

“High” innovators? Marijuana legalization and regional innovation

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Abstract

The past three decades have witnessed a tremendous shift in public health policies toward marijuana legalization in the United States. Adopting the process-based view of innovation, we hypothesize that marijuana’s increased use and related consequences after its legalization affect innovators’ behavior and social environment during the innovation process, which in turn impacts regional innovation. Utilizing the staggered adoption of medical marijuana laws (MMLs) by 20 states between 1996 and 2013 as a quasi-experimental setting, we find that legalizing medical marijuana reduces the overall output of regional innovation as proxied by patents’ total forward-citation count aggregated by innovator location. Further analyses decomposing the overall output into patent quantity and quality reveal that the quantity of certain patents rises after states’ medical marijuana legalization. More importantly, these analyses show that the quality of all patents, especially that of “hit” patents, deteriorates, leading to a net negative effect on the overall output. These tests further suggest that different findings concerning patent quantity and quality are related to marijuana legalization’s diverse influence on innovators’ individual and collaborative effectiveness during the innovation process. The decline in innovation output and quality after the adoption of MMLs is robust to the use of additional identification strategies. The evidence suggests that legalizing medical marijuana has an adverse effect on regional innovation activity.

KEY WORDS

inventor performance, marijuana legalization, patents, public health, regional innovation

1 | INTRODUCTION

Marijuana legalization is an important public health policy. It has received considerable attention from academics, politicians, voters, and the media. Marijuana is the most widely used controlled substance in the United States.¹ While marijuana use remains illegal under federal law, 45% of Americans report using marijuana at some point in their lives (SAMHSA, 2018). Since 1996, 36 states and the District of Columbia have passed state laws to legalize marijuana for medical use. These medical marijuana laws (hereafter, MMLs), despite their medical nature, have led to a substantial increase in illicit marijuana use (Hasin et al., 2017; Liu & Bharadwaja, 2020; Wen et al., 2015). From 2002 to 2018, the number of marijuana users increased by 69% (see Figure 1).² MMLs affect the health of people and the communities where

they live, work, and interact. Medical and social science research show that increased marijuana use adversely affects individuals’ health conditions and achievements (Brook et al., 2013; Marie & Zolitz, 2017; Volkow et al., 2014).

MMLs have also attracted the public and the media’s attention regarding marijuana’s potential effects on innovation. Several high-profile technology entrepreneurs from Silicon Valley have spoken of marijuana’s impacts on creativity and productivity (Love, 2013). For example, Steve Jobs once commented that “the best way I could describe the effect of marijuana and hashish is that it would make me relaxed and creative.” Meanwhile, Elon Musk mentioned in an interview that he was not a regular marijuana user and did not find it helpful for productivity (Fuhrmans, 2018). Alongside the growing marijuana use rates, more employers are concerned about employees’ potential impairment due to marijuana use on the job (e.g., Gee, 2019). For example, as more young people use marijuana with their colleagues, companies face

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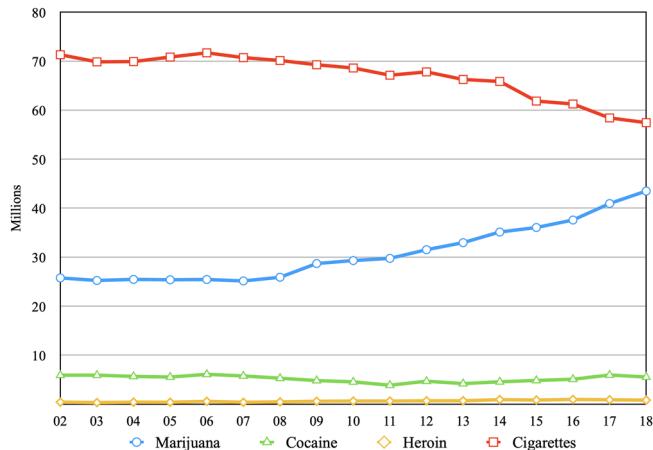


FIGURE 1 Number of users by substance type between 2002 and 2018. *Note:* This figure shows the number of yearly users (those who reported at least one use in the year before the survey) by substance type from 2002 to 2018, according to the National Survey on Drug Use and Health conducted by the Substance Abuse and Mental Health Services Administration, Center for Behavioral Health Statistics and Quality. Marijuana, cocaine, and heroin are listed as controlled substances in the Comprehensive Drug Abuse Prevention and Control Act of 1970. Cigarettes are not classified as a controlled substance. [Color figure can be viewed at wileyonlinelibrary.com]

challenges in setting appropriate boundaries for employee bonding (Varagur, 2021). Such challenges may hinder workplace productivity and innovation. Motivated by anecdotal evidence suggesting a potential link between marijuana use and innovation, we study how the staggered adoption of MMLs, which exogenously increase illicit marijuana use, affects regional innovation activity.

Innovation is an important component of economic activity that drives regional growth (Agrawal et al., 2014) and determines local businesses' long-term success (Schumpeter, 1935; Sorenson et al., 2016). While previous research on innovation focuses on corporate factors, such as reward schemes (e.g., Shalley et al., 2004), evidence on the effects of public health policies on innovation, such as state laws concerning substance use, remains limited and mixed.³ For example, banning cigarette smoking in workplaces enhances innovators' health and productivity and thus improves innovation effectiveness (Gao et al., 2020). However, alcohol prohibitions impair social interactions among knowledge workers and hence adversely affect innovation activity (Andrews, 2019). Given the inconclusive evidence, we develop theoretical expectations regarding the mechanism through which marijuana legalization affects regional innovation.

Economic theory on substance use (e.g., Becker & Murphy, 1988; Grossman, 2005) suggests that although MMLs appear to only legalize medical use, these laws reduce the costs borne by illicit users, such as the perceived health and legal risks of using marijuana and the search cost for finding it (Galenianos et al., 2012; Grossman, 2005; Pacula et al., 2015). Empirical research confirms that MMLs have a spillover effect on illicit users by inducing greater non-

medical marijuana consumption (Cerda et al., 2012; Hasin et al., 2017; Wen et al., 2015). MMLs also tend to be associated with increased marijuana availability and acceptance (Cheng et al., 2022) and thus may have significant implications on economic activity.

Drawing upon the process-based view of innovation, we hypothesize MMLs' specific effects on innovation activity (Amabile et al., 1996; Kanter, 1988; Van de Ven, 1986). In this view, innovation is a process that consists of idea generation and implementation, both of which require considerable individual cognitive effort (e.g., divergent and convergent thinking) as well as team collaboration. Based on this view, we develop expectations regarding MMLs' potential effects on innovators' individual and collaborative effectiveness in various ways through marijuana's direct use and legalization's indirect social influence.⁴

On the one hand, MMLs can improve innovation. For example, legalizing medical marijuana may enhance innovators' individual effectiveness through the direct use of marijuana (which heightens creativity because of cannabis intoxication's effects on divergent thinking; e.g., Green et al., 2003; Kuepper et al., 2013) and through the resulting liberal social environment (which encourages open-mindedness and diversity of thought; Vakili & Zhang, 2018). Further, MMLs can improve innovators' collaborative effectiveness by fostering social interaction and communication (Foltin et al., 1987; Hasan & Koning, 2019).

On the other hand, MMLs can hinder innovation. For instance, although the direct use of marijuana can potentially enhance creativity, it can also weaken the state of cognitive control for convergent thinking, thus harming innovators' individual effectiveness (Curran et al., 2002; Schafer et al., 2012). Legalizing marijuana can also create distracting social issues, such as children's potential exposure to marijuana (Chu & Gershenson, 2018; Marie & Zolitz, 2017), and thus divert innovators' efforts and harm individual effectiveness. In addition, MMLs may undermine innovators' collaborative effectiveness by impairing the sense of shared vision and coordination among collaborators (Brown & Duguid, 2001). Therefore, due to the offsetting mechanisms, it is possible that MMLs have both positive and negative effects on innovation, and MMLs' net effect on innovation is an empirical question.

Our analyses utilize a staggered shock setting, where 20 US states passed MMLs at different times between 1996 and 2013. Specifically, we examine whether there is a change in innovation activity for counties within states that have passed MMLs, relative to those within states that have not. We use a difference-in-differences design with county and year fixed effects to exploit the staggered effective dates of MMLs. This identification strategy has also been used in prior research (Hong & Shao, 2020; Li et al., 2021; Qiu & Kumar, 2017). We find that MMLs reduce counties' total forward citations by 9% to 12%. We further decompose the total forward citations into patent quantity and quality, proxied by patent counts and average citations per patent, respectively. The results show that a reduction in average citations drives the overall decline in total citations. This evidence indicates

that MMLs harm innovation quality and thus total regional innovation output, suggesting a negative spillover effect.

We further buttress these results in the following ways. First, we employ two additional identification strategies: a test that compares the innovation activity of adjacent counties on state borders and a test that employs another staggered change in MMLs' implementation policy (i.e., the establishment of dispensary stores for marijuana's medical use). Our inference remains unchanged. Second, as a robustness check, we further address the data censoring problem associated with patent citations. We examine forward citations accumulated only in the first 5 years following a patent's application and find robust results. Third, we examine the intensive and extensive margins regarding the effect of MMLs on local innovation. We find that the results are driven by a reduction in intensive margins (i.e., inventor productivity) rather than extensive margins (i.e., the number of local inventors). These results help rule out an alternative explanation of inventor mobility.

Next, we provide evidence that our findings are partially explained by marijuana-related consequences after MMLs, such as subsequent increases in marijuana use, availability, and acceptance. Given data limitations, we proxy such consequences with the state-year marijuana use rates obtained from the National Survey on Drug Use and Health (NSDUH; Azofeifa et al., 2016). We find that MMLs' effects on regional innovation's total output and quality are partially mediated by marijuana use rates. These findings are consistent with the idea that increased marijuana use and other marijuana-related consequences are an important channel through which MMLs affect regional innovation, improving our confidence that the main findings are attributable to MMLs.

To further substantiate the hypothesized effects, we attempt to disentangle MMLs' effects through two potential mechanisms: individual and collaborative effectiveness. We partition the main test sample into patents with one inventor, two inventors, and three or more inventors and evaluate MMLs' effect on patents' total output, quantity, and quality in each subsample. We generally observe positive coefficients for the effects of MMLs on quantity and negative coefficients for quality, suggesting that MMLs' effects differ between quantity and quality.⁵ Moreover, we find that MMLs' effects are generally more positive (negative) for patents with more (fewer) inventors. This finding indicates that MMLs' positive influence appears to be magnified through collaboration, while the negative impact seems to be heightened through individual efforts. These results support the idea that MMLs may exhibit both positive and negative influences on regional innovation activity through individual or collaborative effectiveness, providing modest support for our hypothesized effects. With the aim of adding timely evidence to the current debate around marijuana legalization, we explore MMLs' heterogeneous effects by patent importance. We find that the overall decline in total innovation output appears to be driven by the deteriorating quality of "hit" patents.

Taken together, this paper provides timely evidence on a negative spillover effect of an important state public health

policy—medical marijuana legalization—on regional innovation quality. Our findings highlight the relevance of public health to local businesses and talent management. We thus contribute to the emerging literature on the role of public health in management and the current debate on the costs and benefits of legalizing marijuana, enriching innovation research as a multidisciplinary field (Gaimon et al., 2017). We elaborate on the contributions in Section 9.

2 | STATES' MMLs

Marijuana is the most widely used controlled substance in the United States.⁶ It remained popular since the 1930s and became widespread in the 1960s. To mitigate the growing popularity of marijuana among residents, Congress passed the Comprehensive Drug Abuse Prevention and Control Act of 1970. The Act listed marijuana as a controlled substance, along with other abusive drugs such as heroin and cocaine, based on its high potential for abuse and low medical value. Although the cultivation, consumption, and distribution of marijuana by residents are prohibited under federal law, the legalization of medical marijuana has grown in popularity at the state level. In 1996, California passed the first MML—Proposition 215—that legalized the use of marijuana for medical purposes. California's MML allows the medical use of marijuana, when deemed appropriate, to treat illnesses such as cancer, anorexia, acquired immunodeficiency syndrome (AIDS), chronic pain, spasticity, glaucoma, arthritis, and migraine for which marijuana provides relief.⁷ As of May 2021, 36 states and the District of Columbia have passed similar state MMLs. These state laws typically allow residents with a qualifying diagnosis from a licensed physician to possess, consume, and grow marijuana. Table A1 in the Online Appendix provides the effective dates of states' MMLs.

Recent empirical studies report higher marijuana use by adults for both medical and illicit purposes after the adoption of MMLs (Cerda et al., 2012; Hasin et al., 2017; Wen et al., 2015). This finding is consistent with the economic theory on substance use (Becker & Murphy, 1988; Grossman, 2005), suggesting that although MMLs appear to only legalize marijuana for medical use, these laws spill over to illicit users by inducing greater non-medical marijuana consumption. According to this theory, MMLs reduce the costs borne by illicit users, such as the perceived health and legal risks of using marijuana, and the search cost for finding it (Galeanianos et al., 2012; Grossman, 2005; Pacula et al., 2015). Specifically, following states' legal approval, marijuana can be viewed as a medicine rather than an intoxicating substance. Thus, MMLs reduce the perceived health risk associated with using marijuana and favorably alter public attitudes toward it (Kilmer & MacCoun, 2017). MMLs also reduce marijuana's perceived legal risk because law enforcement's ability to separate illicit marijuana users from medical users tends to be low (Lofton, 2019). Moreover, MMLs initiate the development of a legal marijuana industry and greatly expand the production and supply of marijuana

in the marketplace. Marijuana products can be diverted to illicit use through either straw purchases or drug trafficking, resulting in a *de facto* increase in marijuana availability after legalization (Hasin et al., 2017). As such, MMLs expand marijuana availability and thus reduce potential search costs. Consistent with these predictions, recent research validates these arguments and finds that the increase in marijuana use after MMLs is attributable to public perception of lower health and legal risks and to lower search costs (Cheng et al., 2022). In sum, as substance legalization laws, MMLs tend to be associated with increased marijuana availability and use and may have significant implications on economic activity.

Interestingly, recent survey studies indicate that marijuana's use and acceptance are particularly salient for knowledge workers in recent years. For instance, one recent study by researchers at the University of Michigan shows that more than one-third of software programmers (an important group of modern knowledge workers) report marijuana use while working (Endres et al., 2022). Another survey conducted by Teamblind Inc. in 2018 reports that employees at high-tech companies (e.g., Lyft, Netflix, Amazon, and Apple) in the Bay Area and Seattle are more likely to use marijuana than average Americans; nearly 40% of these employees reported marijuana consumption in the 6 months preceding the survey.⁸ Such evidence implies that knowledge workers may be susceptible to a higher likelihood of marijuana use and acceptance due to states' MMLs.

3 | THEORETICAL DEVELOPMENT

Innovation fuels regional growth and thus is important for regional economic activity (Agrawal et al., 2014). This is evidenced by the increasing economic dominance of technology advances in the US economy (Autor et al., 2020). While corporate factors that affect innovation have been of long-standing interest to scholars and practitioners (e.g., Shalley et al., 2004), the effects of public health policies on innovators and the communities where they live and work are not well understood.

Emerging research provides mixed evidence on the relationship between public health laws and innovation, using state laws that prohibit individuals from using certain substances. On the one hand, a recent paper (Gao et al., 2020) shows that state laws that ban cigarette smoking in workplaces improve inventors' health, productivity, and innovation effectiveness. On the other hand, a concurrent study (Andrews, 2019) argues that states' imposition of alcohol prohibition laws impairs social interaction among knowledge workers and hence adversely affects innovation activity. The evidence is inconclusive and indicates that the effects of public health laws may differ depending on the substance. Such effects probably depend on the mechanism through which a particular substance influences knowledge workers' behavior and social environment in the innovation process.

Against this backdrop, we rely on the process-based view of innovation to develop hypotheses specific to marijuana's

behavioral and social influences. We adopt this view because it originates from psychology and emphasizes individuals' cognitive and psychological processes (e.g., cognitive styles or open-mindedness in creativity). Thus, the process-based view of innovation is a useful framework to consider MMLs' effects through individuals' cognitive, social, and behavioral channels during the innovation process.⁹ Section 3.1 reviews the theoretical framework, and Section 3.2 develops the hypotheses.

3.1 | Theoretical framework: The process-based view of innovation

Innovation is a complex process that requires extensive inputs (e.g., time and cognitive effort) from one or more knowledge workers (Fink et al., 2017; Singh & Fleming, 2010). According to the process-based view of innovation (e.g., Amabile et al., 1996; Kanter, 1988; Van de Ven, 1986), the pursuit of innovation consists of two phases: (i) idea generation and (ii) idea implementation. In the idea generation phase, innovators mobilize creativity to generate original ideas, which depart from existing routines and/or ways of doing things (Oldham & Cummings, 1996). During this phase, innovators may engage in divergent thinking and/or collaborative brainstorming to identify distantly relevant information or knowledge to formulate novel ideas (Anderson et al., 2014; Barron & Harrington, 1981). Innovators may also engage in a convergent thinking process in which they filter all possible ideas to converge on a few novel ones. After idea generation, innovators enter the idea implementation phase, where a novel idea is converted into a new or improved product, service, or way of doing things (Kanter, 1988). In this stage, innovators utilize convergent thinking and collaboration to solve challenges and problems that arise from the inherent uncertainty, unknowns, or conflicts embedded in the novel ideas (Basadur et al., 1982).

Furthermore, the innovation process is not linear or progressive but involves trial and error (Rosenberg & Nathan, 1982). For example, innovators can suffer from a lack of ideas (during idea generation) or from unanticipated procedural failures (during idea implementation) but can also learn from these experiences and achieve eventual success (Fleming, 2001). In short, the innovation process requires knowledge workers to continuously devote considerable cognitive effort and maintain collaboration in both idea generation and implementation. Such a process makes knowledge workers and their communities uniquely subject to the influence of public health policies.

3.2 | Hypotheses: Innovation and states' MMLs

Using the process-based view of innovation, we develop theoretical arguments regarding the potential effects of MMLs on local knowledge workers' innovation processes.

Because innovation requires considerable individual cognitive effort and team collaboration, we consider the possible effects of MMLs on innovators' individual effectiveness and collaborative effectiveness during the innovation process.¹⁰

First, MMLs may improve innovators' individual effectiveness through marijuana use and the social values promoted by MMLs. Biomedical research has documented heightened creativity during cannabis intoxication due to delta-9-tetrahydrocannabinol (THC hereafter), the main psychoactive compound in the *Cannabis sativa* plant, which reduces inhibitory control and stimulates striatal dopamine release (e.g., Green et al., 2003; Kuepper et al., 2013). THC weakens marijuana users' cognitive control state that manages top-down guidance, thus enhancing divergent thinking and improving creativity in idea generation (Colzato et al., 2012; Hommel, 2012). Meanwhile, the adoption of MMLs may influence a much broader population by underplaying social and cultural conservatism and by promoting a liberal mentality and open-mindedness (Haines-Saah et al., 2014). A more open and liberal social environment encourages an innovator to tolerate and accept new information (Florida et al., 2008). As such, MMLs may foster the social values of openness and diversity and consequently help innovators generate new ideas (Vakili & Zhang, 2018). Therefore, the adoption of MMLs may facilitate innovators' idea generation.

Second, MMLs can enhance innovators' collaborative effectiveness by fostering social interaction and communication among collaborators. Behavioral research suggests that marijuana use increases individuals' tendency to engage in social interactions in group settings, even for those that do not use marijuana themselves (Pacula et al., 2015). A more liberal social environment after the adoption of MMLs also encourages inventors' social interactions (Vakili & Zhang, 2018). Social interactions expose innovators to more opportunities for inspiring conversations, new information, and novel ideas from others (Hasan & Koning, 2019). Such opportunities in turn trigger innovators' analogical or heuristic thinking, which then generates ideas (Holyoak, & Thagard, 1995). Further, frequent and open communication among collaborators about a diverse set of topics expedites the identification of effective solutions to a problem, aiding innovators in collaboratively implementing ideas (Ebadi & Utterback, 1984). Thus, greater marijuana use after the adoption of MMLs may improve collaboration among innovators in idea generation and implementation.

These impacts indicate that marijuana legalization can improve idea generation and implementation, and thus the innovation process. Accordingly, we state our first hypothesis as follows:

Hypothesis 1a (H1a): The adoption of MMLs has a positive effect on innovation.

Nonetheless, despite the potential benefits, MMLs can reduce innovators' individual effectiveness through

marijuana use and the social issues associated with MMLs. While marijuana use enhances divergent thinking and creativity, it also impairs convergent thinking and problem-solving abilities (Curran et al., 2002; Schafer et al., 2012). As discussed earlier, THC weakens an individual's cognitive control. Thus, although it improves divergent thinking, THC also disrupts the convergent thinking process, in which individuals search for and converge on a single idea/solution among many candidates. As such, marijuana use may hinder an innovator's ability to identify promising ideas during the idea generation phase and their ability to solve problems during the idea implementation phase. More importantly, MMLs are associated with social issues that are of concern to a much broader population (McGinty et al., 2017). For example, greater marijuana accessibility results in poorer academic engagement and performance among students (Chu & Gershenson, 2018; Marie & Zolitz, 2017). Students' lower academic performance could cause knowledge workers to allocate additional time and cognitive effort to their children's education, resulting in reduced working hours.¹¹ A reduction in innovators' working hours could hinder idea generation and implementation. Thus, the adoption of MMLs may impair an innovator's convergent thinking ability and worsen broader social issues that require the innovator's time and effort, adversely affecting idea generation and implementation.

Second, MMLs may undermine innovators' collaborative effectiveness by suppressing the sense of shared vision and coordination among collaborators (Brown & Duguid, 2001). As discussed above, marijuana use impairs convergent thinking, which may create obstacles for team members' convergence on a single common objective and reduce their sense of shared vision. The lack of shared vision may also hinder team members' ability to form mutual understanding, commitment, information sharing, and a sense of ownership in the innovation process (Fleming et al., 2007; Hargadon & Bechky, 2006; Lingo & O'Mahony, 2010). Moreover, because collaboration requires a group of innovators to work together to develop, discuss, modify, and realize new ideas, the group develops a high level of coordination among collaborators (Van der Vegt & Janssen, 2003). The lack of shared vision can create disagreements and conflicts, which destroys group members' coordination and hence their collaborative effectiveness in innovation. In sum, MMLs may impair team members' sense of shared vision and coordination, which adversely affects collaboration in idea generation and implementation.

The impacts discussed above suggest that while H1a is plausible, marijuana legalization can also undermine idea generation and implementation and hence the innovation process. As such, we state a plausible alternative to H1a as follows:

Hypothesis 1b (H1b): The adoption of MML has a negative effect on innovation.

4 | METHODS

4.1 | Sample construction

We use patent data to capture regional innovation (Hall et al., 2005; Jaffe & Trajtenberg, 2002). We collect United States Patent and Trademark Office (USPTO) patent data from PatentsView (www.patentsview.org), a well-curated data source with information about patents, inventors, assignees, and locations of inventors and assignees.¹² Our sample begins in 1990 to allow time to establish pre-MML trends before California passed the first MML in 1996. Our sample ends in 2014 to mitigate concerns over data censoring problems related to patents (Graham & Hegde, 2015) by allowing 5 years for citations to be accounted for (Kuhn et al., 2020).¹³ We obtain 2,309,252 patents with available inventor and assignee locations, containing all technology classifications, between 1990 and 2014. Using inventor locations, we construct county-year-level innovation measures to examine the changes in local innovation activity, following prior research (Acs et al., 2002; Nanda & Nicholas, 2014). The level of analysis is also consistent with prior research on regional economic activity (Li et al., 2021). After eliminating counties with missing values, we have 2991 unique counties over a 25-year horizon. We exclude observations in MMLs' effective years ($n = 507$). Our final sample consists of 74,268 county-year observations ($2991 \times 25 - 507 = 74,268$).

4.2 | Measurement

We use three empirical proxies to measure a county's innovation activity. Our first proxy measures innovation activity's overall output. Following prior studies (e.g., Agrawal et al., 2017; Azoulay et al., 2010; Oettl, 2012), the overall output is the log transformation of one plus a county's total forward citations for all applied patents in a given year (*TotalCitation*; e.g., Sampat & Ziedonis, 2004). Counties are defined based on inventors' location. While overall output is an important aspect of innovation activity, a change in total citations can be driven by either a change in patent counts or a change in patents' average forward citations or both. Hence, to gain further insight into MMLs' effect on regional innovation activity, we decompose the overall output into two components: patent counts (*PatentCount*) and average citations (*AvgCitation*). $PatentCount_{it}$ is the log transformation of one plus a county's total number of patents applied (and subsequently granted) in a given year. Because the patent application counts positively correlate with the frequency of innovation attempts, they can represent the quantity of innovation activity in a region. $AvgCitation_{it}$ is the log transformation of one plus a county's average forward citations of patents applied in a given year. Patents' forward citations are positively associated with innovation quality, as high-quality patents tend to exert strong future influence. Thus, patents' average forward citations represent the quality level of the innovation activity in a region. As such, these two proxies

can provide additional information regarding the quantity and quality aspects of regional innovation activity (Hall et al., 2001). Thus, this decomposition helps us disentangle whether MMLs' effect on the overall output of patents is driven more by quantity or quality.

We measure marijuana legalization using a state's MML. *MML* is an indicator that equals one after the effective year of the corresponding state's MML and zero otherwise. Control variables include a county's unemployment rate (*Unemployment*), income per capita (*Income*), and population (*Population*). *Income* and *Population* are log-transformed values. All continuous variables are winsorized at the 1% and 99% levels. Table 1 reports the summary statistics and correlation matrix.

4.3 | Model

To estimate the effect of states' marijuana legalization on local innovation, we use a difference-in-differences design with a strict fixed-effects structure, which exploits states' staggered adoption of MMLs as a plausible source of exogenous variation in marijuana legalization.¹⁴ The staggered shocks design significantly reduces the likelihood of having a confounding event that explains the treatment effect (Li et al., 2021). We employ a county fixed-effect structure in the regression analyses to address potential concerns over county-specific and time-invariant omitted variables. Further, we include time fixed effects to absorb economy-wide shocks and time trends. We estimate the effect of MMLs on innovation activity at the county-year level, using an ordinary least squares (OLS) regression with the following model:

$$Y_{it} = \alpha + \beta MML_{jt} + \gamma' X_{it} + \eta_i + \mu_t + e_{it}, \quad (1)$$

where i denotes the county, j denotes the state, and t denotes the year. As defined in Section 4.2, Y_{it} is one of the three innovation measures (*TotalCitation*, *PatentCount*, and *AvgCitation*) and MML_{jt} proxies for states' marijuana legalization. X_{it} is a vector of county-year-level variables, including *Unemployment*, *Income*, and *Population*, to control for changes in a region's labor market factors and economic conditions, which may confound MMLs' effect on knowledge workers' innovation activity.¹⁵ η_i denotes county fixed effects. μ_t denotes year fixed effects. We cluster standard errors by county. The coefficient on MML_{jt} gauges the effect of medical marijuana legalization on counties' innovation activity relative to that of the unaffected counties.

5 | MAIN RESULTS

Table 2 presents the estimates of the impacts of MMLs on regional innovation activity. Column 1 examines the effect of MMLs on the overall output of a county's innovation activity. The coefficient on *MML* is negative (-0.092) and statistically significant at the 5% level. In terms of economic

TABLE 1 Descriptive statistics

Panel A: Summary statistics						
Variable	Obs.	Mean	Std. dev.	Min	Median	Max
Overall Output (Total Citations)	74,268	2.79	2.70	0.00	2.48	9.69
Quantity (Patent Counts)	74,268	1.57	1.68	0.00	1.10	6.68
Quality (Average Citations)	74,268	1.49	1.35	0.00	1.50	4.30
MML	74,268	0.07	0.26	0.00	0.00	1.00
Unemployment	74,268	6.33	2.81	2.00	5.80	15.60
Income	74,268	10.08	0.35	9.33	10.08	10.94
Population	74,268	10.28	1.34	7.45	10.15	13.93

Panel B: Correlations						
Variable	(1)	(2)	(3)	(4)	(5)	(6)
1 Overall Output (Total Citations)						
2 Quantity (Patent Counts)	0.91					
3 Quality (Average Citations)	0.86	0.59				
4 MML	0.03	0.10	-0.05			
5 Unemployment	-0.18	-0.13	-0.18	0.14		
6 Income	0.17	0.38	-0.09	0.24	-0.13	
7 Population	0.77	0.83	0.51	0.07	0.04	0.25

Note: Panel A presents the summary statistics of our main dependent variables and independent variables. Panel B presents the correlations of our main dependent variables and independent variables.

TABLE 2 Medical marijuana laws (MMLs) and regional innovation activity

	(1)	(2)	(3)
	Overall output	Quantity	Quality
MML	-0.092** (-2.49)	-0.008 (-0.46)	-0.111*** (-3.77)
Unemployment	-0.002 (-0.47)	0.008*** (4.15)	-0.009** (-2.58)
Income	1.427*** (14.80)	0.426*** (10.21)	0.865*** (11.42)
Population	0.040 (0.44)	1.087*** (25.72)	-0.785*** (-11.41)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	74,268	74,268	74,268
Adjusted R^2	0.82	0.92	0.58

Note: This table provides the main results for the effect of MMLs on innovation activity. Columns 1, 2, and 3 show MMLs' effects on overall innovation output (total citations), innovation quantity (patent counts), and innovation quality (average citations), respectively. We cluster standard errors by county.

* , **, and *** indicate statistical significance at the 10%, 5%, and 1% levels using two-tailed tests, respectively.

significance, MMLs lead to a 9% decrease in a county's overall innovation output. Columns 2 and 3 further disentangle MMLs' effect on the overall output along two dimensions: patent quantity and quality, respectively. Column 2 shows that the number of patents does not significantly change after the adoption of MMLs, suggesting that patent quantity does not

appear to change. However, Column 3 suggests that MMLs lead to an 11% decrease in average citations, suggesting lower patent quality. Overall, the results indicate that MMLs adversely affect the overall output of regional innovation activity, particularly patent quality.

We validate our assumption of parallel trends to ensure that the estimated coefficients in Table 2 are not driven by pre-existing trends. Specifically, we estimate the effects of MMLs by year relative to the effective years. Figure 2 presents the results. In Panel A, we do not observe any significant differences in the pre-MML period trends of total citations between MML counties and non-MML counties. This result supports the parallel trends assumption required for the results in Table 2, Column 1. In Panels B and C, we find that the pre-MML period trends of both patent counts and average citations are generally not statistically different between MML and non-MML counties, except for one of the six pre-MML years in Panel B for patent counts. Based on the average coefficient effects prior to the adoption of MMLs, we believe that our assumption of parallel trends is reasonable. Notably, MMLs' adverse impacts on the overall output and quality of regional innovation activity kick in from the second year after MMLs' adoption and persist through and beyond 6 years after MMLs. We observe insignificant effects in MMLs' first adoption year, likely because it takes some time for MMLs' effects (e.g., marijuana's greater consumption and acceptance) to incubate.

We address potential concerns over the data censoring problem associated with using recent citation records by carefully setting the sample period in a way that mitigates such concerns (see Section 4.1). As a robustness check, we employ

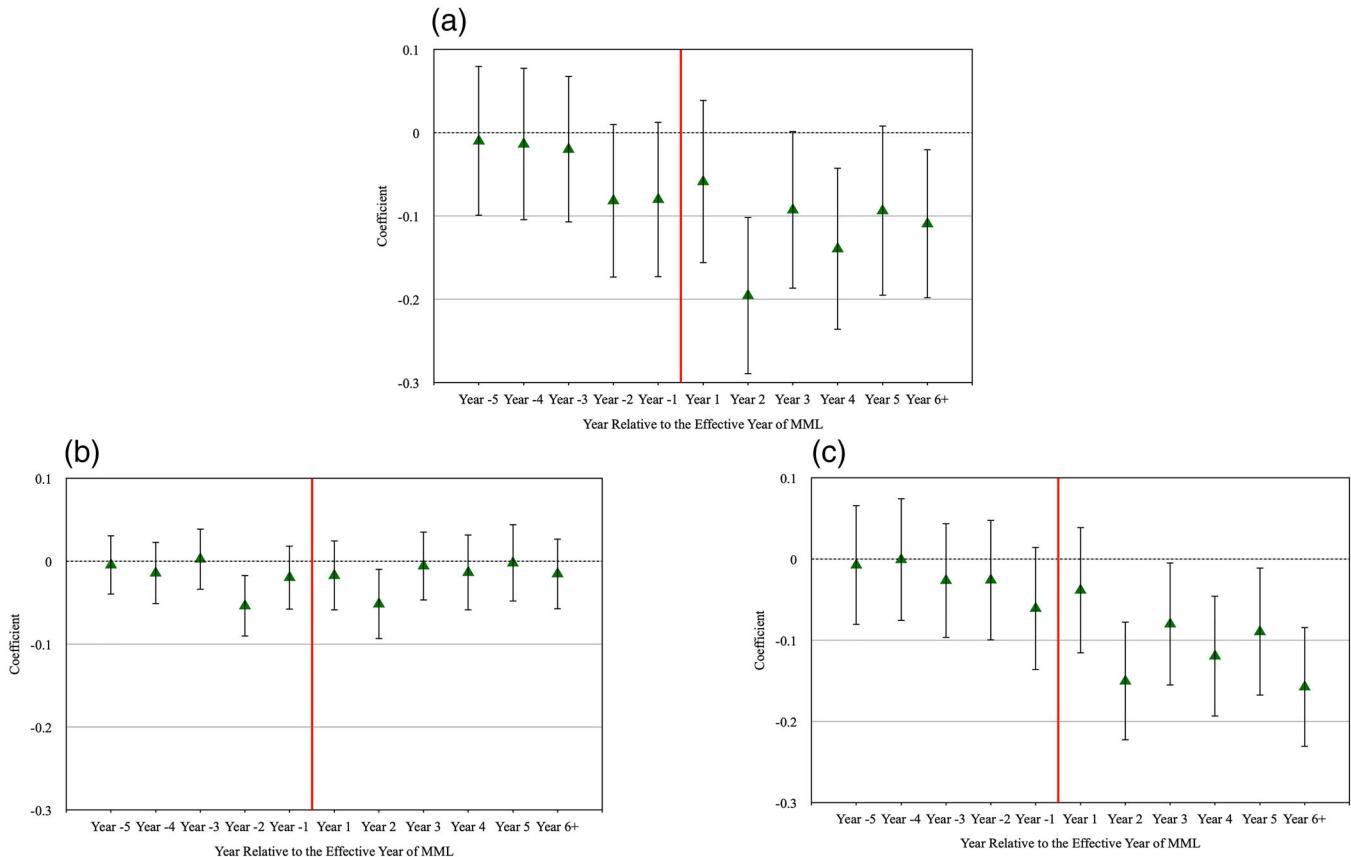


FIGURE 2 Parallel trends assumption. (a) Overall output (total citations), (b) quantity (patent counts), and (c) quality (average citations). *Note:* (a), (b), and (c) examine the parallel trends assumption for the three dependent variables. We plot the incremental effects of medical marijuana laws (MMLs) on the three aspects of innovation activity (i.e., overall output, quantity, and quality) by the number of years relative to state MMLs' effective years. The x-axis denotes the year relative to the year when a state's MML became effective. The y-axis plots the coefficient for each event year estimated using the regression specification used in Columns 1–3 of Table 2. This specification includes both time and county fixed effects. As such, the estimated coefficients reveal the effects after removing the general trends in patent data. The triangles represent coefficient estimates, and the lines represent 90% confidence intervals. [Color figure can be viewed at wileyonlinelibrary.com]

an alternative method to count citations for *TotalCitation* and *AvgCitation*. Specifically, we limit a patent's citations to 5 years after the patent is applied. Table 3 provides the results of these robustness checks. The coefficients on *MML* continue to be negative in Column 1 (-0.049 ; $p = 0.107$) and Column 2 (-0.061 ; $p < 0.01$), consistent with the results in Columns 1 and 3 of Table 2, respectively. Moreover, untabulated tests show that the inference from Column 3 of Table 2 remains unchanged if we use a county's median number of citations rather than the average number of citations.

Our staggered shocks design implies that any alternative events that could confound our results must coincide with the staggered adoption of MMLs across states. Nonetheless, we further bolster our identification by employing two additional identification strategies. First, we strengthen the causal inference using a geographic regression discontinuity design (Hahn et al., 2001). Without a random assignment of MMLs to counties, we identify the causal effect of MMLs on innovation activity by selecting a counterfactual county that is similar to the treated one, and then compare the differences in the pair's innovation activity around the MMLs' adoption.

We compare the innovation activity between two adjacent counties on state borders, whose economic, social, and cultural characteristics are likely to be similar in the absence of MMLs' adoption. This test alleviates the concern that unmeasurable time-variant state-level differences may explain both the adoption of MMLs and our findings. Specifically, we limit our sample to counties residing on state borders. We pair treatment counties with control counties with replacements.¹⁶ The sample includes 1211 unique county pairs over a 25-year horizon. We further exclude observations in MMLs' effective years ($n = 467$). Our final sample for this test consists of 60,083 county-year observations ($1211 \times 2 \times 25 - 467 = 60,083$). Table 4 shows the results of the regressions with county pair and year fixed effects, using the sample of adjacent counties on state borders. These results are qualitatively similar to the main results. The estimated coefficients on *MML* in Columns 1–3 exhibit similar economic significance to those in Table 2 (albeit with weaker statistical significance).¹⁷ This evidence increases the likelihood that the relationship between MMLs and regional innovation activity is causal.

TABLE 3 Alternative measurement of citation-based dependent variables

	Using 5-year forward citations	
	(1)	(2)
	Overall output	Quality
MML	-0.049 (-1.61)	-0.061*** (-3.10)
Unemployment	0.003 (0.89)	-0.003 (-1.37)
Income	1.245*** (16.51)	0.695*** (13.82)
Population	0.610*** (8.31)	-0.256*** (-5.48)
County FE	Yes	Yes
Year FE	Yes	Yes
Obs.	74,268	74,268
Adjusted <i>R</i> ²	0.85	0.54

Note: This table provides the results of the robustness tests for the effect of MMLs on innovation activity. Columns 1 and 2 provide MMLs' effects on overall innovation output (total citations) and innovation quality (average citations), respectively, using only forward citations accumulated in the first 5 years after patent application. The effect of MMLs on 5-year total citations in Column 1 is marginally significant with a *p*-value of 0.107. We cluster standard errors by county.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels using two-tailed tests, respectively.

TABLE 4 MMLs and innovation activity, using a sample of adjacent counties on state borders

	(1)	(2)	(3)
	Overall output	Quantity	Quality
MML	-0.123* (-1.65)	0.036 (0.75)	-0.160*** (-3.61)
Unemployment	-0.044*** (-5.70)	-0.018*** (-4.27)	-0.024*** (-4.28)
Income	2.419*** (17.95)	1.338*** (15.02)	0.969*** (11.65)
Population	1.323*** (54.72)	0.908*** (51.52)	0.439*** (30.69)
County Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	60,083	60,083	60,083
Adjusted <i>R</i> ²	0.79	0.88	0.52

Note: This table provides the results for the effect of MMLs on innovation activity with a geographic regression discontinuity design. The sample consists of adjacent counties on state borders paired with control counties (with replacements). Columns 1, 2, and 3 provide MMLs' effects on overall innovation output (total citations), innovation quantity (patent counts), innovation quality (average citations), respectively. Figure A1 of the Online Appendix illustrates this sample. We cluster standard errors by county.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels using two-tailed tests, respectively.

TABLE 5 Establishment of state-licensed dispensary stores and innovation activity

	(1)	(2)	(3)
	Overall output	Quantity	Quality
Dispensary Opening	-0.101** (-2.56)	-0.0008 (-0.43)	-0.129*** (-4.12)
Unemployment	-0.002 (-0.47)	0.008*** (4.15)	-0.009*** (-2.58)
Income	1.430*** (14.86)	0.426*** (10.23)	0.868*** (11.50)
Population	0.039 (0.43)	1.087*** (25.89)	-0.785*** (-11.42)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	74,268	74,268	74,268
Adjusted <i>R</i> ²	0.82	0.92	0.56

Note: This table presents the results for the effect of dispensaries' opening on regional innovation. *Dispensary Opening* is an indicator that equals one after the year of the establishment of the first state-licensed dispensary stores for marijuana's medical use and zero otherwise. Columns 1–3 show the effects for the states that open dispensary stores on overall innovation output (total citations), innovation quantity (patent counts), and innovation quality (average citations), respectively. We cluster standard errors by county.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels using two-tailed tests, respectively.

Our second identification strategy involves another staggered change in MMLs' implementation policy: the establishment of the first state-licensed dispensary stores for marijuana's medical use. This second policy shock is not perfectly correlated with MML's initial adoption, but it is similar to MMLs in the sense that the establishment of state-licensed dispensaries also increases marijuana availability and consumption (Baggio et al., 2020; Pacula et al., 2015). Table 5 shows that the establishment of state-licensed dispensaries reduces both total citations and average citations (Columns 1 and 3), while the effect is muted for patent counts (Column 2). This evidence corroborates the results in Table 2 and mitigates the possibility that confounding events drive our main results.

Theoretically, the deterioration in regional innovation can be the result of (i) lower intensive margins (i.e., effectiveness and productivity reduction) and/or (ii) lower extensive margins (i.e., inventor loss). Our hypotheses focus on lower intensive margins. To mitigate the concern that our findings are mainly driven by lower extensive margins, we conduct three additional tests. Table 6 provides the results. First, we assess whether extensive margins are lower after the adoption of MMLs. We measure extensive margins using the number of inventors and the net flow of inventors in a county. Column 1 shows that the number of inventors residing in a county does not change after MMLs. Column 2 indicates no significant shifts in the net flow of inventors after MMLs.

TABLE 6 Extensive and intensive margins

	Extensive margins (inventor mobility)		Intensive margins (inventor/assignee productivity)		Removing effects of extensive margins (focusing on static inventors)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Inventors	Net Flow of Inventors	Citations per inventor	Citations per assignee	Overall output	Quantity	Quality
MML	-0.013 (-0.83)	0.019 (1.05)	-0.100*** (-3.47)	-0.081*** (-2.61)	-0.109** (-2.37)	-0.014 (-0.95)	-0.110*** (-3.02)
Unemployment	0.007*** (4.23)	-0.004** (-2.37)	-0.009** (-2.38)	-0.020*** (-6.74)	0.003 (0.48)	0.005*** (2.92)	-0.001 (-0.20)
Income	0.394*** (11.08)	0.128*** (3.66)	0.967*** (12.91)	0.883*** (13.58)	1.736*** (15.56)	0.326*** (10.21)	1.428*** (15.55)
Population	0.983*** (27.30)	0.165*** (5.18)	-0.636*** (-9.29)	-0.408*** (-5.93)	0.708*** (5.96)	0.719*** (19.69)	0.009 (0.10)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	74,268	74,268	74,268	74,268	74,268	74,268	74,268
Adjusted <i>R</i> ²	0.93	0.12	0.58	0.55	0.88	0.91	0.82

Note: This table provides the results for the assessment of the extensive and intensive margins regarding the effect of MMLs on regional innovation. Columns 1 and 2 assess the extensive margins by examining the mobility of inventors after MMLs. *Number of Inventors* is the count of active inventors in a county in a given year. *Net Flow of Inventors* is net changes in the count of active inventors who move in or out of a county. Columns 3 and 4 assess the intensive margins by examining MMLs' effects on innovation quality at the inventor and for-profit assignee levels, measured as the average forward citations per inventor and the average forward citations per for-profit assignee, respectively. Columns 5–7 provide further support for the results for intensive margins by limiting the sample to patents from inventors who do not switch locations in our sample period. We cluster standard errors by county.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels using two-tailed tests, respectively.

These results suggest that extensive margins do not seem to drive the deteriorating regional innovation activity after the adoption of MMLs. Second, we assess whether intensive margins are lower following the adoption of MMLs. We proxy intensive margins using citations per inventor and citations per (for profit) assignee (Moser et al., 2014). Columns 3 and 4 show that citations per inventor and per assignee are significantly lower after MMLs. This evidence suggests that lower intensive margins plausibly explain the deteriorating regional innovation activity after MMLs. Last, we provide a robustness check of Table 2 by estimating the treatment effects using a sample of patents whose inventors do not move between counties in our sample period. Columns 5–7 show that the inferences from Table 2 remain unchanged after removing patents whose inventors switch locations. The evidence in Table 6 suggests that the deteriorating innovation activity after the adoption of MMLs is likely due to lower intensive margins rather than extensive margins, validating our hypotheses.

In sum, the collective evidence on the staggered shock of MMLs presented in Tables 2–6—using a sample of all counties, a sample of adjacent counties, and a second staggered policy shock, supplemented with parallel trends tests, robustness checks using alternative measures, and a test for extensive versus intensive margins—provides strong support for a causal inference that MMLs reduce the overall output and average quality of regional innovation activity.

6 | MARIJUANA-RELATED CONSEQUENCES

To lend more credibility to our findings, we conduct an analysis to show that our findings are partially explained by marijuana-related consequences after MMLs' adoption. As explained in Section 2, MMLs expand marijuana's availability, increase marijuana consumption, and enhance social acceptance of marijuana use. These consequences are necessary conditions for attributing the main findings to MMLs because, as discussed in Section 3.2, our hypotheses build on the argument that due to marijuana's greater use, availability, and social acceptance, MMLs bring about behavioral and social changes, which affect innovators' individual and collaborative effectiveness in the innovation process. For example, while not every knowledge worker uses marijuana after the adoption of MMLs, the hypotheses are built on the argument that at least some knowledge workers in the region start using marijuana. As such, these marijuana-related consequences should at least partially mediate MMLs' adverse effects on a county's total innovation output and patent quality.¹⁸

We conduct a three-step mediation analysis following Baron and Kenny (1986). We employ marijuana use rates as a proxy for marijuana-related consequences. We obtain data on the state-year-level marijuana use rates between 2002 and 2014 from surveys conducted by the NSDUH.¹⁹ The use rate is measured by the percentage of a state's

TABLE 7 Impact of MMLs on innovation partially mediated by marijuana use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Step 1			Step 2	Step 3		
	Overall output	Quantity	Quality	Marijuana use	Overall output	Quantity	Quality
MML	-0.177*** (-3.23)	-0.012 (-0.58)	-0.148*** (-3.69)	1.045*** (30.00)	-0.150*** (-2.72)	-0.007 (-0.34)	-0.131*** (-3.24)
Marijuana Use					-0.026*** (-3.67)	-0.005 (-1.42)	-0.016*** (-3.20)
Unemployment	0.003 (0.46)	-0.012*** (-4.07)	0.010** (2.06)	-0.027*** (-4.31)	0.002 (0.36)	0.002 (0.36)	0.009** (1.96)
Income	1.163*** (11.14)	0.118*** (2.59)	0.825*** (10.50)	-0.874*** (-10.25)	1.141*** (10.94)	1.141*** (10.94)	0.811 (10.32)
Population	-1.771*** (-9.14)	0.738*** (8.85)	-1.809*** (-13.99)	0.231* (1.72)	-1.765*** (-9.10)	-1.765*** (-9.10)	-1.806 (-13.96)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	35,376	35,376	35,376	35,376	35,376	35,376	35,376
Adjusted R ²	0.84	0.93	0.55	0.80	0.84	0.93	0.55

Note: This table presents the results for a mediation analysis, using marijuana use rates as a potential mediator. *Marijuana Use* is measured with the state-year marijuana use rates from the National Survey on Drug Use and Health. Columns 1–3 report the benchmark results for the associations between MMLs and innovation metrics without the inclusion of the mediator. Column 4 reports the association between MMLs and state marijuana use. Columns 5–7 report the results for the complete mediation model of marijuana use rates on the innovation metrics. We cluster standard errors by county.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels using two-tailed tests, respectively.

population who reported marijuana use in the year before the survey.²⁰ Because the use data first became available in 2002, we further eliminate states that passed MMLs before 2002 from this test to allow the establishment of pre-trends. The sample includes 2741 counties over a 13-year horizon. After excluding observations in MMLs' effective years ($n = 257$), the sample for this test consists of 35,376 county-year observations ($2741 \times 13 - 257 = 35,376$).

Table 7 presents the results. In Step 1, we estimate the benchmark results, using the 2002–2014 sample, by regressing innovation metrics on *MML*. Columns 1–3 show that MMLs reduce a county's total citations and average citations, consistent with the main results presented in Section 5. In Step 2, we estimate MMLs' effect on marijuana use by regressing the state-year marijuana use rates on *MML*. Column 4 shows that MMLs increase marijuana use rates, consistent with prior research (Hasin et al., 2017). In Step 3, we estimate both MMLs' and marijuana use's effects on innovation by regressing innovation metrics on both *MML* and marijuana use rates. Columns 5–7 reveal that both *MML* and marijuana use are negatively associated with a county's total citations and average citations.

We next quantify the partial mediation effect in two ways. First, we use the estimates from Steps 2 and 3 to perform the Sobel Test (Sobel, 1982). Using the coefficient on *MML* in Column 4 and that on *Marijuana Use* in Column 5, the mediation effect of marijuana use rates is calculated as -0.027 (1.045×-0.026 ; $p < 0.01$) for MMLs' adverse effect on total citations. Similarly, Columns 4 and 7 show that the

mediating effect of marijuana use rates on the relationship between MMLs and patents' average citations is -0.017 (1.045×-0.016 ; $p < 0.01$). Second, we use the bootstrapping method suggested by Preacher and Hayes (2008). We estimate the mediating effects of marijuana use rates on the relationship between MMLs and total citations and average citations with 2000 bootstrap iterations and arrive at 95% confidence intervals of $[-0.0414, -0.0116]$ and $[-0.0277, -0.0058]$, respectively.

Moreover, the coefficients on *MML* in Columns 5 and 7 remain large after controlling for marijuana use rates relative to those in Columns 1 and 3, suggesting that other mediators that are not perfectly correlated with the survey proxy for marijuana use rates (e.g., marijuana's social acceptance and availability and changes in the social environment) account for a significant portion of the total MML–innovation effect.²¹ The collective results show that marijuana use rates modestly mediate the adverse effects of MMLs on a county's total innovation output and average patent quality. The findings supplement the results in Section 5 and provide evidence that the documented effects are partially explained by the marijuana-related consequences of the adoption of MMLs.²²

7 | INNOVATOR EFFECTIVENESS

To substantiate our hypotheses, we provide evidence to illustrate how MMLs can affect innovators' effectiveness and thus regional innovation activity. As discussed in Section 3.2,

TABLE 8 Innovators' individual and collaborative effectiveness

	(1)	(2)	(3)
	Overall output	Quantity	Quality
MML coefficient	-0.138*** (-3.47)	-0.011 (-0.78)	-0.131*** (-4.40)
Using patents filed by a single inventor			
MML coefficient	-0.063* (-1.70)	0.028** (1.98)	-0.109*** (-3.43)
Using patents filed by two inventors			
MML coefficient	-0.019 (-0.53)	0.046** (2.31)	-0.083** (-2.35)
Using patents filed by three or more inventors			
Coefficient difference			
A Single Inventor LESS Three or More Inventors	-0.119*** 0.004	-0.057*** 0.006	-0.048 0.127
p-value			

Note: This table provides the select results for the coefficients of MMLs on patents by their inventor team size, using the model specifications in Table 2. We cluster standard errors by county.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels using two-tailed tests, respectively.

MMLs may affect innovators' individual and collaborative effectiveness in the innovation process. As such, we explore whether and how MMLs' effect varies depending on the degree of collaboration involved in the innovation process. We categorize patents into three groups: patents with a single inventor, two inventors, and three or more inventors. We aggregate patents to the county level for each group to derive its respective sample. We estimate MMLs' effects for each patent group using the models in Table 2. Table 8 shows the results. Column 1 shows a monotonic increase in the coefficient on *MML* from patents with a single inventor and two inventors to three or more inventors. The results imply that MMLs' negative influence on the overall output of regional innovation activity is more pronounced for patents with fewer inventors (coefficient difference of -0.119 with a *p*-value of 0.004). Next, we present nuanced results by decomposing the overall output of patents along two dimensions: quantity and quality. Columns 2 and 3 show monotonic patterns similar to that observed in Column 1. That is, the coefficient on *MML* increases as the number of inventors increases (coefficient differences of -0.057 and -0.048 with *p*-values of 0.006 and 0.127 in Columns 2 and 3, respectively). Notably, the coefficients on *MML* in Column 2 are positive or insignificant, while those in Column 3 are generally negative. Given that the impact of public health laws on innovation is still relatively understudied and the inference remains largely inconclusive, our initial evidence should be interpreted with caution.

With this caveat in mind, we draw three preliminary inferences by interpreting the evidence in Table 8 in totality. First, MMLs have both positive and negative influences on regional innovation through various channels. We find that although MMLs' net effects on the overall output and quality of patents are generally negative (Columns 1 and 3), MMLs positively influence the quantity of certain types of patents (e.g., those that involve collaboration among inventors; Column 2).

Second and more importantly, the observed patterns are consistent in Columns 1–3. This finding alludes to the idea

that MMLs' positive influence is magnified through innovators' collaboration (e.g., frequent social interaction and open communication). This finding also implies that the negative impact is heightened through innovators' individual efforts (e.g., impaired problem-solving and distractions from professional commitments). For example, innovators can become distracted if they reallocate time and effort away from innovation activity due to concerns over their children's poorer academic performance after MMLs. For the positive influence, prior research also provides corroborating evidence, suggesting that innovators' social interactions facilitate innovators' collaboration. For instance, Ebadi and Utterback (1984) suggest that frequent and diverse communications among engineers can improve the success rate of technological innovation. Last, the net effect of MMLs may differ between patent quantity and quality. The positive effect outweighs the negative effect, leading to a net positive effect on patent quantity (Column 2). However, the negative influence dominates the positive impact, resulting in a net negative effect on patent quality (Column 3).

In sum, the preponderance of the evidence is in line with H1b, while some evidence consistent with H1a also exists, highlighting the importance of providing nuanced analyses in understanding MMLs' effects. Specifically, the nuanced results in Table 8 further explain the main findings in Table 2 and suggest that (i) the overall output and quality of patents deteriorate after the adoption of MMLs (largely driven by patents that involve little collaboration), but (ii) the patent quantity of certain types (i.e., those that involve collaboration) increases after the adoption of MMLs.

8 | HETEROGENEOUS IMPACTS BY PATENT TYPE

In this section, we present the results of MMLs' heterogeneous effects on patents of different types according to the patents' importance.²³ Although we do not make *ex-ante*

TABLE 9 Heterogeneous impacts: "Hit" and "weak" patents

	Using 10% threshold			Using 5% threshold			Using 15% threshold		
	(1)			(4)			(7)		
	Overall output	(2) Quantity	(3) Quality	Overall output	(5) Quantity	(6) Quality	Overall output	(8) Quantity	(9) Quality
MML coefficient	-0.128***	0.031**	-0.186***	-0.099***	0.039***	-0.164***	-0.149***	0.017	-0.195***
Using "hit" patents	(-3.36)	(2.22)	(-5.00)	(-2.71)	(3.02)	(-4.68)	(-3.74)	(1.17)	(-5.13)
MML coefficient	-0.116***	0.079***	-0.034***	-0.052**	0.115***	-0.010*	-0.126***	0.067***	-0.038**
Using "weak" patents	(-3.03)	(3.22)	(-2.58)	(-2.47)	(3.61)	(-1.65)	(-2.88)	(3.08)	(-2.34)
Coefficient difference									
"Hit" Patents LESS "Weak" Patents	-0.012	-0.048**	-0.152***	-0.047	-0.076***	-0.154***	-0.023	-0.050***	-0.157***
p-value	0.778	0.019	< 0.001	0.207	0.006	< 0.001	0.629	0.007	< 0.001

Note: This table provides the select results for the coefficients of MMLs on "hit" patents and "weak" patents, using the model specifications in Table 2. We define "hit" patents as patents that are ranked among the top 5%, 10%, or 15% in the distribution of patents' forward citations in a given year. "Weak" patents are patents that are ranked among the bottom 5%, 10%, or 15% in the distribution of patents' forward citations in a given year. We cluster standard errors by county.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels using two-tailed tests, respectively.

predictions of MMLs' heterogeneous effects, we provide *ex-post* reasonable interpretations of our findings in accordance with the process-based view of innovation. This section is primarily intended to contribute timely empirical evidence regarding MMLs' implications on innovation to the recent debate around marijuana legalization among policymakers, academics, the media, and the general public in the United States.

Patents vary in their importance and thus can be classified as "hit" patents and "weak" patents based on their relative rankings in the distribution of patents' forward citations (Oettl, 2012). We explore how MMLs' effects on innovation activity vary by this patent characteristic.²⁴ Following prior research (Vakili & Zhang, 2018), we define a "hit" patent as a patent that is ranked above the 90th percentile in the distribution of forward citations for a given year and a "weak" patent as a patent ranked below the 10th percentile.²⁵ We separately aggregate "hit" patents and "weak" patents for a given county in a given year to derive their respective samples. We estimate MMLs' effects for each patent group using the models in Table 2.

Table 9 presents the results. MMLs adversely influence the overall output of all patents (Column 1). When decomposing the overall output, MMLs positively affect the quantity of both "hit" and "weak" patents (Column 2) and negatively influence the quality of these two types of patents (Column 3). The evidence is largely in line with that in Table 8 and again suggests that MMLs have both positive and negative effects on the innovation process depending on the perspective. The increase in patent quantity may be explained by MMLs' positive influence during idea generation, such as improved divergent thinking ability, frequent social interaction, and open communication. These positive impacts outweigh the potential negative effects and thus lead innovators to generate a greater number of ideas for patenting consideration. The net positive effects on the quantity of "hit" and "weak" patents also find support in prior research

(e.g., Simonton, 2018), suggesting that excessive creativity can lead to both "novel and influential" and "wild but useless" ideas. The decrease in patent quality, however, may be caused by MMLs' pronounced negative effects during idea implementation, such as diminished convergent thinking ability, impaired problem-solving, and distractions from professional commitments, which outweigh MMLs' potential positive influence, and thus lead to lower patent quality. Our results hence echo prior research (e.g., Vakili & Zhang, 2018) that documents an increase in inventors' share of "hit" patents after the legalization of medical marijuana and highlight another consequence of an increase in the number of "weak" patents.²⁶

Further, the coefficients on *MML* for "hit" patents are less positive in Column 2 and more negative in Column 3 than those for "weak" patents (coefficient differences of -0.048 and -0.152 with *p*-values of 0.019 and < 0.001 in Columns 2 and 3, respectively). The results indicate that the increase in patent quantity is more notable in the subpopulation of "weak" patents, and importantly both types of patents, especially the "hit" patents, become substantially less impactful after the adoption of MMLs. It may be the case that "weak" patents require a much lower level of individual and collaborative efforts relative to "hit" patents and thus are more susceptible to MMLs' net positive effect during idea generation, leading to a greater increase in the number of "weak" ideas/patents after MMLs. Similarly, because "hit" ideas require careful individual deliberation and effective collaboration during implementation relative to "weak" ideas, MMLs' net negative effect during idea implementation is more likely to hinder the implementation of "hit" ideas, resulting in a greater reduction in the quality of "hit" patents. Columns 4–9 show robustness checks, using the 95th and 5th percentiles and the 85th and 15th percentiles as alternative thresholds. The inferences remain unchanged. Collectively, the evidence suggests that MMLs may lead to value destruction in regional innovation activity.²⁷

9 | DISCUSSION AND FUTURE RESEARCH

This study provides new evidence that state-level public health policies of marijuana legalization adversely affect regional innovation activity, using a quasi-experimental research design. MMLs have a net negative effect on the overall output of regional innovation activity, which is driven by deteriorating innovation quality. Guided by the process-based view of innovation, we further reveal that MMLs' positive influence on the innovation process is magnified through innovators' collaboration and is likely to be driven by the idea generation for "weak" patents. The negative impact, however, is strengthened through individual efforts and is plausibly driven by the implementation of "hit" patents.

The paper makes the following contributions. First, our paper introduces public health policies into the innovation management literature as an external factor that constitutes organizations' external environment. Scholars have recognized that it is important to extend our understanding of the potentially complex and nuanced implications of wellness and health on managerial challenges (Vakili & McGahan, 2016). Nonetheless, recent research mainly focuses on organizations' internal policies, such as wellness programs or safety rules (Gubler et al., 2018; Pagell et al., 2020), and pays less attention to organizations' external conditions, such as regional public health policies. Our results imply that external public health policies, such as marijuana legalization, have substantial effects on knowledge workers' individual and collaborative effectiveness in the innovation process. The findings suggest that managers should consider the potential influence of external public health policies in designing and deploying internal policies. Further, our findings provide a rationale for organizations' engagement in corporate social responsibility practices and for their lobbying to influence public policymaking and secure a favorable public health environment. Thus, our findings add to research that studies organizations' corporate social responsibility (Godfrey et al., 2009; Gubler et al., 2018; Pagell et al., 2020) and non-market strategy (Barber & Diestre, 2019). Relatedly, organizations' strategic location choices also hinge upon favorable local public health policies (Alcácer & Chung, 2014). In sum, this paper adds to the research stream that considers innovation management as a multidisciplinary realm (Gaimon et al., 2017).

Second, this study contributes to our understanding of how marijuana legalization affects regional economy. Research shows that the increased use of controlled substances (e.g., marijuana and opioids) negatively affects local economies by causing higher public financing costs (Cheng et al., 2022) and lower business valuations (Ouimet et al., 2021). Our findings contribute to this research by adding new evidence that marijuana legalization leads to the destruction of economic value. Our findings are especially timely considering the many proponents in the United States and worldwide

of legalizing recreational marijuana use.²⁸ Regulators should consider MMLs' adverse effect on innovation activity when estimating the net social welfare of similar policies. For instance, we find that MMLs dampen for-profit assignees' innovation activity, which has been shown to be closely associated with a region's economic development (Agrawal et al., 2014). Specifically, a reduction in the innovation effectiveness of for-profit assignees implies that these firms may find it challenging to gain or maintain a competitive advantage. Firms' reduced innovation activity may also negatively affect knowledge exchange or spill over across firms in the region, further limiting firms' innovation effectiveness and thus competitiveness (Jaffe et al., 1993). As a result, the regional economy may face issues such as increased unemployment rates and greater public social welfare expenditures. Public health policies may thus have negative spillover effects on the regional economy. Future research can further explore MMLs' potential negative spillover effects on the broader regional economy through deteriorating innovation activity.

Moreover, our study complements recent research focusing on the potential implication of MMLs on regional innovation. Vakili and Zhang (2018) adopt the perspective of social liberalization and document a positive link between MMLs and patent counts at the state level. They attribute such a link to an increase in social interactions among inventors within a more liberal environment. In contrast, we analyze marijuana legalization from a public health perspective and develop our hypotheses within the framework of the process-based view of innovation. This framework allows us to comprehensively consider the complex effects of MMLs on innovators' individual and collaborative efforts during idea generation and implementation of the innovation process. Thus, we are able to better develop competing arguments for MMLs' potential positive and negative effects. The framework also guides our empirical exploration into finding a predominantly negative impact of MMLs on overall innovation output and nuanced, heterogeneous impacts when decomposing innovation by quantity and quality (in which case the effect can be insignificant or positive depending on the patent type). By doing so, we complement Vakili and Zhang (2018) in three ways. First, while our results confirm the finding that MMLs have positive effects on the quantity of certain patents (e.g., patents that involve more collaboration), we further show that MMLs have a net negative impact on total citations, which is driven by deteriorating patent quality. Also importantly, this adverse impact is mitigated through collaboration. Second, our results not only confirm Vakili and Zhang's (2018) finding of the benefits of MMLs in increasing the number of "hit" patents but also show the cost of MMLs in terms of increasing the number of "weak" patents and reducing patent quality (for both "hit" and "weak" patents). Third, our results in the Online Appendix also imply that the impact of MMLs on a region's overall innovation output varies by the technological focus of the region.

The present study has several limitations. First, although our quasi-experiment uncovers robust evidence for the effect of MMLs on innovation activity, we cannot further prove the exact mechanisms underlying how inventors and businesses are harmed by this increase in marijuana use, availability, and social acceptance. For example, marijuana's increased availability and use may directly affect some innovators who use marijuana (Marie & Zolitz, 2017). Increased marijuana availability may also have spillover effects on innovators who do not necessarily use marijuana, through other channels. Future research can further delineate the social dynamics that mediate MMLs' effects on innovators. Second, while MMLs' effects may go beyond knowledge workers, we are unable to further elaborate on how MMLs may shape the productivity of individuals in other economic domains, given that our hypothesis development is closely guided by the theory of innovation. Future research can adopt theories specific to other worker types to shed light on MMLs' implications on other types of workers. Third, due to data limitations, we are unable to examine innovation activities in forms other than patenting or to establish boundary conditions in terms of individual or organizational characteristics. Future studies can investigate other forms of innovation activity and explore the moderating effects of individual or organizational characteristics on MMLs' impact to extend our understanding about the relationship between innovation and public health policies, such as MMLs. Last, we acknowledge that the scope of this paper is limited to marijuana legalization's effects on local innovators' patenting activity. Legalizing marijuana may also affect local firms' management decisions, which would determine the effectiveness of their knowledge recombination. In addition, public health covers a wide array of domains, many of which (e.g., pandemics and aging) are at least equally consequential for corporate management. Future research can examine the implications of marijuana legalization and other public health issues on a broader set of management outcomes. For instance, the recombinant view of innovation (e.g., Ganco, 2017; Kauffman & Levin, 1987) can be adopted to examine the public health implications on firms' resource allocation and strategic decisions in the innovation context. Such decisions may include whether and how firms update their organizational structure (e.g., centralized vs. localized research and development [R&D]) and adjust their acquisition plans (e.g., choosing targets) in response to marijuana legalization or other changes in public health policies. Notwithstanding these limitations, this study provides novel evidence that contributes to our understanding of the relationship between public health policies and innovation activity.

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ENDNOTES

¹ Data from the NSDUH conducted by the Substance Abuse and Mental Health Services Administration, Center for Behavioral Health Statistics and Quality.

² For comparison, the number of alcohol users increased by 16% and the number of cigarette users decreased by 19% from 2002 to 2018.

³ Despite limited research, innovation provides a unique setting to study the effects of substance use because the innovation process requires creativity, cognitive engagement, collaboration, and endurance (Amabile et al., 1996; Van de Ven, 1986), all of which are susceptible to the direct or indirect influences of a change in local substance consumption. Furthermore, innovation is a useful way to evaluate MMLs' effects on local knowledge workers and businesses because innovation output is measurable using patents and their citation information, which signal knowledge workers' and businesses' intellectual output (Gao et al., 2020).

⁴ We provide a few examples in this section and discuss them in detail in Section 3.2.

⁵ That being said, we do not observe a net positive effect for quantity in the full sample, which is probably due to the insignificant effects for patents with a single inventor.

⁶ Based on the Substance Abuse and Mental Health Services Administration, Center for Behavioral Health Statistics and Quality.

⁷ https://leginfo.legislature.ca.gov/faces/codes_displaySection.xhtml?sectionNum=11362.5.&lawCode=HSC (Access date: February 7, 2021).

⁸ <https://www.teamblind.com/blog/index.php/2018/04/18/survey-results-40-percent-of-tech-employees-say-they-consumed-cannabis-in-the-past-six-months/>

⁹ Another important theoretical framework is the recombinant view of innovation, which is rooted in economics and emphasizes agents' boundedly rational combination/use of economic resources (Ganco, 2017; Kauffman & Levin, 1987). This alternative framework is often used to study firms' organizational structure and strategic moves, such as mergers and acquisitions (Sears & Hoetker, 2014).

¹⁰ Prior research of the innovation process (as discussed in Section 3.1) allows us to make specific predictions regarding MMLs' effects on innovators. The mechanisms for other types of workers may be different depending on their job requirements and processes, which are beyond the scope of this paper.

¹¹ Anecdotal evidence suggests that parents can be disturbed by their children's potential exposure to marijuana and its related negative consequences. For example, a news article reports that during Halloween of 2021, parents received warnings from several state attorneys about cannabis edibles that were deceptively designed to resemble standard treats, against the backdrop of surging child marijuana overdoses in the United States (cbsnews.com/news/halloween-candy-snacks-cannabis-edibles-warning).

¹² We cannot examine innovation activities in forms other than patents due to a lack of location data. For example, public firms' R&D expenses are aggregated at the firm level and cannot be distributed to different states.

¹³ We cannot examine the effect of recreational marijuana laws because few states legalized recreational use during the sample period. For example, Colorado and Washington passed the first recreational laws in 2012, resulting in a limited number of observations in the treated group after the treatment.

¹⁴ As explained in Section 2, the unintended consequences of MMLs include marijuana's increased availability, social acceptance, and illicit use. Because states' MMLs are intended to only legalize marijuana's restricted medical use, their unintended consequences are plausibly exogenous to innovators.

¹⁵ For example, MMLs may affect a region's general labor market supply, and thus, the MML-innovation relation via channels other than the proposed knowledge worker mechanisms. On the one hand, MMLs may provide an additional workforce to the labor market by providing medical relief for chronic illnesses and bring in extra tax revenue via the sales of marijuana-related products (Cerda et al., 2012; Hasin et al., 2017; Wen et al., 2015). These effects positively affect the local labor market supply. On the other hand, greater illicit use of marijuana after MMLs is associated with higher health, legal, and career risks, and thus may negatively shock the local labor market. Therefore, we control for changes in county-level economic conditions, using *Unemployment*, *Income*, and *Population*, to estimate MMLs' impact on knowledge workers' innovation.

¹⁶ Figure A1 in the Online Appendix illustrates this sample on a map.

¹⁷ The weaker statistical significance may be due to excluding observations for innovation activities that occur in central areas of states, as R&D centers are less likely to be located on state borders.

¹⁸ We appreciate the review team's suggestion of performing a mediation analysis.

¹⁹ NSDUH collects information about tobacco, alcohol, and drug use from around 70,000 respondents aged 12 or above via household face-to-face interviews across different states every year. Individual-level data are then aggregated by NSDUH at a state year using weights based on poststratification to population estimates from Census Bureau.

²⁰ As a caveat, this analysis may not fully reflect the mediating effect of marijuana use because the percentage of the population that reports marijuana use cannot incorporate the multi-dimensional nature of marijuana use, such as users' consumption pattern (frequency and intensity) and location (workplace, home, or public areas).

²¹ MMLs may lead to consequences that are not perfectly correlated with the marijuana use rates variable, and these effects are not included in this mediation test. For example, the use rates do not incorporate information about users' consumption frequency, intensity, and location (workplace, home, or public areas). As another example, higher marijuana acceptance after MMLs can affect a region's social environment and thus non-users' productivity due to collaborative frictions. We do not intend to present a comprehensive mediation analysis because many potential mediators are not easily and reliably measurable. The purpose of this analysis is to present a mediation test using a proxy to represent marijuana-related consequences.

²² Untabulated tests show that MMLs' effect on patent citations is greater for states with more favorable conditions for growing marijuana (i.e., those with average monthly temperatures that tend to fall into the ideal temperature range of 24 and 30°C) and is driven by states with lower marijuana user bases in the pre-MML period. Due to the heterogeneity in MMLs' effect on innovation, we acknowledge that it is challenging to draw inferences for a specific state and/or using a specific channel.

²³ We also explore MMLs' heterogeneous effects by patent technology section in Material A2 in the Online Appendix.

²⁴ We appreciate the suggestion from an anonymous reviewer to explore along this direction.

²⁵ Weak patents per se may be less valuable to study due to their lack of future influence. However, processing such patent applications still brings non-negligible costs to the institutional system that supports innovation activity. For instance, a surge in the number of patent applications can drain public resources by negatively impacting patent examiners, who constitute a core public resource dedicated to the patenting process (Kim & Oh, 2017). Specifically, a large number of patent applications causes processing backlogs. Examiners thus have less time to examine patent filings (e.g., less time for searching for relevant prior arts and in assessing the improvements of a focal patent), resulting in lower examination quality and poorer assessment of patents' innovativeness (Picard & de la Potterie, 2013). This change in examiners' behavior reduces the patenting system's efficiency and damages patent holders' protection in the judicial system. Thus, examining how MMLs may affect weak patents is still valuable to understanding the impact of MMLs on regional innovation.

²⁶ Untabulated tests show that the results are consistent when using the 5-year forward citation distribution to identify "hit" and "weak" patents.

²⁷ We acknowledge that such a reduction in patents' future impact may also be partially explained by a reduction in the novelty of ideas. For instance, overly creative ideas may be impractical and thus uninformative in future innovation attempts. To explore this possibility, we examine MMLs' effect on patent novelty. Following Hall et al. (2001), we measure novelty, using the "originality" and "generality" indices, which are proxied by the Herfindahl indices based on backward and forward citations, respectively. A higher value suggests that the focal patent draws from broader inventive origins, makes a more diverse impact on future invention, and thus represents a more novel idea (Hall et al., 2001). We do not find evidence that MMLs significantly change patent novelty, suggesting that a reduction in novelty is unlikely to explain our main findings and inferences.

²⁸ Between 2012 and 2022, 19 states and the District of Columbia have further legalized the recreational use of marijuana after passing MMLs. More states are debating and considering the expansion of marijuana laws. Marijuana legalization has also become widespread worldwide. For instance, Canada legalized marijuana for recreational use in 2018.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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