.0109	−8.83e-09	0.0907
Annual Average$_t$	(0.00708)	(1.20e-06)	(0.0789)
Population$_t$	−0.0305***	−6.03e-07	0.0173**
	(0.00704)	(1.20e-06)	(0.00810)
Nighttime Lights$_t$	−0.000777	−9.45e-08	0.00922

enforcement demand, including current-year and lagged-year gross state product, lagged-year state (ICPSR, 2017) and Forest Service law enforcement (USDA Forest Service, 2018) full-time equivalent officers nationwide, the lagged Forest Service law enforcement budget nationwide, and the lagged mandatory sentencing policy indicator. Notably, the price index instrumental regressions are based on the entire panel of observations, effectively allowing for the residuals from the instrumental equations to vary across national forests within each year.

We computed values for biophysical variables in a geographic information system (GIS). Road features came from 2016 TIGER/Line geospatial data (US Census Bureau, 2016). We acquired these data at the county level and then assembled them into a single data set for the coterminous USA and another for Alaska. In TIGER/Line data, road features are labeled with one of 15 different feature class codes (e.g., primary road, secondary road, 4-wheel-drive vehicular trail). We included all of these classes in our analysis. We intersected the road data sets with the national forest data layer to calculate the total road length (in km) within each national forest, which we divided by the forest's total area (km^2) to estimate road density.

River and stream features came from the high-resolution version of the National Hydrography Dataset (NHD) (US Geological Survey, 2017). We acquired the data by state and then assembled them into separate data sets for the coterminous USA and Alaska. We retained all perennial stream and river linear features as well as simplified, centerline representations of lakes, ponds, and reservoirs. We also included simple linear representations of any areas of complex channels (e.g., marshes). After refining the two data sets, we intersected them with the national forest data layer to calculate the total waterway length (in km) within each national forest, which we divided by the forest's total area (km^2) to estimate waterway density.

To represent elevation, we used an 800-m resolution digital elevation model (DEM) for the coterminous USA (PRISM Climate Group, 2017; used in calculating 30-year climatological normals as described below) and a 1-km resolution DEM for Alaska (US Geological Survey, 1996), which we resampled to 800-m resolution using bilinear interpolation. In addition, we calculated percent slope raster layers from each of these DEMs. From these layers, we computed the mean elevation (m) and mean percent slope of all raster cells within each national forest.

With respect to climate, we acquired raster data sets depicting 30-year annual normals (i.e., 30-year means) for precipitation as well as minimum and maximum temperature. For the coterminous USA, we used 4-km resolution data with a normal period of 1981–2010 (PRISM Climate Group, 2017), while the data for Alaska were ≅ 771 m resolution (resampled to 4 km) with a normal period of 1971–2000 (Gibson, 2009a, b, c). As with elevation and percent slope, we computed mean values of these variables from the raster cells that fell within each national forest.

For each national forest, we estimated the percent of its area covered by tree canopy (i.e., by vertical projection of tree canopies). As the basis for these estimates, we used 30-m resolution raster data sets of percent tree canopy cover for the coterminous USA and southeastern Alaska (US Geological Survey, 2014, 2015). These data sets were developed in cooperation with the USDA Forest Service as supplementary products of the 2011 National Land Cover Database (NLCD). The percent canopy cover estimate for each national forest is the mean cover percentage computed from all raster cells falling within the forest.

Remotely sensed nighttime lights data are known to correlate with urbanization, human population distribution, and other geospatially referenced socioeconomic factors (Bennett and Smith, 2017). We used multi-temporal nighttime lights data from the Defense Meteorological Satellite Program - Operation Linescan System (DMSP-OLS). The version 4 DMSP-OLS nighttime lights time series (NOAA National Geophysical Data Center, 2017) includes a number of image data composites, at 2.7-km resolution, from the period 1992–2013; we chose a composite depicting average visible light levels for 2013, which had

Table 4 (*continued*)

	Price change equation	LEI FTE per capita equation	Count model
	(0.00174)	(2.96e-07)	(0.0192)
Cannabis Percent Price $Change_t$			1.604***
			(0.403)
Cannabis Percent Price Change Equation $Residuals_t$			−1.414***
			(0.417)
LEI FTE Per $Capita_t$			−1005**
			(405.6)
LEI FTE Per Capita Equation $Residuals_t$			4276***
			(1419)
Constant	0.270**	−3.83e-06	−3.439***
	(0.114)	(1.93e-05)	(1.269)
Ln(r)			0.515***
			(0.154)
Ln(s)			0.807***
			(0.200)
Observations	1443	1443	1443
R^2	0.134	0.988	
Number of National Forests	111	111	111
Final Log-likelihood			−2817.28

*** indicates significantly different from zero at α = 0.01, ** at α = 0.05, and * at α = 0.10. Ln(r) and Ln(s) refer to the estimated parameters of the Beta(r,s) distribution of the dispersion parameter. A likelihood ratio test of the random effects negative binomial model versus a pooled data negative binomial model (with constant dispersion) was rejected at < 0.01 ($\chi^2(1) = 1023$).

been further edited to include only stable (i.e., non-ephemeral) lights from cities, towns, and other locations with persistent lighting. Values in this raster data set ranged from 0 (no data) to 63. To summarize this data set, we defined a 50 km buffer zone around each national forest. The forests themselves were not included in the buffers. As an index of nighttime lights density, we computed the mean value of all raster cells that fell within each forest's buffer zone.

3. Results

The negative binomial random effects estimate of Eq. (7), the count of reported grows on national forests for the tax-adjusted indicator model is presented in the last column of Table 4. (An estimate of the tax-ignorant version of the model is contained in Table S1, in an online supplement.) Table 4 also presents the estimates of the control function equations for cannabis price changes and the numbers of Forest Service law enforcement officers per capita (FS LEI Per Capita). The control function results include statistically significant coefficients on variables of interest. For example, for the price equations, lagged gross state product is significantly and positively related to price changes, consistent with demand-driven shifts in cannabis. In these same equations, state-level (non-Forest Service) law enforcement is negatively related to price changes, which is consistent with negative demand shifts.

The count model estimate shows that legalization of recreational and medical cannabis is associated with lower numbers of reported grows on national forests of the United States. Tests of the random effects negative binomial model against a comparable specification of a pooled negative binomial model with constant dispersion reject the pooled versions in favor of the random effects versions ($\chi^2(1) = 1023$).

Table 4 shows that indicators of recreational cannabis legalization within a state are negatively related to reported grows (α = 0.01). Neighboring states' recreational cannabis legalization is also negatively and significantly (α = 0.05) related to reported grows. Medical cannabis has a negative but weakly significant (α = 0.10) effect on grows. Neighboring states' medical cannabis legalization, on the other hand, is significantly (α = 0.01) and positively related to the number of reported grows, suggesting that, for the medical cannabis market, legalization that occurs in neighboring states offsets the effect of medical legalization within a state; without neighboring states' medical legalization, the effect is to drive down reported grows on national forests.

From a sanctions perspective, we find that decriminalization laws—which have often, but not always, pre-dated legalization—have no discernible independent association with the number of reported grows. Laws closely regulating CBD in medical applications are associated with fewer reported grows in a state (α = 0.05), although similar laws in neighboring states have no apparent effects. Laws mandating minimum sentences for cannabis law violations in a state are negatively associated with reported grows (α = 0.05), indicating that penalties are effective at reducing illegal growing, while similar laws in neighboring states are not significantly related to reported grows.

Of the two labor market variables in our models, the unemployment rate has a highly significant (α = 0.01) and positive effect on reported grows on national forests, consistent with an economic model of crime, while the wage rate for retail workers has no significant relationship. The only significant biophysical variable affecting grow productivity is annual precipitation (negative and significant at α = 0.01), an effect consistent with the notion that growers prefer drier climates, where water status can be managed by the grower to maximize yields and minimize fungal infections. Stream density has no added explanatory effect on the number of reported grows, nor do temperature (minimum or maximum) or elevation. Variables measuring reporting likelihood (see Table 2), after accounting for other hypothesized driving factors, are sometimes significant. For example, average slope in the national forest is statistically significant (α = 0.05) and positive—an effect explained by both the ability to hide grows in more broken terrain and the opportunity to place grows on slopes that can modulate the amount of received sunshine. The amount of canopy provided by the forest is positively and significantly (α = 0.01) related to grow counts, an effect expected if growers are able to more easily hide their operations under such canopies. Road density, which might index the propensity to discover and report grows but also greater accessibility to the forest to establish grows, is not significant. Population has a positive effect (α = 0.05) on reported grows, as expected, because larger populations generally mean more opportunities for grows to be discovered and reported. Forest area is a strongly significant (α = 0.01) and positive predictor of reported grows; larger forests have more reported grows, ceteris paribus. The lagged LEI budget, hypothesized to increase the likelihood of grow discovery and reporting, is positively related to the number of reported grows and statistically significant (α = 0.01).[7]

As expected, the change in the price of cannabis is a positive and statistically significant (α = 0.01) predictor of the number of reported grows. The coefficient on the residuals of the price instrumental (control function) equation is negative and significant (α = 0.01), demonstrating that the residuals effectively capture the endogenous (demand-shifting) component of cannabis price. Likewise, and also consistent with expectations, the number of Forest Service law enforcement officers per capita is negatively related to the number of grows (α = 0.05). The residuals of the law enforcement per capita instrumental equation are positively and significantly related (α = 0.01) to the number of reported grows, capturing the endogeneity of law enforcement resources and the number of reported grows.

Policy simulation results are presented in Table 5. Results are shown for the model reported in Table 4 as well as for tax-ignorant and tax-adjusted versions of model alternatives: the tax-ignorant random effects

[7] Parsimonious versions of the tax-ignorant and the tax-adjusted versions of the random effects negative binomial model are shown in Tables S2 and S3 in the online supplement. These versions dropped insignificant non-policy variables and produced nearly identical findings—but in some cases slightly more statistically significant—as in the full specifications of both the tax-adjusted estimate (Table 4) and the tax-ignorant estimate (Table S1).

Table 5
Percentage changes in total expected number of reported cannabis grows on national forests of the United States in 2016, under six simulations of alternative counter-factual policy changes.

Simulation	Policy Change	Model Specification[b]	Tax-Ignorant Legalization Indicators		Tax-Adjusted Legalization Indicators	
A	No Legal Recreational Cannabis	NB Random Effects	39.7	***	42.2	***
		NB Random Effects, Parsimonious	48.1	***	51.5	***
		NB Pooled	131.6	***	156.7	***
		NB Random Effects with Offset	39.7	***	42.4	***
		ZINB	136.4	***	162.5	***
B	No Legal Recreational or Medical Cannabis	NB Random Effects	30.4		16.5	
		NB Random Effects, Parsimonious	51.9	*	38.6	
		NB Pooled	110.0	**	70.6	*
		NB Random Effects with Offset	29.7		16.3	
		ZINB	82.6	**	35.0	
C	2016 Expansion States Legalize	NB Random Effects	−20.4	**	−25.0	**
		NB Random Effects, Parsimonious	−22.8	***	−28.6	***
		NB Pooled	−33.4	*	−40.4	*
		NB Random Effects with Offset	−20.1	**	−24.7	**
		ZINB	−31.3	*	−37.5	*
D	All Medical-Legal Become Recreational-Legal	NB Random Effects	−35.2	***	−45.8	***
		NB Random Effects, Parsimonious	−38.5	***	−50.5	***
		NB Pooled	−42.5	**	−59.1	***
		NB Random Effects with Offset	−35.1	***	−45.8	***
		ZINB	−38.5	*	−55.5	**
E	Zero Taxes on Legal Recreational and Medical Cannabis	NB Random Effects	a		−5.7	***
		NB Random Effects, Parsimonious	a		−7.1	***
		NB Pooled	a		−12.0	***
		NB Random Effects with Offset	a		−5.7	**
		ZINB	a		−12.9	***
F	Increase LEI FTE's by 20%	NB Random Effects	−2.4	***	−2.3	***
		NB Random Effects, Parsimonious	−2.3	***	−2.2	***
		NB Pooled	−1.9	***	−1.8	***
		NB Random Effects with Offset	−2.3	**	−2.3	**
		ZINB	−1.8		−1.7	

*** indicates significantly different from zero at α = 0.01, ** at α = 0.05, and * at α = 0.10, based on 1000-iteration bootstraps.
[a] Collinearity of tax rates with the simple legalization indicator prevented direct inclusion of the tax rate; tax rate effects were calculable in the tax-adjusted model by adjusting the legalization indicator by $(1 + T_.)^{-1}$, where $T_.$ is the applicable decimal percent tax rate. The effects of taxes were not simulated with the tax-ignorant model.
[b] NB Random Effects is a negative binomial specification with random effects; NB Pooled is a pooled negative binomial specification with national forest cluster-based heteroscedasticity; NB Random Effects with Offset is a negative binomial specification with random effects and a single offset variable (natural logarithm of lagged LEI real dollar spending); and ZINB is a zero-inflated negative binomial specification with national forest cluster-based heteroscedasticity.

negative binomial model (S1), parsimonious versions of the random effects negative binomial model (dropping insignificant non-policy variables) for the tax-ignorant (S2) and tax-adjusted model (S3), a pooled negative binomial model with national forest level heteroscedasticity (S4, S5), a true exposure specification of a negative binomial random effects model (where the lagged real law enforcement budget is the single exposure element) with national forest level heteroscedasticity (S6, S7), and a zero-inflated negative binomial model with national forest level heteroscedasticity (S8, S9).[8] Statistical bounds on the point-estimates of the non-marginal changes in the simulations were based on 1000 bootstrap iterations, sampling with replacement.

Under the random effects model, removing states' abilities to allow for legal production and consumption of recreational cannabis (simulation (A)) would lead to a 40% to 52% increase (depending on the random effects negative binomial model specification) in the amount of growing on national forests nationwide, in both the tax-ignorant and tax-adjusted random effects negative binomial models (and their parsimonious versions). The strong significance (α = 0.01) of these findings is a product of the importance of the in-state and out-of-state indicators of recreational legalization (see Tables 4, S1, S2, and S3). Alternative model specifications also produce strongly significant effects estimates, ranging from a 40% increase to a 163% increase. Under simulation (B), eliminating legal production and consumption of both recreational and medical cannabis would increase growing on national forests, but significance varied and was generally weak. The weaker statistical effect is due to the non-significance or positive and statistically significant coefficient estimates for neighboring states' medical cannabis legalization status (cf. Tables 4, S1, S2, S3). The nonsignificant or significant positively signed coefficients add uncertainty to the overall size of the expected effect when combined with recreational legalization revocation.

The effect of implementing legal production and consumption of cannabis in the states which passed recreational cannabis laws in late 2016 (simulation (C)) would be to decrease such grows by 20% to 29% (depending on the random effects negative binomial model specification) in random effects negative binomial models (all significant at α = 0.05 or stronger). Significance was in some instances weaker (α = 0.05 and α = 0.10) for the alternative specifications, with effects sizes from −20% to −40%. For simulation (D), implementing legal recreational cannabis in all states with legalized medical cannabis would decrease national forest grows nationwide by 35% to 51% for random effects negative binomial specifications, all significant at α = 0.01. Alternative specifications also produced significant effects estimates (α = 0.05 or stronger), ranging from −35% to −59%. Under simulation (E), reducing to zero all wholesale and retail sales taxes applied to recreational and medical cannabis in states where those products are currently legal, the models predict decreases in grows on national forests nationwide by about 5.7% under the full specification

[8] A Wald test of the pooled zero-inflated negative binomial model with constant dispersion against a pooled Poisson model with constant dispersion rejected (α = 0.01) the latter in favor of the zero-inflated negative binomial $\chi^2(29) = 664$ and $\chi^2(29) = 672$ for the tax-ignorant (Table S1) and the tax-adjusted (Table 4) indicator models, respectively.

of the random effects negative binomial model ($\alpha = 0.05$) and by 7.1% for the parsimonious version of that model, with alternative specifications producing similarly scaled effects estimates (−5.7% to −12.9%) but varying in significance from $\alpha = 0.01$ to 0.05. Finally, increasing the number of law enforcement officers in the Forest Service by 20%, simulation (F), would decrease grows by about 2.2% to 2.4%, depending on the specification of the random effects negative binomial model, all significant at $\alpha = 0.01$. In other words, the elasticity of grow establishment with respect to law enforcement officer presence averaged about −0.13 for this non-marginal change. For alternative specifications, effects are similar and also significant, $\alpha = 0.05$ or stronger, for the pooled negative binomial and the random effects with the included offset variable but not for the pooled zero-inflated negative binomial specification. We caution that this simulation considers merely augmenting the number of law enforcement officers on the ground and the overall law enforcement budget by 20%.

4. Discussion

We found that policies legalizing recreational cannabis production and consumption are associated with significantly lower numbers of reported illegal grows on national forests. The effects are economically and operationally meaningful; simulated elimination of existing state legalization provisions would result in double-digit percentage increases in reported grows on national forests, while further expansion of the set of states with such laws passed by statewide referenda in 2016 (but only instituting applicable laws in 2017 or later, post-dating our dataset) would be expected to reduce growing on national forests by a fifth or more. Much of this simulated reduction from legalization, it appears, would occur in California, the state with the highest number of cannabis grows on national forests. Simulated application of recreational cannabis legalization to all states where medical cannabis is currently legal would also be expected to bring down illegal cannabis production on national forests, by a third to a half. On the other hand, taxes levied on legal sales, which currently centered at a rate of about 20%, have positive impacts on the number of grows on national forests. The response to such taxes appears to be inelastic, with simulated elimination of such taxes decreasing grows by 6 to 13%. States that reduce such taxes, therefore, could expect to see fewer grows on national forests but would absorb losses in tax revenues. Legalization of medical cannabis, based on our empirical results and with Wall et al. (2011), Cerdá et al. (2012), and Schuermeyer et al. (2014), may have either no effect or a positive effect on illegal growing on national forests. Law enforcement officer presence was found to be negatively related to growing, though reported grow response appears to be inelastic, with a simulated 20% increase in law enforcement officers leading to a reduction in reported grows by < 2.5%.

Decriminalization appears to have no significant effect on illegal growing on national forests, in spite of the expansion in demand for illegal cannabis that such decriminalization would be expected to generate. However, model results show that higher penalties for being sentenced for illegal production and possession of cannabis and tighter regulations on the production and consumption of CBD oil and similar cannabinoid products are associated with reduced growing on national forests.

Many of the policies that we evaluated in the statistical models, and also simulated to assess their impacts, are beyond the control of the Forest Service. One policy that is under agency purview is the size of its own (Law Enforcement and Investigations) sworn law enforcement officer corps. While law enforcement resources help to find existing grows, law enforcement officers act as significant deterrents to grow establishment. According to our models, if law enforcement budgets and officer counts were to double and be applied in the same way that resources have been applied in the past, we would expect reported grows to decline by about 10%.

The negative impacts of illegal cannabis cultivation are well documented (see citations in Table 1), but in dealing with the problem on national forests or other public lands, decision-makers face some difficult choices. For instance, focusing on cannabis interdiction efforts diverts law enforcement resources away from needs to address other criminal activities. Mitigating the ecological impacts of illegal growing similarly consumes often-scarce resources at the expense of other land management priorities. As a practical matter, the number of cannabis grows on national forests could be reduced in two opposite ways: (1) legalization, or (2) increased efforts to deter, incarcerate, and otherwise discourage participation in the illegal market. Redefining what is legal perhaps would yield reductions that are costless for the Forest Service, at least in the narrow sense of cannabis law enforcement demands, and would reduce the damages associated with cannabis cultivation.

Presumably, the effectiveness of legalization depends on whether legal production can increase enough to satisfy the coincident increase in legal demand, creating the market conditions in which illegal production is disincentivized. In contrast, success at ramping up legal supply—facilitated by low license fees, low taxes, and an absence of caps on the number of licenses issued to growers—can at least temporarily result in a build-up of unsold inventory if demand growth is less than anticipated, as documented in the case of Oregon (Oregon Liquor Control Commission, 2019). Separate from issues of supply and demand, the imposition of taxes on legal cannabis sales, which is a common aspect of most of the recent legalization legislation, appears to make illegal cannabis growing somewhat more frequent on national forests. Thus, even though legalization of recreational cannabis markets tends to reduce illegal national forest growing, taxes appear to dampen some of that effect. This dampening may be related to the effect of taxes on the price of legal cannabis. Amlung et al. (2018) asserted that the availability of legal cannabis does not encourage illegal cultivation unless the after-tax price for legal cannabis is substantially elevated relative to the illegal product.

Our results also show that neighboring states' policies play a role in cannabis establishment on national forests, highlighting the part that the cannabis market plays in transmitting policy shocks across space: neighboring states' recreational legalization policies apparently provide space for enough legal production to substitute for illegally grown products. A natural extension of our policy simulations, motivated by our findings on the effects of state-level legalization, would be to evaluate outright (i.e., both medical and recreational) cannabis legalization nationwide. Arguably, our models hint that outright, national recreational cannabis legalization would be one means by which illegal growing on national forests could be made to disappear. However, such a large simulated departure from the recent historical experiences that are embedded in our data and models would stretch their capabilities.

5. Conclusions

With information on illegal cannabis growing on national forests nationwide, 2004–2016, we estimated negative binomial random effects models of the number of reported grows. These models demonstrated statistically significant and positive price responsiveness of grows as well as statistically significant and large effects of policy variables. Most notably, our models suggest a linkage between state-level legalization of recreational and medical cannabis and a reduction in illegal growing on national forests.

Future research could use information contained in our data and additional, finer-scale information on grow occurrences nationwide to evaluate the finer-scale implications of policies on particular landscapes. Because our data on reported grows are only from national forests, we cannot make valid statements about the effects of state legalization and decriminalization policies on illegal cannabis growing on other kinds of public land or private lands. A more complete picture of illegal growing in the United States could emerge if analysts gathered reported grow data from each category of land ownership and estimated similar models to what we and others have described.

Finally, we reiterate that legalization policies carry with them potential downsides, both inside and outside the boundaries of national forests. One concern could be the effects of cannabis legalization on other forms of crime (e.g., Chu and Townsend, 2019), including crime occurring on national forests. And although cannabis production could shift away from national forests and toward private producers, such production can have significant environmental downsides (e.g., Carah et al., 2015). Gaining a comprehensive assessment of the overall effects of legalization therefore merits additional scrutiny.

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Appendix A. Supplementary data

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