The Real Effect of Smoking Bans: Evidence from Corporate Innovation

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Abstract

We identify a positive causal effect of healthy working environments on corporate innovation, using the staggered passage of U.S. state-level smoke-free laws that ban smoking in workplaces. We find a significant increase in patents and patent citations for firms headquartered in states that have adopted such laws relative to firms headquartered in states without such laws. The increase is more pronounced for firms in states with stronger enforcement of such laws and in states with weaker pre-existing tobacco controls. We present suggestive evidence that smoke-free laws affect innovation by improving inventor health and productivity and by attracting more productive inventors.

I. Introduction

Smoking is the world's leading preventable cause of death, killing nearly six million people every year. Over the last two decades, a large number of U.S. states have adopted smoke-free laws that ban smoking in the workplace. Although these laws are shown to have reduced cigarette consumption, their effect on the real economy has not been fully explored. In this paper, we examine the impact of smoke-free laws from the perspective of knowledge creation and identify a positive causal effect of smoke-free laws on corporate innovation.

Our tests exploit the staggered passage of smoke-free laws by various U.S. states since 2002, which ban smoking in workplaces. The setting is highly appealing from an empirical analysis standpoint for two reasons. First, the motivation behind introducing smoke-free laws centers on state legislatures' determination to protect nonsmokers from exposure to secondhand smoke and to reduce cigarette consumption. These laws were not introduced with the primary intention of promoting corporate innovation, any potential effect on innovation is likely to be an unintended consequence. Second, the staggered passage of statewide smoke-free laws enables us to identify their effect on corporate innovation in a difference-in-differences framework (see, e.g., Bertrand and Mullainathan (2003)). Because multiple exogenous shocks affect different firms at different points in time, we can avoid a common identification challenge faced by studies with a single shock: the potential biases and noise coinciding with the shock that directly affect the dependent variable to be explained (Roberts and Whited (2013)).

We propose that smoke-free laws will have a positive effect on corporate innovation for the following reasons. First, smoking generates thousands of chemicals that are toxic to the brain, cardiovascular, and pulmonary systems (Longstreth, Diehr, Manolio, Beauchamp, Jungreis, and Lefkowitz (2001), Longstreth, Arnold, Beauchamp, Manolio, Lefkowitz, Jungreis, Hirsch, O'Leary, and Furberg (2005), and Swan and Lessov-Schlaggar (2007)), and thus has a negative impact on inventors' creative activities.[1] After a state adopts smoke-free laws, both smoker inventors and their nonsmoker colleagues become more capable of engaging in innovative activities, leading to greater patenting output. Second, smoking and exposure to secondhand smoke are known to lead to more frequent employee breaks, longer sick leaves, and early retirement, hampering productivity (see, e.g., Halpern, Shikiar, Rentz, and Khan (2001), Bunn, Stave, Downs, Alvir, and Dirani (2006)).[2] Since corporate innovation is human capital intensive and mostly teamwork (Hall and Lerner (2010)), smoke-free laws promote healthy and group working environments which improve productivity. Third and finally, after a state adopts smoke-free laws, nonsmoker inventors tend to relocate into the state. A large literature in labor economics has established that skilled labor such as inventors are more mobile than unskilled labor (see, e.g., Stark and Bloom (1985), Autor and Dorn (2013)). Given that nonsmokers are likely to be more creative than smokers, smoke-free laws trigger inventor relocation by attracting more productive nonsmoker inventors, resulting in more corporate innovation.

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[1] There are a large number of studies showing that smoking is harmful to cognitive abilities including learning, creativity, information processing speed, and cognitive flexibility (Hill (1989), Galanis, Petrovitch, Launer, Harris, Foley, and White (1997), Kalmijn, van Boxtel, Verschuren, Jolles, and Launer (2002), Ott, Andersen, Dewey, Letenneur, Brayne, Copeland, Dartigues, Kragh-Sorensen, Lobo, Martinez-Lage, Stijnen, Hofman, and Launer (2004), Starr, Deary, Fox, and Whalley (2007), and Piper, Kenford, Fiore, and Baker (2012)).

[2] Anecdotally, Piala Inc., a marketing firm in Tokyo, gives its nonsmoker staff an additional 6 vacation days per year because smoker staff would leave their desks for about 40 minutes each day, which sum up to be 12 working days per year. See http://money.cnn.com/2017/11/01/news/japan-smoke-employees-vacation-benefit/index.html and http://www.newsweek.com/japan-smoking-vacation-697499.

On the other hand, it is also possible that smoke-free laws will have a negative impact on corporate innovation. From a neuropharmacological perspective, nicotine and caffeine can facilitate creativity by enhancing attention, memory, and learning ability (Levin, McClernon, and Rezvani (2006), Schweizer (2006)). In addition, smoking reflects individuals' risk-taking behavior (see, e.g., Borghans, Duckworth, Heckman, and ter Weel (2008)). Furthermore, smoking creates (short-term) positive affective feeling that enhances self-confidence, optimism, and creativity (Isen, Daubman, and Nowicki (1987), Seo, Barrett, and Bartunek (2004)). All these findings support a negative effect of smoke-free laws on corporate innovation.

Using a panel data sample of 36,337 U.S. public firm-year observations over the period 1997–2015 and a difference-in-differences specification, we show that the passage of state-level smoke-free laws is associated with a significant increase in corporate innovation output. On average, firms headquartered in states that have introduced smoke-free laws experience an increase in the number of patents by 7.4% and an increase in the number of patent citations by 15%, relative to firms headquartered in states without such laws. The productivity of individual inventors, measured by the number of patents (citations) per 1,000 employees, also increases by 9.4% (16%) in firms headquartered in states that have introduced smoke-free laws. It is worth noting that we control for other state-level law changes known to affect corporate innovation including antitakeover laws (Atanassov (2013)) and labor laws (Acharya, Baghai, and Subramanian (2014)), and that using a number of alternative measures of innovation including innovative efficiency, patent quality, patent originality, patent generality, patent value, and research and development (R&D), we continue to find a positive effect of smoke-free laws on innovation.

We perform a number of robustness checks on our main findings. We exclude firms headquartered in California or Massachusetts—two states with the highest corporate innovation output; we focus on patent output of inventors who reside in a firm's headquarters state as these inventors would be more directly subject to headquarters state-level smoke-free laws; we include firms that have never filed a patent; we consider other less strict smoke-free laws; and we additionally control for state-level employment nondiscrimination acts (ENDAs) (Gao and Zhang (2017)). The positive effect of smoke-free laws on innovation remains.

The identification assumption central to a causal interpretation of the difference-in-differences estimates is that the treated firms (located in states that have introduced smoke-free laws) and the control firms (located in states without such laws) share parallel trends in their innovation output prior to the law changes. Our tests show that the pre-treatment trends in corporate innovation output are indeed indistinguishable between these two groups of firms, and that most of the effect of smoke-free laws on innovation output occurs 2 to 3 years after the laws' passage, suggesting a causal effect.

It is possible that the passage of state-level smoke-free laws is triggered by some unobservable local economic conditions, which in turn affect corporate innovation (noting that we do control for a host of observable state characteristics such as R&D expenditures and the education level of labor force). To mitigate this concern, we exploit the fact that (unobservable) local economic conditions are likely to be similar across neighboring states, whereas the effect of state-level smoke-free laws stops at a state's border. After differencing away changes in local economic conditions using a sample of treated and close-by control firms that are located on either side of a state's border, we continue to find a significant increase in the treated firms' innovation output relative to their control firms.

To provide further evidence that the effect of state-level smoke-free laws on innovation is indeed tied to restricting smoking in workplaces, we employ a triple-differences specification to assess heterogeneous treatment effects. We first show that the treatment effect is stronger for firms in states with stronger enforcement of smoke-free laws measured by the percentage of smokers who quit smoking in response to such laws, suggesting that the treatment effect likely results from a decline in employee smoking. We further show that the treatment effect is stronger for firms in states with weaker pre-existing tobacco controls measured by a state's funding per smoker for tobacco prevention and control, suggesting that such effect is likely due to restrictions on smoking in workplaces (i.e., we show that employees in states with weaker pre-existing tobacco controls are subject to more restrictions after such laws).

Finally, we investigate possible channels through which smoke-free laws affect innovation. We first show that local residents' health condition improves after the passage of state-level smoke-free laws. We then examine the patenting output and productivity of inventors who have never moved during the sample period, and find a significant increase in the number of patents and patent citations (per employee or per inventor) for them after the passage of state-level smoke-free laws. In addition, we find that labor productivity also increases after the passage of state-level smoke-free laws. These results support the view that smoke-free laws reduce smoking and exposure to secondhand smoke and thus improve the health and working conditions of inventors, leading to improved inventor productivity. Next, we find that following the passage of such laws, legislating states experience a significant net inflow of inventors from other states. Importantly, we find that at the individual-inventor level, newly arrived inventors are more productive at patenting than departed ones, which is consistent with prior findings that smokers tend to have lower productivity than nonsmokers. In summary, these tests help establish the mechanisms underlying our findings—improving inventor health and productivity and attracting more productive inventors.

Our paper adds to the growing economics and finance literature that examines the drivers of corporate innovation, which is crucial for sustainable growth and economic development (Solow (1957), Romer (1990)). Our paper provides suggestive evidence that a healthy working environment is an important factor in knowledge creation in the real economy. Our paper also has important policy implications. Although 33 U.S. states and the District of Columbia had adopted smoke-free laws by the end of 2012, legislators in the remaining states are still debating whether to follow suit, partially because the impact of smoke-free laws on society and the real economy (in particular) is still under-explored.[3] Prior studies on the effect of smoke-free laws typically focus on medical expenses and smoking-related costs such as health and fire insurance premiums, and building maintenance and cleaning costs (see, e.g., Javitz, Zbikowski, Swan, and Jack (2006), Juster, Loomis, Hinman, Farrelly, Hyland, Bauer, and Birkhead (2007)). Extending this strand of research, our paper provides new evidence that this legislation spurs employees' productivity in corporate innovation.

The remainder of this paper is organized as follows: We provide some background on state-level smoke-free laws in Section II. In Section III, we development our hypotheses on the effect of those laws on corporate innovation. In Section IV, we describe our sample formation

[3] According to Pfizer (2007), 91% of the workforce is employed at establishments that have official smoking restriction policies. Nevertheless, even in workplaces with the most stringent policy—smoking not permitted in any work area, or in any indoor public or common area—the prevalence of smoking is 16%. In establishments with less restrictive smoking policies, or none at all, the prevalence of smoking among employees increases to 24% and 30%, respectively.

and key variable construction. We present the main results in Section V, and delineate the channels for smoke-free laws to affect innovation in Section VI. We conclude in Section VII.

II. Background on State-Level Smoke-Free Laws

By 2013, nearly 18 out of every 100 American adults aged 18 years old or older (approximately 42 million adults) smoked cigarettes. Cigarette smoking is the leading cause of preventable disease and death in the United States, accounting for more than 480,000 deaths every year, or 1 in every 5 deaths. More than 16 million Americans live with a smoking-related disease (U.S. Department of Health and Human Services (2014)). Smoking is harmful not only to smokers, but also to nonsmokers who are exposed to secondhand smoke. Among adults who have never smoked, secondhand smoke can cause various deceases, including heart problems, lung cancer, and stroke.

Over the last two decades, U.S. state governments have increasingly banned smoking in workplaces as a means of limiting nonsmokers' exposure to secondhand smoke and to discourage smoking. The 2006 report by the U.S. Surgeon General concludes that these smoke-free policies have decreased the number of cigarettes smoked per day, increased the number of attempts to quit smoking, and increased smoking cessation rates (U.S. Department of Health and Human Services (2006)).

Jacobson, Wasserman, and Raube (1993) identify a number of political economy factors that have significantly influenced state-level smoking-control legislation. The first is the presence of key legislators committed to enacting smoking-control legislation. The second factor is the formation of a strong and inclusive anti-smoking coalition (e.g., the American Lung Association) engaged in an aggressive grassroots and media campaign to elicit public support for smoking restrictions. The third factor is the presence of an active executive branch (e.g., the State Department of Health) that places additional political pressure on the legislature to act, especially when the executive branch makes such legislation a policy priority. The fourth factor is the enactment of strong local ordinances created by a policy environment that facilitates the enactment of statewide smoking restrictions. The last factor is the absence of tobacco industry opposition. In summary, the primary purpose of smoking bans is to promote public health and reduce cigarette consumption (rather than promoting corporate innovation). Later in the paper (Table 3), we conduct a formal test to show that the passage of smoke-free laws is indeed exogenous to statewide innovation activities.[4]

Although the U.S. does not have any federal legislation that prohibits smoking in workplaces, different states have started to enact laws to ban smoking in workplaces. Delaware and South Dakota are the first states to enact such laws. Typically, a state first passes smoke-free laws that only apply to some specific areas, and then expands to other places. For example, Utah passed laws to ban smoking in restaurants in 1995, expanded the restrictions to private workplaces in 2006, and then expanded them further to include taverns and private clubs in 2009. Because of our focus on laws that ban smoking in workplaces, we identify 2006 as the year that Utah's smoke-free laws became effective.

The Centers for Disease Control and Prevention (CDC) categorizes workplace smoke-

[4] Even though the passage of these laws may be subject to firms' or interest groups' lobbying efforts, *a priori*, there is no perceived link between lobbying for a smoke-free working environment and corporate innovation. Further, if innovative firms had wanted specifically to promote a healthy lifestyle, they could have adopted smoke-free policy in workplaces without relying on state legislation, which would bias against us finding any significant effect of smoke-free laws on innovation.

free laws into three categories: “banned,” “separately ventilated areas,” and “designated areas,” and it only deems the laws in the first category as effective workplace smoke-free laws. Because the laws that restrict smoking to separately ventilated areas or designated areas cannot eliminate the exposure to secondhand smoking (U.S. Department of Health and Human Services (2006)), we use the CDC’s first category in identifying smoke-free laws. A state may pass weak laws first, and then strengthen them over time. For example, the 1984 Wisconsin Clean Indoor Air Act permitted smoking in workplaces where the main occupants are smokers or in designated smoking areas; the 2010 Amendment of Wisconsin’s Clean Indoor Air Act prohibited smoking in workplaces. In this case, we identify 2010 as the year that Wisconsin’s smoke-free laws became effective. Table 1 lists the states and their years of adoption provided by the CDC.

[Table 1]

III. Hypothesis Development

In this section, we review prior literature on the possible effects (and associated mechanisms) of smoking on individual inventors’ output. The medical, psychology, and public health literature has examined and debated on the consequences of tobacco smoking with inconclusive findings due to differences in experiment designs, samples, cognitive function metrics, and time horizons (see the review by Heishman, Taylor, and Henningfield (1994)).

Although nicotine may be beneficial to certain cognitive functioning in the short run, other ingredients in tobacco or generated from smoking are toxic to the brain, cardiovascular, and pulmonary systems (Swan and Lessov-Schlaggar (2007)). Researchers have examined the mechanisms through which smoking adversely influences cognitive functioning by releasing *thousands* of chemical compounds. As summarized in the review by Swan and Lessov-Schlaggar

(2007) of clinical experiments, smoking is found to be associated with brain atrophy, silent lacunar infarcts, silent cerebral infarction, and white matter hyperintensities (WMHIs) that are related to dementia, through oxidative stress, inflammation, and atherosclerotic processes. In addition, Swan, DeCarli, Miller, Reed, Wolf, and Carmelli (2000) report that, in a sample of 383 elder men, the number of smoking years works as a strong predictor for brain atrophy and WMHIs. Using a large-scale magnetic resonance imaging (MRI) data, Longstreth et al. (2001) and Longstreth et al. (2005) find that smoking positively and significantly correlates with brain atrophy and WMHIs. All these studies identify negative effects of smoking on the brain, which likely adversely affect cognitive abilities.

Researchers have also examined the direct connection between smoking and cognitive abilities related to learning and creative activities. Hill (1989) finds that, after controlling for other health factors, nonsmokers on average perform better than smokers in many cognitive functioning metrics such as problem solving, psychomotor speed, and language fluency in a sample of 76 healthy elder volunteers. Galanis et al. (1997) report that smoking is associated with an increased risk of cognitive impairment in 3,429 Japanese-American men. Kalmijn et al. (2002) find that smoking is inversely related to psychomotor speed and cognitive flexibility in a 1,927 randomly selected, predominantly middle-aged individuals. Ott et al. (2004) show that smoking is associated with significant decline in cognitive performance based on 17,006 individuals aged 65 and older. Starr et al. (2007) report that nonsmokers perform significantly better than smokers in information processing speed based on 298 individuals in their mid-sixties. Using a sample of 1,504 smokers, Piper et al. (2012) find that individuals who successfully quitted smoking during the experiment period feel that they have improved in learning and creative activities.

In addition to its effects on the brain and cognitive performance, smoking also affects inventors' health conditions and working hours and hence hampers corporate innovation. As pointed out by Thomas Edison "Genius is one percent inspiration and ninety-nine percent perspiration." To create something new, it is not only good ideas – inspiration/creativity, but more importantly, hard work and team effort to turn ideas into quantifiable output such as patents that we use to measure corporate innovation (Singh and Fleming (2010)). Smoking is known to lead to significant productivity losses because of smoker employees' frequent breaks, longer sick leaves, and early retirement due to smoking-related diseases; and smoker employees have a negative impact on nonsmoker colleagues due to secondhand smoke (see, e.g., Halpern et al. (2001), Bunn et al. (2006), and Weng, Ali, and Leonardi-Bee (2013)).[5] After a state adopts smoke-free laws, both smoker and nonsmoker inventors become healthier and more productive working together, leading to more patenting output.

Moreover, the clustering of nonsmokers also has implication on the effect of smoke-free laws on innovation as smoke-free laws may trigger inventor relocation by attracting more productive inventors. Smokers derive (short-term) utility from consuming cigarettes, while nonsmokers suffer from exposure to secondhand smoke. Smoke-free laws make smoker inventors worse off by restricting them from smoking at work, and make nonsmoker inventors better off by providing them with a smoke-free working environment. Thus, following a state's adoption of smoke-free laws, we expect that nonsmoker inventors will be more likely to relocate into the state. A large literature in labor economics has established that skilled labor such as inventors are more mobile than unskilled labor (Stark and Bloom (1985), Autor and Dorn

[5] The CDC estimates that the productivity loss resulting from smoking-related health problems was around $92 billion over the period 1997–2001 (http://www.cdc.gov/media/pressrel/r050630.htm).

(2013)), which supports the relocation channel. As a result, the relocation channel through which smoke-free laws affect innovation is the relocation of nonsmoker inventors into the legislating state who are likely to be more creative and productive.

Based on the above discussions, we therefore form our first hypothesis:

Hypothesis 1. Smoke-free laws have a positive effect on corporate innovation.

On the other hand, smoking may have a positive effect on inventors' output for the following reasons. First, it is well-documented that nicotine has an immediate positive effect on (some) cognitive performance metrics. From a neuropharmacological perspective, nicotine and caffeine can facilitate creativity by enhancing attention, memory, and learning ability (Levin et al. (2006), Schweizer (2006)), which is consistent with observations that some most creative people in history rely heavily on stimulants such as smoking or drinking in their work. Such an image may also prompt the co-occurrence of smoking and innovative activities: people who think smoking is pro-creativity are more likely to smoke (Hsieh, Yen, Liu, and Lin (1996)). Thus, individuals who engage in creative activities may choose to smoke, and such behavior works as a self-fulling prophecy.

Second, risk-taking provides another explanation for smoking to enhance innovation. The literature has shown that smoking, along with other sensation seeking activities including drinking, unprotected sex, juvenile delinquency, and adult criminal behavior, reflect risk-taking (Borghans et al. (2008)). All these risk-taking activities or illicit traits are shown to be positively correlated with entrepreneurship (Levine and Rubinstein (2017)).

Third and finally (short-term) positive affective feeling associated with smoking may enhance flexibility in thinking and thus facilitate creativity (Isen et al. (1987)). Positive affective feeling may also enhance self-confidence and optimism, which encourage individuals to pursue riskier activities as they anticipate that their effort will produce desirable outcomes (Seo et al. (2004)). On the other hand, when individuals are under pressure and stress, they tend to pay too much attention to external pressure and thus become less responsive to their surroundings. It has been documented that negative affective feeling thus adversely influences individuals' creativity by consuming attentional resources (Beal, Weiss, Barros, and MacDermid (2005)) and increasing their rigidity in responding to new problems (Staw, Sandelands, and Dutton (1981)). These medical and psychological studies thus support a potentially positive effect of smoking on innovation through promoting positive affective feeling.

All these discussions lead to our alternative hypothesis:

Hypothesis 1A. Smoke-free laws have a negative effect on corporate innovation.

IV. Sample Formation and Variable Construction

We start with all U.S. public firms in the Compustat/CRSP data set with a book value of total assets exceeding $5 million to focus on economically significant firms that are likely to be innovative. We exclude firms in financial (SIC codes 6000–6999) and utility (SIC codes 4900–4999) industries due to their different regulatory oversight that might have implications on innovation output. We use historical location and incorporation data from SEC's EDGAR service which started to provide such information since 1996, 1 year before the beginning of our sample period (1997–2015).[6]

We collect patent and citation information from the U.S. Patent and Trademark Office (USPTO) PatentsView database, which covers all patents awarded by the USPTO over the period 1976–2017.[7] We then link each patent and its citations to a Compustat/CRSP firm (if the assignee is a public firm) in three steps. In the first step, we use CRSP firm identifier (permno) for patents granted by the end of 2010 compiled by Kogan, Papanikolaou, Seru, and Stoffman (2017). In the second step, for patents granted since 2011, we use fuzzy matching algorithm and manual checking to match the assignee names of those patents to the assignee names that have ever appeared in the National Bureau of Economic Research (NBER) patent database (including patents granted to the end of 2006) and Kogan et al. (2017). In the third step, for the assignee names of patents granted since 2011 that cannot be matched in the second step, we use fuzzy matching algorithm and manual checking to match all public firm names that have appeared in the Compustat/CRSP database.[8] As a result, the expanded patent data set allows us to better identify the real impact of state-level smoke-free laws on corporate innovation, as all of the smoke-free laws took effect after 2000 (see Table 1).[9]

[6] It can be downloaded from Bill McDonald's Web site (http://www3.nd.edu/~mcdonald/10-K_Headers/10-K_Headers.html).

[7] The USPTO PatentsView database is derived from its bulk data files and is supported by the USPTO Office of the Chief Economist, with additional support from the US Department of Agriculture.

[8] We follow the matching procedure of Gao, Hsu, and Li (2018) which is used to construct patent data for private firms.

[9] In contrast, the commonly used NBER Patent Database of Hall, Jaffe, and Trajtenberg (2005) ends its coverage in 2006.

Following prior work (see, e.g., Aghion, Van Reenen, and Zingales (2013), Bloom, Schankerman, and Van Reenen (2013)), we drop firms that have never applied for a single patent during our entire sample period. We start our sample in 1997, 5 years prior to the first enactment of state-level smoke-free laws by Delaware and South Dakota in 2002. We use the application year of a patent as the time of its invention to measure a firm's innovation output, which is common in the literature (Hall, Jaffe, and Trajtenberg (2001), Hall et al. (2005)). Given the typical two- to three-year lag between patent application and approval (Hall et al. (2005)), patents applied for in 2016 and 2017 may not be awarded and show up in the database. For this reason, we end our sample of patents applied for in 2015. Our final panel data sample consists of 36,337 firm-year observations over the period 1997–2015.

To assess the performance of corporate innovation, we employ four measures based on patent count and patent citations.[10] The first is the number of patents applied for (and subsequently awarded) by a firm in a given year. The second is the sum of forward citation counts received by patents applied for by a firm in a given year, which captures the significance of its patent output. Because citations can be received many years after a patent is awarded, patents awarded near the end of the sample period have less time to accumulate citations. To address this truncation bias, we follow Hall et al. ((2001), Sec. III.2) to adjust patent citations.[11] In the first step, we calculate the average of forward citations of all patents in the same

[10] Economists have used firm-level patent records as indicators of corporate innovation performance since Scherer (1965). Although there are limitations in using patent data to measure inventions (Lerner and Seru (2015)), Griliches ((1990), p. 1702) notes, "Nothing else even comes close in the quantity of available data, accessibility, and the potential industrial, organizational, and technological detail."

[11] We thank an anonymous referee for bringing this adjustment approach to our attention.

technology class and filed in the same year, and name this number as a class-year average.[12] In the second step, we calculate the average of forward citations of all patents in the same technology class, and name this number as a class average. The adjustment factor for each class in each filing year will then be a class-year average scaled by the corresponding class average. This adjustment factor thus captures the variation across years but not across classes. In the third step, we scale each patent's forward citation count by the corresponding adjustment factor. Since the adjustment factor only captures yearly variation, the adjusted citation count still contains class variation but is purged of yearly variation.[13] In the last step, we sum up the adjusted citation counts of all patents filed by a firm in a year.

Given our interest in determining whether healthy working environments affect employees' productivity in innovative projects, our last two measures are the number of patents applied for (and subsequently awarded) and the number of citations per 1,000 employees (Acharya et al. (2014)). Due to the positive skewness in patent data, we take the natural logarithm of 1 plus the value of each innovation measure (Lerner (1994), Aghion et al. (2013)).

[12] We use the Cooperative Patent Classification (CPC) instead of the U.S. Patent Classification (USPC) because the latter is no longer available from the USPTO after May 26, 2015. We use the first one digit in the CPC in our main analysis: A denotes Human Necessities; B denotes Performing Operations and Transporting; C denotes Chemistry and Metallurgy; D denotes Textiles and Paper; E denotes Fixed Constructions; F denotes Mechanical Engineering, Lighting, Heating, Weapons, Blasting Engines or Pumps; G denotes Physics; H denotes Electricity; Y denotes General Tagging of New Technological Developments. We obtain consistent results when we use the first three digits in the CPC.

[13] In robustness checks, we also consider another adjustment approach by Hall et al. (2001) that simply scales each patent's forward citation count by the average of forward citations of all patents filed in the same year.

We control for a number of firm characteristics that may affect corporate innovation including firm size, cash holdings, R&D expenditures, return on assets (ROA), asset tangibility, leverage, capital expenditures, Tobin's *Q*, industry concentration (the Herfindahl index based on sales), and firm age. Following Aghion, Bloom, Blundell, Griffith, and Howitt (2005), we also include the squared Herfindahl index in our regressions to account for any possible nonlinear effect of product market competition on innovation output.

We also control for a number of state-level variables in our regressions. Since larger and richer states may have more innovative projects, we control for state gross domestic product (GDP) and population. We include state unemployment rate to control for local business conditions. Further, we control for state expenditures in R&D, political climate (whether or not a state is governed by a Democrat), and population characteristics including the percentage of college graduates and the percentage of smokers, because these variables are likely to be correlated with innovation output and/or the propensity of a state passing smoke-free laws. Lastly, we control for two important state-level laws that are known to influence innovation: business combination laws (Atanassov (2013)), and wrongful discharge laws, in particular the good-faith exception, that protect employees against unjust dismissal (Acharya et al. (2014)).[14] Data on state GDP is obtained from the Bureau of Economic Analysis, data on state population is obtained from the U.S. Census Bureau, data on state unemployment rate is from the U.S. Bureau

[14] Legal scholars distinguish three distinctly different wrongful discharge laws: the good-faith exception, the public-policy exception, and the implied-contract exception. Among them, the good-faith exception is considered as the most far-reaching (Kugler and Saint-Paul (2004)). Acharya et al. (2014) find that the good-faith exception has a significant positive effect on corporate innovation, while the effects of the public-policy exception and implied-contract exception are much weaker.

of Labor Statistics Local Area Unemployment Statistics Series, data on state R&D expenditures is from the National Center for Science and Engineering Statistics and the National Patterns of R&D Resources of the National Science Foundation, data on state governors' party affiliations is via Web search, and data on state-level college graduates and smokers in the population is from the Behavioral Risk Factor Surveillance System (BRFSS). Data on business combination laws is collected from Bertrand and Mullainathan (2004), and data on the good-faith exception is collected from Autor, Donohue, and Schwab (2006). To minimize the effect of outliers, we winsorize all continuous variables at the 1st and 99th percentiles. Detailed variable definitions are provided in the Appendix.

Table 2 provides summary statistics. On average, firms in our sample have 31.2 patents applied for (and subsequently awarded) per year and receive 518 citations. After normalizing the number of patents and patent citations by the number of employees, we find that on average, firms in our sample generate 18.9 patents and 426 citations per 1,000 employees.

[Table 2]

The average sample firm hires about 8,690 employees and is 21 years old. The average sample firm holds a sizable amount of cash, with a cash-to-assets ratio of 26.9%. The sample average R&D and capital expenditures are 11.7% and 5.3% of total assets, respectively. The average sample firm is moderately levered, with a leverage ratio of 19.0%, and its tangible assets (i.e., property, plant, and equipment) account for 43.2% of total assets. In terms of performance, the sample average ROA is 1.1% and the sample average Tobin's *Q* is 2.4.

V. Results

A. The Timing of Adopting Smoke-Free Laws

Our empirical tests are based on the assumption that a state's adoption of smoke-free laws is not related to the prevailing innovation activities of firms in that state. To validate this assumption, we follow Acharya et al. (2014) and estimate a Weibull hazard model where the "failure event" is the adoption of the smoke-free laws in a given U.S. state. The sample consists of all U.S. states over our sample period with treated states dropped from the sample once they have adopted the smoke-free laws. The independent variables of interest, AVG_ln(1+PATENT), AVG_ln(1+CITATION), AVG_ln(1+PATENT_PER_EMPLOYEE), AVG_ln(1+CITATION_PER_EMPLOYEE), are the average ln(1+PATENT), ln(1+CITATION), ln(1+PATENT_PER_EMPLOYEE), and ln(1+CITATION_PER_EMPLOYEE) of sample firms headquartered in a state. ln(1+PATENT) denotes the natural logarithmic value of 1 plus patent count, ln(1+CITATION) denotes the natural logarithmic value of 1 plus adjusted citation count, ln(1+PATENT_PER_EMPLOYEE) denotes the natural logarithmic value of 1 plus patent count scaled by the number of employees (in 1,000s), and ln(1+CITATION_PER_EMPLOYEE) denotes the natural logarithmic value of 1 plus adjusted citation count scaled by the number of employees (in 1,000s). We also control for a number of state-level variables, including state GDP, population characteristics, unemployment rate, R&D expenditures, political climate (whether or not a state is governed by a Democrat), and state-level business combination laws and the good-faith exception associated with wrongful discharge laws.

Table 3 presents the results from estimating the hazard model. We show that the coefficients on AVG_ln(1+PATENT), AVG_ln(1+CITATION), AVG_ln(1+PATENT_PER_EMPLOYEE), and AVG_ln(1+CITATION_PER_EMPLOYEE) are not statistically significant across all four columns. Take column 1 for example, the coefficient on AVG_ln(1+PATENT) is small in magnitude (0.012) and is statistically insignificant. These results indicate that a state's adoption of smoke-free laws is not related to the prevailing innovation outputs of its local firms, supporting our assumption that the adoption of smoke-free laws is likely to be exogenous to local firms' innovation activities.

[Table 3]

B. Baseline Regression

A large number of U.S. states have adopted smoke-free laws at different points in time during the sample period. Thus, we can examine the before versus after effect of the passage of such laws on corporate innovation in affected states (the treated firms) vis-à-vis the before versus after effect in states without such laws (the control firms). This is a difference-in-differences test design involving multiple groups of the treated firms and multiple periods of the before versus after comparison as employed by Bertrand, Duflo, and Mullainathan (2004), Imbens and Wooldridge (2009), and Acharya et al. (2014). We implement the test by running the following regression:

$$(1)\ \mathrm{INNOVATION}_{ist} = \alpha + \beta_1 \mathrm{SMOKE\_FREE}_{st} + \beta_2 \mathrm{FIRM\_CHARACTERISTICS}_{ist} + \beta_3 \mathrm{STATE\_CHARACTERISTICS}_{st} + \mathrm{FIRM\_FE} + \mathrm{REGION\_YEAR\_FE} + \varepsilon_{ist}\ ,$$

where $\mathrm{INNOVATION}_{ist}$ is the natural logarithm of 1 plus the number of patents (citations received by these patents) applied for in year *t* by firm *i* in state *s*, and is scaled by the number of employees (in 1,000s) for the third and fourth innovation measures. $\mathrm{SMOKE\_FREE}_{st}$ is an indicator variable that takes the value of 1 if smoke-free laws are adopted in state *s* and year *t*, and 0 otherwise. That is, for a state that has adopted such laws, the variable SMOKE_FREE takes the value of 1 for the period after the adoption (beginning from year t+1), and 0 for the period leading up to the adoption year. For states without such laws during our sample period, the variable SMOKE_FREE always takes the value of 0. We include a set of control variables that may affect a firm's innovation output, as discussed in Section IV. We also include firm fixed effects to control for time-invariant differences in patenting and citation practices across firms. Finally, we include interaction terms between regional and year indicator variables to control for time-varying differences between geographic regions of the United States in corporate innovation and in the passage of smoke-free laws.[15] Controlling for regional time trends helps alleviate potential endogeneity concerns about the passage of smoke-free laws, considering that these regions might have different innovation opportunities. Given that our treatment is defined at the state level, we cluster standard errors by state.

The coefficient of interest in equation (1) is the coefficient β_1. As explained by Imbens and Wooldridge (2009), after controlling for all fixed effects, β_1 is the estimate of *within-state* difference between the periods before and after the passage of smoke-free laws relative to a similar difference between the periods before and after in states without such laws.

It is helpful to consider an example. Suppose we want to estimate the effect of smoke-free laws adopted by Florida in 2003 on innovation output. We can subtract the number of patents (citations) before the passage of such laws from the number of patents (citations) after the passage for firms headquartered in Florida. However, economy-wide shocks may occur in the same year and affect corporate innovation. To difference away such factors, we calculate the same difference in the number of patents (citations) for firms in a state without such laws. Finally, we calculate the difference between these two differences, which represents the incremental effect of the passage of smoke-free laws on the innovation output of firms in Florida compared to that of firms in states without such laws.

[15] Following Acharya et al. (2014), we consider four regions based on the U.S. Census Bureau's classification: Northeast, South, Midwest, and West.

Table 4 presents the regression results. The coefficient estimates of the effect of the passage of smoke-free laws on corporate innovation are positive and statistically significant in all columns. In column 1 where the dependent variable is ln(1+PATENT), we show that the coefficient estimate on the indicator SMOKE_FREE is 0.071 and significant at the 1% level, suggesting a positive effect of smoke-free laws on corporate innovation. The economic magnitude of the impact of such laws is also sizable: the passage of such laws leads to an increase in the number of patents by approximately 7.4% ($= \mathrm{e}^{0.071} - 1$), when compared to firms located in states without such laws.

[Table 4]

In column 2 of Table 4 where the dependent variable is ln(1+CITATION), we show that the coefficient on the indicator SMOKE_FREE is 0.138 and significant at the 5% level. In terms of economic significance, the passage of smoke-free laws leads to an increase in the number of patent citations by approximately 15% ($= \mathrm{e}^{0.138} - 1$).

In columns 3 and 4 of Table 4 where the dependent variables are ln(1+PATENT_PER_EMPLOYEE) and ln(1+CITATION_PER_EMPLOYEE), the number of patents and the number of citations scaled by the number of employees (in 1,000s), we show that the coefficients on the indicator SMOKE_FREE are 0.090 (significant at the 1% level) and 0.148 (significant at the 5% level), respectively. These results imply that the number of patents and the number of citations per 1,000 employees increase by approximately 9.4% and 16%, respectively, in states that have passed smoke-free laws as compared to states without such laws. Our results suggest that employees' productivity in innovation increases significantly after the passage of smoke-free laws.

Atanassov (2013) finds that the adoption of business combination laws leads to a decrease in the number of patents (citations per patent) by approximately 11% (16%). Acharya et al. (2014) find that the adoption of the good-faith exception associated with wrongful discharge laws leads to an increase in the number of patents (patent citations) by approximately 12% (19%). Our main results show similar economic significance as those studies' results.

We show that the coefficients on firm-level control variables are broadly consistent with prior findings (see, e.g., Aghion et al. (2005)). We generally do not find any consistent association between state-level controls and firm innovation output, possibly because we have controlled for firm fixed effects and region × year fixed effects in the regression. Business combination laws are largely negatively associated with innovation output, consistent with Atanassov (2013), whereas wrongful discharge laws do not have any significant effects.

C. Robustness Checks

We perform a large number of robustness checks in Table 5 on our main findings.

[Table 5]

First, we examine whether our results are driven by the states of California and Massachusetts (the two most innovative states in the United States). Panel A of Table 5 presents the results when we repeat the analysis in Table 4 by excluding firms headquartered in these two states and our inference remains unchanged. The coefficients on SMOKE_FREE are 0.067 (significant at the 5% level) and 0.123 (significant at the 10% level) when the dependent variables are ln(1+PATENT) and ln(1+CITATION), respectively (see columns 1 and 2).

Second, there is a concern that a firm's headquarters state may not always be the state where its R&D employees are, which could lead to some measurement error in the indicator

SMOKE_FREE. To address this concern, we obtain the residential information (city and state) of individual inventors, available from the USPTO PatentsView database. We re-compute a firm's number of patents and patent citations by limiting to patents whose inventors reside in the firm's headquarters state. We continue to find a positive effect of smoke-free laws on corporate innovation in Panel B of Table 5.

Third, we include firms that have never filed any patent during our sample period and repeat the analysis in Table 4, and show that our main findings remain unchanged in Panel C of Table 5.

Fourth, while we rely on the most stringent definition of smoke-free laws in our main analysis, we are aware of other less stringent smoke-free laws and have tried to control for them in the regression specification of equation (1). Specifically, following the CDC's categorization, SMOKE_FREE_S is an indicator variable that takes the value of 1 if a firm's headquarters state has passed state-level smoke-free laws that allow smoking in separately ventilated areas, and 0 otherwise, and SMOKE_FREE_D is an indicator variable that takes the value of 1 if a firm's headquarters state has passed state-level smoke-free laws that allow smoking in designated areas, and 0 otherwise. Panel D presents the results where we additionally control for these two state-level smoke-free laws. We find that the coefficients on SMOKE_FREE remain significantly positive and comparable to their counterparts in Table 4. On the other hand, the coefficients on SMOKE_FREE_S and SMOKE_FREE_D are insignificant in most cases. This result validates our choice of adopting the most stringent definition of smoke-free laws, which appears to be more effective in influencing innovation.[16]

[16] We thank an anonymous referee for suggesting to use the most stringent smoke-free laws in our main analysis, and the two more lenient laws as robustness checks.

Fifth, we employ various alternative innovation measures based on patents and citations in Panel E of Table 5. Columns 1–3 present the results when the dependent variables are ln(1+PATENT_PER_RD), ln(1+CITATION_PER_RD), and ln(1+CITATION_PER_PATENT). The coefficient on SMOKE_FREE is positive and significant at the 1% level for ln(1+PATENT_PER_RD), at the 5% level for ln(1+CITATION_PER_RD), and at the 10% level for ln(1+CITATION_PER_PATENT). These results suggest that smoke-free laws have a positive effect on innovative efficiency measured by patent output scaled by R&D input (Cohen, Diether, and Malloy (2013), Hirshleifer, Hsu, and Li (2013)) and the average quality of patent (Hall et al. (2005)). In column 4, we adopt a different approach to adjust forward citations as proposed by Hall et al. (2001). For each patent, we simply scale its forward citation count by the average of forward citations of all patents filed in the same year. We show that the coefficient on SMOKE_FREE is positive and significant at the 5% level.

Sixth, we employ other innovation measures including ln(1+ORIGINALITY), ln(1+GENERALITY), ln(1+PATENT_VALUE), and RD (Trajtenberg, Henderson, and Jaffe (1997), Hsu, Tian, and Xu (2014), and Kogan et al. (2017)) in Panel F of Table 5. In columns 1–3, we show that the coefficients on SMOKE_FREE are positive and significant. In column 4, we find that smoke-free laws also positively affect a firm's R&D expenditures with marginal significance (at the 10% level) and small economic magnitude (0.003). Nonetheless, it is worth noting that the effect of smoke-free laws on innovation cannot be simply attributed to the increase in R&D expenditures because we have shown significantly positive coefficients on SMOKE_FREE in Panel E. Overall, Panels E and F show that the positive effect of smoke-free laws on innovation is robust to different measures that capture firms' innovation output in multiple dimensions.

Finally, there is a general concern that a state's adoption of smoke-free laws might be part of a general program to improve its local firms' business/working conditions and hence we might not be capturing the role of smoking ban in corporate innovation. In particular, Acharya et al. (2014) find that state-level laws that protect employees against unjust dismissal (in particular, the good-faith exception) are positively associated with corporate innovation, and Gao and Zhang (2017) show that the state-level adoption of ENDAs spurs innovation. We note that for the six states that adopted both the good-faith exception and smoke-free laws, the average gap between the two adoptions is 18 years ranging from 9 years apart in Louisiana and 27 years apart in Massachusetts.[17] So it is unlikely that a state's adoption of smoke-free laws that comes on average almost 20 years later is part of a general program that leads to the adoption of better labor protection laws. Nonetheless, we control for the adoption of good-faith exception in all specifications. For the 17 states that adopted both ENDAs and smoke-free laws, the average gap between the two adoptions is 10 years but in a number of cases, the two adoptions are adjacent to each other (New York, Washington, Colorado, and Iowa).

To ensure that our results are not driven by the adoption of ENDAs, we repeat the analysis in Table 4 by controlling for an indicator variable, ENDA, which takes the value of 1 if a firm's headquarters state adopts employment nondiscrimination acts, and 0 otherwise. Panel G of Table 5 presents the results. The coefficients on SMOKE_FREE are 0.067 (significant at the 5% level) and 0.122 (significant at the 5% level) when the dependent variables are ln(1+PATENT) and ln(1+CITATION), respectively.

[17] New Hampshire and Oklahoma adopted and repealed the good-faith exception before the beginning of our sample period. So these two states are not treated as states with the good-faith exception.

Taken together, the results from Table 5 suggest a robust positive impact of smoke-free laws on innovation output.

D. Placebo Tests

To ensure that our main results are not driven purely by chance, we run the following placebo test: for each one of the 34 legislating events, we "assign" a pseudo passage state that is randomly chosen from all the states, and that does not pass such a law within 2 years.[18] We then estimate the baseline regressions in columns 1 and 2 of Table 4 based on those pseudo event years and save the coefficient estimates on the indicator SMOKE_FREE. We repeat this procedure for 5,000 times.

Figure 1 plots the histogram of the coefficient estimates on the indicator SMOKE_FREE based on those pseudo events. Graph A presents the distribution of the coefficient estimates when the dependent variable is ln(1+PATENT). We find that the coefficient estimate of the true effect based on column 1 of Table 4 lies well to the right of the distribution of coefficients estimates from the placebo test. The actual coefficient estimate on SMOKE_FREE (0.071) is about three standard deviations (0.038) above the mean (−0.029) of the distribution. Graph B presents the distribution of the coefficient estimates when the dependent variable is ln(1+CITATION). We find a similar pattern to Graph A: the coefficient estimate of the true effect based on column 2 of Table 4 lies well to the right of the distribution of coefficient

[18] For example, Florida adopted the smoke-free law in 2003. For this legislating event, we "assign" to another state that did not adopt the law over the period 2001–2005 (i.e., a state that adopted the law before 2001, or a state that adopted the law after 2005, or a state that never adopted the law).

estimates generated from the placebo test. These results suggest that it is the passage of smoke-free laws that is behind our main findings.

[Figure 1]

E. The Pre-Treatment Trends

The validity of difference-in-differences tests depends on the parallel trends assumption: without smoke-free laws, the treated firms' innovation output would have evolved in the same way as that of the control firms. To examine pre-treatment trends in innovation output of the treated firms and their control firms, we introduce 7 indicator variables, YEAR_BEFORE3, YEAR_BEFORE2, YEAR_BEFORE1, YEAR_0 (the year in which such laws are passed), YEAR_1, YEAR_2, and YEAR_3_AND_AFTER, to flag the year relative to the passage year. For example, YEAR_BEFORE2 indicates that it is 2 years before the laws' passage; and YEAR_3_AND_AFTER indicates that it is 3 or more years after the laws' passage. We then reestimate equation (1) by replacing the indicator SMOKE_FREE with the 7 indicators as defined previously. The coefficients of interest are those on the indicators YEAR_BEFORE3, YEAR_BEFORE2, and YEAR_BEFORE1 because their magnitude and significance indicate whether there are parallel trends in innovation output between the treated firms and their control firms prior to the treatment. Table 6 presents the results.

[Table 6]

We show that across all 4 columns of Table 6, the coefficients on all three indicators (YEAR_BEFORE3, YEAR_BEFORE2, and YEAR_BEFORE1) are close to 0 and not statistically significant, suggesting that the parallel trends assumption of the difference-in-differences tests is likely met.

The absence of any significant lead effects has at least three implications. First, the adoption of smoke-free laws seems not to be anticipated by the treated firms. Second, even if some treated firms anticipated such law changes, the actual smoking activities in the workplace did not change until the laws took effect. Third, the positive effect of smoke-free laws on innovation is not the result of state lawmakers simply responding to booming innovation activities, which is consistent with the results in Table 3, and further mitigates the reverse causality concern.

We further show that across all 4 columns of Table 6, the coefficients on the indicators YEAR_0 and YEAR_1 are small in magnitude and not statistically significant (except that the coefficient on YEAR_1 is significant at the 10% level in columns 3 and 4). The effect of smoke-free laws shows up 2 years after the laws' passage: the coefficients on the indicator YEAR_2 are positive and significant for all innovation measures (except for column 2), and the coefficients on the indicator YEAR_3_AND_AFTER are many times larger than the coefficients on the indicator YEAR_0 for all four innovation measures, indicating that it takes several years for smoke-free laws to affect corporate innovation.

To further assuage the concern that the parallel trends assumption is not violated, following the method of Autor et al. (2006) and Acharya et al. (2014), Figure 2 provides a visual illustration showing that innovation output increases significantly only after the passage of smoke-free laws.

[Figure 2]

In summary, Table 6 together with Figure 2 shows that the treated firms and their control firms share a similar time trend in innovation output prior to the passage of smoke-free laws, thus supporting the parallel trends assumption necessary for the difference-in-differences tests.

Moreover, it also shows that most of the effect of smoke-free laws on innovation occurs several years after the laws' passage, suggesting a causal interpretation.

F. Unobservable Confounding Local Economic Conditions

Although we have controlled for *observable* local economic conditions in the regression specification of equation (1), some *unobservable* local economic conditions may be associated with both the passage of smoke-free laws and corporate innovation. In this subsection, we difference away unobservable local economic conditions by focusing on treated firms that are on one side of a state's border and their close-by control firms on the other side of the same border.

To do so, we exploit the discontinuity in smoke-free laws across the state's border and examine the change in innovation output of the treated firms on one side of the state's border with such laws in effect relative to their close-by control firms on the other side of the same border without such laws. The logic for this analysis is as follows. Suppose that smoke-free laws are driven by unobservable changes in local economic conditions, and that it is those changes, rather than smoke-free laws, that spur corporate innovation. Then both the treated firms in states with smoke-free laws and their close-by control firms in adjacent states without such laws would spuriously appear to react to the laws' changes, because local economic conditions, unlike the state-level laws, have a tendency to spread across the state's border (Heider and Ljungqvist (2015)). The change in innovation output of the treated firms should be no different from that of their close-by control firms.

To examine this possibility, we match each treated firm to a control firm in the same industry (based on Fama–French 48-industry classification), in an adjacent state without smoke-free laws, and closest in total assets in the year before such laws' passage. Obviously, a treated firm may not necessarily share the same local economic conditions with its control firm in an adjacent state if the treated firm is in the middle of a large state. To alleviate this concern, we further require the distance between the treated firm and its matched control firm to be within 100 miles.[19] If the distance is more than 100 miles, we drop the pair from our sample, resulting in a sample of 1,966 firm-year observations. By doing so, we increase our confidence that the treated firm and its control firm are truly close to each other geographically and thus face similar local economic shocks.[20] We then reestimate equation (1) by using this sample of treated and close-by control firms sharing a common state border. Table 7 presents the results.

[Table 7]

We find that by focusing on close-by firms across state borders to control for unobservable local economic conditions, the coefficients on the indicator SMOKE_FREE are positive and significant (except for column 3 of Table 7). Under the identifying assumption that the control firms are exposed to similar local economic conditions and hence the change in innovation output of the treated firms should be no different from that of their control firms, our findings suggest that any unobservable confounding local economic conditions cannot be driving the observed impact of smoke-free laws on corporate innovation.

G. Heterogeneous Treatment Effects

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[19] As robustness checks, we require the distance between the treated firm and its control firm to be within 60, 80, or 120 miles, and our inferences remain unchanged.

[20] The average distance between the treated and control firm is 58 miles, indicating that they are indeed geographically close.

To provide further evidence that the effect of smoke-free laws on innovation is indeed due to (the absence of) smoking in workplaces, we implement triple-differences tests to explore any heterogeneity in the treatment effect. Evidence of heterogeneous treatment effects helps alleviate the concern that some omitted firm or state variables are driving our results, because such variables would have to be uncorrelated with all the control variables we include in the regression model and would also have to explain the cross-sectional variation in the treatment effect. As pointed out by Claessens and Laeven (2003) and Raddatz (2006), it is less likely to have an omitted variable correlated with the interaction term than with the linear term. We thus explore two possible sources of heterogeneity in the treatment effect.

First, if the improved innovation output after the passage of smoke-free laws is due to reduced cigarette consumption in the workplace, we expect this treatment effect to be stronger for states with stronger enforcement of such laws. We measure the extent of enforcement using the percentage of smokers who have quit smoking in response to such laws, as stronger enforcement is expected to lead to more smokers quitting smoking. We obtain information about the number of smokers who quit smoking in a state and in a given year from the BRFSS, which conducts health-related telephone surveys of U.S. residents across states (see http://www.cdc.gov/brfss/about/index.htm). MORE_QUIT_SMOKING (LESS_QUIT_SMOKING) is an indicator variable that takes the value of 1 if a state's number of smokers who quit smoking normalized by the state's total number of smokers is above (below) the sample top quartile, and 0 otherwise. We then reestimate equation (1) by replacing the indicator SMOKE_FREE with two interaction terms SMOKE_FREE × MORE_QUIT_SMOKING and SMOKE_FREE × LESS_QUIT_SMOKING. Panel A of Table 8 presents the results.

[Table 8]

We show that across all 4 columns of Panel A in Table 8, the coefficients on SMOKE_FREE × MORE_QUIT_SMOKING are positive and significant, while the coefficients on SMOKE_FREE × LESS_QUIT_SMOKING are much weaker in terms of both economic and statistical significance. Take column 1, for example, where the dependent variable is ln(1+PATENT), we show that the coefficient on SMOKE_FREE × MORE_QUIT_SMOKING is 0.193 and significant at the 1% level, while the coefficient on SMOKE_FREE × LESS_QUIT_SMOKING is much smaller in magnitude (only 0.063) and significant at the 5% level. The *F*-test on the equality of these two coefficients indicates that they are significantly different at the 1% level. This result indicates that the treatment effect is more pronounced for firms in states with a large percentage of smokers who have quit smoking (i.e., stronger enforcement of smoke-free laws), and is much weaker for firms in states with a small percentage of smokers who have quit smoking (i.e., weaker enforcement).

Second, if the impact of smoke-free laws on innovation output is truly due to restrictions on smoking, we expect the treatment effect to be stronger for states with weaker pre-existing tobacco controls, which we measure by public funding per smoker in a state for tobacco prevention and control. The data is collected from the University of Illinois at Chicago Health Policy Center – Funding Database, which starts to record state funding for tobacco prevention and control since 1991. To capture the "pre-existing" level of a state's funding for tobacco prevention and control and to avoid using future levels as the conditioning variable that may be endogenous to the passage of smoke-free laws, we lag this variable for 5 years. The HIGH_ PREEXISTING_TOBACCO_CONTROL (LOW_ PREEXISTING_TOBACCO_CONTROL) is an indicator variable that takes the value of 1 if a state's funding per smoker for tobacco prevention and control is above (below) the sample top quartile, and 0 otherwise. We then reestimate equation (1) by replacing the indicator SMOKE_FREE with two interaction terms SMOKE_FREE × HIGH_ PREEXISTING_TOBACCO_CONTROL and SMOKE_FREE × LOW_ PREEXISTING_TOBACCO_CONTROL. Panel B of Table 8 presents the results.

We show that across all 4 columns of Panel B in Table 8, the coefficients on SMOKE_FREE × LOW_ PREEXISTING_TOBACCO_CONTROL are positive and significant, while the coefficients on SMOKE_FREE × HIGH_ PREEXISTING_TOBACCO_CONTROL are much smaller in magnitude and not statistically significant. Take column 1 for example, where the dependent variable is ln(1+PATENT), we show that the coefficient on SMOKE_FREE × LOW_ PREEXISTING_TOBACCO_CONTROL is 0.102 and significant at the 1% level, while the coefficient on SMOKE_FREE × HIGH_ PREEXISTING_TOBACCO_CONTROL is only 0.023 and not significantly different from 0. The *F*-test shows that these two coefficients are significantly different at the 5% level. This result indicates that the treatment effect is significant for firms in states with weaker pre-existing tobacco controls, and is virtually absent for firms in states with stronger pre-existing tobacco controls.

Taken together, the effect of smoke-free laws on corporate innovation is stronger for firms in states with stronger enforcement of such laws and for firms in states with weaker pre-existing tobacco controls. These results suggest that the impact of smoke-free laws on innovation is indeed tied to smoking bans in workplaces.

VI. Channels for Smoke-Free Laws to Affect Innovation

In this section, we provide suggestive evidence that possible channels for smoke-free laws to affect innovation are to improve inventors' health, working environment, and thus their productivity, and to attract more productive inventors.

A. Evidence on Local Residents' Health Improvement

In this subsection, we provide some direct evidence on whether smoke-free laws improve local residents' health conditions, which are closely related to several channels (brain functioning, creativity, and productivity) discussed in Section III. We obtain data from the BRFSS which records individual health conditions since 1993. For each individual, the BRFSS assigns his/her general health condition to one of the following categories: poor, fair, good, very good, and excellent. For our purpose, we convert the category to a numeric value, HEALTH_SCORE, ranging from 1 (poor) to 5 (excellent).

The sample consists of 1,830,905 individuals who have at least 4 years' college education from 1997 to 2015 (because we are particularly interested in the group of people who are more likely to be inventors). [21] In columns 1 and 2 of Table 9, we estimate ordered logistic regressions in which the dependent variable is HEALTH_SCORE. In columns 3 and 4, we estimate logistic regressions in which the dependent variable is GOOD_HEALTH, an indicator variable that takes the value of 1 if the overall health conditions are "very good" or "excellent," and 0 otherwise. In all regressions, we control for various state-level variables used in the baseline regression in Table 4. We also additionally control for an individual's age, gender, and race. Table 9 presents the results. The coefficients on the indicator SMOKE_FREE are positive and significant at the 5%

[21] No states adopted business combination laws after 1997. For this reason, the indicator BUSINESS_COMBINATION is dropped from this analysis due to its collinearity with state fixed effects.

(10%) level when individual's age, gender, and race are included (excluded). These results indicate that smoke-free laws indeed help improve local residents' health conditions, and suggest that smoke-free laws have similar positive effects on local inventors' health.

[Table 9]

B. Evidence on Inventor Productivity

As discussed in Section III, smoke-free laws positively affect innovative activities through improving inventors' productivity. To measure inventors' productivity, we first collect the information on individual inventors from the USPTO PatentsView database. For each patent, the database has the identity and residential information (city and state) of the inventor(s) (i.e., the individual(s) who creates (create) the patent) and the assignee (i.e., the public firm that owns the patent). For each firm in a year, we construct six proxies for inventor productivity: ln(1+PATENT), ln(1+CITATION), ln(1+PATENT_PER_EMPLOYEE), ln(1+CITATION_PER_EMPLOYEE), ln(1+PATENT_PER_INVENTOR), ln(1+CITATION_PER_INVENTOR). We construct the first four variables as defined earlier except that we only consider the patents (and their citations) that are produced by inventors who have stayed in the same firm and in the same state in the sample period to ensure that their output and productivity are not affected by other factors. ln(1+PATENT_PER_INVENTOR) (ln(1+CITATION_PER_INVENTOR)) is defined as the natural logarithmic value of 1 plus the number of patents (citations) created by those stayer inventors divided by the number of those inventors.

Panel A of Table 10 presents the results when we reestimate equation (1) for the aforementioned inventor productivity measures. The unit of analysis is firm-year observation. We find that across columns 1–4, the coefficients on the indicator SMOKE_FREE are positive and significant, and are largely comparable to their counterparts in our baseline result reported in Table 4. Moreover, we find that each inventor indeed produces more patents or patents with more citations (columns 5 and 6). All these results suggest that the innovative productivity of inventors who did not relocate improved after the passage of smoke-free laws. However, due to a lack of data on individual inventors' smoking habits, we are unable to pin down whether the productivity change is mainly driven by smoker or nonsmoker inventors, which can be an interesting question for future research.

[Table 10]

C. Evidence on Labor Productivity

Prior studies have shown that smoke-free laws significantly reduce employees' exposure to secondhand smoke, improve their working environment, cut the productivity loss associated with smoking-related diseases, and thus enhance employees' productivity (Sargent, Shepard, and Glantz (2004), Bartecchi, Alsever, Nevin-Woods, Thomas, Estacio, Bartelson, and Krantz (2006), and World Health Organization (2007)). To examine the effect of smoke-free laws on labor productivity in general, we follow Schoar (2002) to estimate the log-linear Cobb–Douglas production function for firms in each industry-year group (with at least 10 firms). The dependent variable is the natural logarithm of net income (in millions),[22] and the independent variables include the natural logarithm of PPE (in millions), the natural logarithm of the number of employees (in thousands), and the natural logarithm of 1 plus R&D expenditures (in millions). We then use the coefficient on ln(EMPLOYEE) as the measure of labor productivity for each industry in the year. We then assign this productivity estimate to all firms in the same year, and

[22] If the value of net income is negative, the dependent variable is set as –ln(net income). For example, when the value of net income is –3 million$, the dependent variable is –ln (3).

reestimate equation (1) using this labor productivity measure as the dependent variable. Panel B of Table 10 shows that the coefficient on the indicator SMOKE_FREE is 0.039 and significant at the 5% level, suggesting a positive effect of smoking ban on employee productivity.[23]

D. Evidence on Inventor Relocation

In this subsection, we provide suggestive evidence that another channel for smoke-free laws to affect innovation is by attracting more productive inventors.

We implement a difference-in-differences test examining the impact of smoke-free laws on inventor relocation by running the following regression:

$$(2)\ \mathrm{INVENTOR\_FLOW}_{st} = \alpha + \beta_1 \mathrm{SMOKE\_FREE}_{st} + \beta_2 \mathrm{STATE\_CHARACTERISTICS}_{st} + \mathrm{STATE\_FE} + \mathrm{REGION\_YEAR\_FE} + \varepsilon_{ist}\ ,$$

where $\mathrm{INVENTOR\_FLOW}_{st}$ is the natural logarithm of 1 plus the number of inventors coming in (moving out) for state *s* in year *t*. Panel A of Table 11 presents the results. The unit of analysis is state-year observation.

[Table 11]

[23] The improvement in productivity of general workers may also enhance the productivity of inventors in the following way. Suppose that a firm's production function includes both the innovative human capital (innovators) and non-innovative human capital (e.g., blue-collar workers, who are more likely to be smokers), that are complements. Productivity increases from workers in manufacturing and sales could spur innovators to develop more patents that help improve firms' products. Thus, it is possible that smoke-free laws enhance innovation by first increasing productivity of general workers. A formal test of this channel would require detailed data on the role of these two types of human capital in a firm's production function, which could be an interesting area for future research.

In column 1 of Table 11, the dependent variable is ln(1+INFLOW_FROM_STATES_WITHOUT_SMOKE_FREE_LAWS), capturing the number of newly arrived inventors who previously worked in a state without smoke-free laws. We show that the coefficient on the indicator SMOKE_FREE is positive and significant at the 5% level, suggesting that inventors are more likely to move from states without smoke-free laws to states with such laws. In column 2, the dependent variable is ln(1 + OUTFLOW_TO_STATES_WITHOUT_SMOKE_FREE_LAWS), capturing the number of departed inventors who relocate into a state without such laws. We show that the coefficient on the indicator SMOKE_FREE is negative but insignificant.

To capture the net effect of the passage of smoke-free laws on inventor relocation from states without such laws, we define NET_INFLOW_FROM_STATES_WITHOUT_SMOKE_FREE_LAWS = INFLOW_FROM_STATES_WITHOUT_SMOKE_FREE_LAWS – OUTFLOW_TO_STATES_WITHOUT_SMOKE_FREE_LAWS. Column 3 of Table 11 presents the results.[24] We find a significantly positive coefficient on the indicator SMOKE_FREE, suggesting that the number of newly arrived inventors from states without smoke-free laws significantly exceeds the number of departed inventors who relocate into states without such laws. This finding is not surprising, considering that about 80% of the U.S.

[24] If the value of NET_INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS is negative, the dependent variable is set as –Ln (1 + the absolute value of NET_INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS). For example, when the value of NET_INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS is –5, the dependent variable is –Ln (6).

population are nonsmokers and thus there are more nonsmoker inventors likely to relocate to benefit from smoke-free laws.

As a placebo test, we examine the effect of the passage of smoke-free laws on inventor relocation from states with such laws. In column 4 of Table 11, the dependent variable is ln(1+INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS), and we show that the coefficient on the indicator SMOKE_FREE is not significantly different from 0. In column 5, the dependent variable is ln(1+OUTFLOW_TO_STATES_WITH_SMOKE_FREE_LAWS), and we show that the coefficient on the indicator SMOKE_FREE is not significantly different from 0. To capture the net effect, we define NET_INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS = INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS – OUTFLOW_TO_STATES_WITH_SMOKE_FREE_LAWS. Column 6 presents the results. We show that the coefficient on the indicator SMOKE_FREE is not significantly different from 0, suggesting that among states with smoke-free laws, a similar number of inventors arrive and depart. In summary, Panel A shows that the passage of smoke-free laws indeed attracts inventors.[25]

Next, we examine the productivity of newly arrived and departed inventors. Newly arrived inventors are those who relocated from other states within 3 years after their destination

[25] This result could also be driven by the relocation of firms (instead of only some of their inventors) to states that have adopted smoke-free laws. However, we find very few cases of firm relocation: only 65 firms relocated from states without smoke-free laws to states with smoke-free laws. On average the relocation occurred 4 years after the laws' passage in the destination states. We thus conclude that our finding is primarily driven by inventor relocation.

state adopted smoke-free laws. Departed inventors are those who moved to other states within 3 years after their home state adopted smoke-free laws. For each inventor, we track her patents applied for (and eventually awarded), and the number of patent citations received by those patents over our sample period. Panel B of Table 11 presents the results. The unit of analysis is at the inventor level.

We show that at the median, newly arrived inventors have 9 patents (or 13% more) during our sample period, while departed inventors have 8 patents. The difference is significant at the 1% level. In terms of the number of citations, the median newly arrived inventor receives a significantly larger number of 98 citations (or 9% more), while the median departed inventor receives 90 citations. We obtain similar findings when using the mean values. These results indicate that the productivity of newly arrived inventors is significantly greater than that of departed inventors, consistent with the observed increase in corporate innovation following the passage of smoke-free laws. Overall, Table 11 provides supporting evidence that one mechanism through which smoke-free laws affect innovation is the relocation of more productive inventors into states with such laws.

Taken together, Tables 9–11 provide supportive evidence on the possible channels for smoke-free laws to affect innovation: improving inventor health and productivity as well as attracting more productive inventors.[26]

E. Other Possible Channels

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[26] It is also worth noting that these channels could reinforce each other: the inflow of more productive inventors could further enhance the productivity of all inventors when working with more productive colleagues.

An alternative possible channel is through reducing smoking-related expenditures. Smoke-free laws could reduce firms' smoking-related expenses such as maintenance costs, legal liabilities coming from nonsmokers, and insurance policies due to risk of fires and accidental injuries. Cash windfall from lower smoking-related expenditures could lead to more financial slacks available to corporate innovation and thus generating greater patenting output. A formal test of such channel would require information on firms' smoking-related expenses and how firms allocate their cash windfall from those savings, which is unfortunately not available at this moment.

Another possible channel is through reducing employee resentment. Smoker and nonsmoker employees may have disagreement over their firm policy regarding smoking in workplaces. This resentment could prevent communications, idea exchanges, and cooperation among employees, especially among smoker and nonsmoker employees, which hinders innovations. A state-wide ban on smoking in workplaces helps settle the matter, leading to better employee cooperation and thus greater innovation output. Investigating this channel would require detailed information on employees' attitudes toward smoking bans, which is beyond the scope of this paper.

F. Further Discussions

Thus far, we have provided evidence on the causal effect of smoke-free laws on corporate innovation. In addition to state-level smoke-free laws, nonsmoker inventors may obtain some protection from firm or local municipality smoking-related policies prior to the passage of state-level laws. Although state-level smoke-free laws complement those policies, the presence of pre-existing (firm- or municipality-level) smoking-related policies would work against us finding a significant effect of such state-level laws on corporate innovation. It is thus likely that we actually underestimate the real effect of state-level smoke-free laws on innovation in this paper.

It is also possible that the observed effect of state-level smoke-free laws on corporate innovation is part of legislating states' general programs to improve business/working conditions, which couple smoke-free laws with other business-promoting policies that may foster innovation. We have already explored and dismissed the possible confounding effect from the adoption of ENDAs, and believe that the above concern is less likely to be valid for the following reasons.

First, as we discussed in Section II, a review of the political economy behind the adoption of smoke-free laws shows that their adoption largely depends on the support of political elites, public opinions toward smoking control, and the relative strength of anti-smoking groups and the tobacco industry. To the best of our knowledge, there is no evidence that the above factors are directly related to corporate innovation and our Table 3 confirms that the adoption of smoke-free laws are exogenous to firms' innovation activities. Second, throughout our analyses, we have included firm fixed effects, various state characteristics, and regional time trends, which should help account for the effect of other business-promoting policies to a certain degree. Third, cross-sectional variations in the treatment effect documented in Section V.G indicate that the effect of smoke-free laws on corporate innovation is indeed tied to restrictions on smoking in workplaces. This helps alleviate the omitted variable concern, because an omitted variable is more likely to be correlated with the linear term, but less likely to be correlated with the interaction terms (Claessens and Laeven (2003), Raddatz (2006)). Nevertheless, as in any research design that uses policy variations, we cannot completely rule out the existence of unexplored confounds whose influence coincides geographically with that of the variation in smoke-free laws we exploit for identification. The readers should be aware of this possible limitation when deciding how our findings might be generalized.

VII. Conclusions

In this paper, we investigate the effect of U.S. state-level smoke-free laws on corporate innovation. We find a significant increase in firms' innovation output and productivity following the passage of smoke-free laws, relative to firms in states without such laws. We further show that our results are robust to various alternative measures of innovation and that the observed effect of smoke-free laws on innovation is unlikely driven by chance. We then conduct a number of tests in support of a causal interpretation of our findings. Our tests of parallel trends show that there is no time trend difference in innovation output between firms in states that later adopt smoke-free laws and firms in states without such laws, and that the improvement in innovation output occurs several years after the passage of such laws. Our tests employing the treated firms and their close-by control firms just across a state's border show that our results are unlikely to be driven by unobservable confounding local economic factors that would have affected both the treated and control firms similarly. Further, we present cross-sectional variations in the treatment effect suggesting that the treatment effect is indeed related to smoking bans in workplaces: the impact of smoke-free laws on corporate innovation is more pronounced for firms in states with stronger enforcement of such laws and for firms in states with weaker pre-existing tobacco controls.

Finally, we provide some suggestive evidence on the underlying mechanisms: i) the improvement in local residents' health conditions after their states' adoption of smoke-free laws; ii) the productivity increase of inventors who did not move following the law change, and iii) the relocation of more productive nonsmoker inventors into the legislating state. Overall, our findings are consistent with the notion that a healthy working environment helps spur corporate innovation.

Our paper has important policy implications for curbing smoking. Our results suggest that policies aimed at promoting healthier working environments can have real economic consequences in terms of promoting creative and innovative activities. This finding is particularly timely and relevant because of the ongoing debate on whether to ban smoking in workplaces across the United States and the rest of the world.

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Appendix. Variable Definitions

Measures of Innovation

PATENT: Number of patents that are applied for (and subsequently awarded) by a firm in a given year.

ln(1+PATENT): The natural logarithm of (1 + PATENT).

CITATION: The sum of adjusted forward citation counts received by patents applied for by a firm in a given year. We follow Hall et al. ((2001), Sec. III.2) to adjust patent citations. In the first step, we calculate the average of forward citations of all patents in the same technology class and filed in the same year, and name this number as a class-year average. In the second step, we calculate the average of forward citations of all patents in the same technology class, and name this number as a class average. The adjustment factor for each class in each filing year will then be a class-year average scaled by the corresponding class average. This adjustment factor thus captures the variation across years but not across classes. In the third step, we scale each patent's forward citation count by the corresponding adjustment factor. Since the adjustment factor only captures yearly variation, the adjusted citation count still contains class variation but is purged of yearly variation. In the last step, we sum up the adjusted citation counts of all patents filed by a firm in a year.

ln(1+CITATION): The natural logarithm of (1 + CITATION).

PATENT_PER_EMPLOYEE: PATENT scaled by the number of employees (in 1,000s).

ln(1+PATENT_PER_EMPLOYEE): The natural logarithm of (1 + PATENT_PER_EMPLOYEE).

CITATION_PER_EMPLOYEE: CITATION scaled by the number of employees (in 1,000s).

ln(1+CITATION_PER_EMPLOYEE): The natural logarithm of (1 + CITATION_PER_EMPLOYEE).

CITATION_PER_PATENT: CITATION scaled by PATENT

PATENT_PER_INVENTOR: PATENT scaled by the number of inventors.

CITATION_PER_INVENTOR: CITATION scaled by the number of inventors.

CITATION_YEAR: The sum of adjusted forward citation counts received by patents applied for by a firm in a given year. We scale each patent's forward citation count by the average of forward citations of all patents filed in the same year.

PATENT_PER_RD: PATENT scaled by R&D expenditures (in millions).

CITATION_PER_RD: CITATION scaled by R&D expenditures (in millions).

ORIGINALITY: Sum of originality scores of patents applied for (and subsequently awarded) by a firm in a given year. The originality score of each patent is defined as 1 minus the Herfindahl index of the CPC technology class distribution of all patents that have been cited by the designated patent.

GENERALITY: Sum of generality scores of patents applied for (and subsequently awarded) by a firm in a given year. The generality score of each patent is defined as 1 minus the Herfindahl index of the CPC technology class distribution of all patents that have cited the designated patent.

PATENT_VALUE: Sum of market values of patents applied for (and subsequently awarded) by a firm in a given year. The market value of each patent is measured by the market capitalization change (benchmarked against the market return) over a 3-day window (*t*,

t + 2) starting on the announcement day of a patent being approved (day t), following Kogan et al. (2017).

Firm Characteristics

FIRM_SIZE: The natural logarithm of the number of employees.

CASH: Cash and short-term investments normalized by book value of total assets.

RD: R&D expenditures normalized by book value of lagged total assets. If R&D expenditures is missing, we set the missing value to 0.

RD_MISSING: An indicator variable that takes the value of 1 if R&D expenditures is missing, and 0 otherwise.

ROA: EBITDA normalized by book value of lagged total assets.

PPE: Gross property, plant, and equipment normalized by book value of total assets.

LEVERAGE: Total debt normalized by book value of total assets.

CAPEX: Capital expenditures normalized by book value of lagged total assets.

TOBIN_Q: Market value of equity plus book value of total assets minus book value of equity minus balance sheet deferred taxes, normalized by book value of total assets.

H_INDEX: Sum of squared sales-based market shares of all firms in the same industry. Industry is defined using the Fama–French 48-industry definitions.

FIRM_AGE: Number of years since a firm’s first appearance in Compustat/CRSP.

LABOR_PRODUCTIVITY: Following Schoar (2002), we run the log-linear Cobb–Douglas production function for firms in each industry-year group (with at least 10 firms). The dependent variable is the natural logarithm of net income (−1 times the natural logarithm of the absolute value of net income), and the independent variables include the natural logarithm of PPE, and the natural logarithm of the number of employees, and the natural logarithm of 1 plus R&D expenditures. We then use the coefficient on ln(EMPLOYEE) as the measure of labor productivity for each industry in the year.

State Characteristics

SMOKE_FREE: An indicator variable that takes the value of 1 if the state (where a firm's headquarters are located) has passed state-level smoke-free laws that ban smoking in workplaces, and 0 otherwise.

SMOKE_FREE_S: An indicator variable that takes the value of 1 if the state (where a firm's headquarters are located) has passed state-level smoke-free laws that allow smoking in separate ventilated areas, and 0 otherwise.

SMOKE_FREE_D: An indicator variable that takes the value of 1 if the state (where a firm's headquarters are located) has passed state-level smoke-free laws that allow smoking in designated areas, and 0 otherwise.

STATE_GDP: Annual GDP of a state.

STATE_POPULATION: Population of a state.

STATE_UNEMPLOYMENT: The unemployment rate of a state, calculated as the average unemployment rate over a 12-month period.

STATE_RD_EXPENDITURES: Total R&D expenditures in a state normalized by state nominal GDP.

DEMOCRAT_GOVERNOR: An indicator variable that takes the value of 1 if the state is governed by a Democrat in a given year, 0 otherwise.

STATE_COLLEGE_DEGREE: Percentage of adults who are college graduates in a state.

STATE_SMOKER: Percentage of adults who are smokers in a state.

BUSINESS_COMBINATION: An indicator variable that takes the value of 1 if a state (where a firm is incorporated) has passes business combination laws in a given year, and 0 otherwise.

GOOD_FAITH: An indicator variable that takes the value of 1 if the state (where a firm's headquarters are located) has recognized the "good faith exception" to employment-at-will in a given year, and 0 otherwise.

ENDA: An indicator variable that takes the value of 1 if the state (where a firm's headquarters are located) has adopted ENDAs in a given year, and 0 otherwise.

MORE_QUIT_SMOKING: An indicator variable that takes the value of 1 if the percentage of smoke quitters in a state is in the top quartile of the sample in the year after the adoption of state-level smoke-free laws, and 0 otherwise. Smoke quitter is a person who has consumed more than 100 cigarettes in his lifetime but is currently not a smoker. We normalize the number of smoke quitters with the number of people who have consumed more than 100 cigarettes in their lifetime in that state.

LESS_QUIT_SMOKING: 1 − MORE_QUIT_SMOKING.

HIGH_PREEXISTING_TOBACCO_CONTROL: An indicator variable that takes the value of 1 if a state's funding per smoker for tobacco prevention and control 5 years ago is in the top quartile of the sample in the year, and 0 otherwise.

LOW_PREEXISTING_TOBACCO_CONTROL: 1 − HIGH_PREEXISTING_TOBACCO_CONTROL.

INFLOW_FROM_STATES_WITHOUT_SMOKE_FREE_LAWS: The number of newly arrived inventors who previously applied for patents in a state that has not adopted smoke-free laws.

OUTFLOW_TO_STATES_WITHOUT_SMOKE_FREE_LAWS: The number of departed inventors to a state that has not adopted smoke-free laws.

NET_INFLOW_FROM_STATES_WITHOUT_SMOKE_FREE_LAWS: INFLOW_FROM_STATES_WITHOUT_SMOKE_FREE_LAWS − OUTFLOW_TO_STATES_WITHOUT_SMOKE_FREE_LAWS.

INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS: The number of newly arrived inventors who previously applied for patents in a state that has adopted smoke-free laws.

OUTFLOW_TO_STATES_WITH_SMOKE_FREE_LAWS: The number of departed inventors to a state that has adopted smoke-free laws.

NET_INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS: INFLOW_FROM_STATES_WITH_SMOKE_FREE_LAWS − OUTFLOW_TO_STATES_WITH_SMOKE_FREE_LAWS.

Personal Characteristics

HEALTH_SCORE: It ranges from 1 to 5, corresponding to the overall health condition being "poor," "fair," "good," "very good," and "excellent."

GOOD_HEALTH: An indicator variable that takes the value of 1 if the overall health conditions are "very good" or "excellent," and 0 otherwise.

AGE: The age of the person.

MALE: An indicator variable that takes the value of 1 if the person is a male, and 0 otherwise.

WHITE: An indicator variable that takes the value of 1 if the person is white, and 0 otherwise.

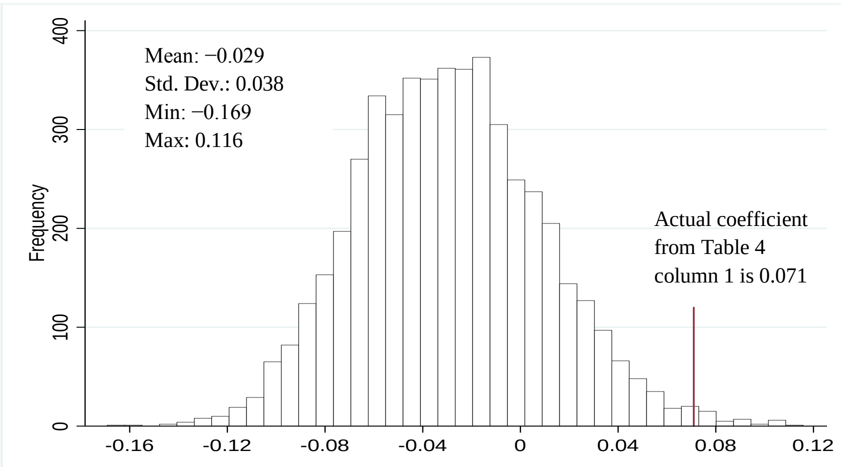
FIGURE 1

Placebo Tests

Figure 1 plots the histogram of the coefficient estimates on the indicator SMOKE_FREE from 5,000 bootstrap simulations of the baseline model used in Table 4. For each legislating event, we "assign" a pseudo passage state that is randomly chosen from all the states, and that does not pass such a law within 2 years. We then estimate the baseline regressions in columns 1 and 2 of Table 4 based on those pseudo event years and save the coefficient estimates on the indicator SMOKE_FREE. We repeat this procedure for 5,000 times. Graph A reports the distribution of the coefficient estimates when the dependent variable is ln(1+PATENT). Graph B reports the distribution of the coefficient estimates when the dependent variable is ln(1+CITATION).

FIGURE 1 (continued)

Graph A. The Histogram of the Coefficient Estimates on SMOKE_FREE When the Dependent Variable Is ln(1+PATENT)



Graph B. The Histogram of the Coefficient Estimates on SMOKE_FREE When the Dependent Variable Is ln(1+CITATION)

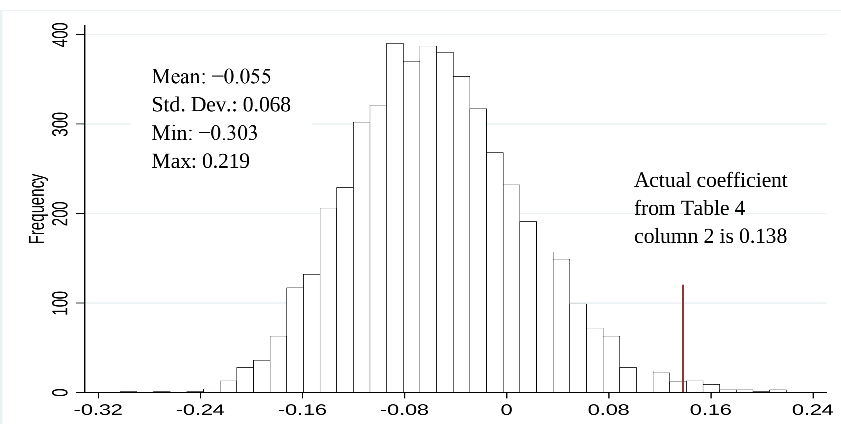


FIGURE 2

Effects of State-Level Smoke-Free Laws on Corporate Innovation

Following the method of Autor et al. (2006) and Acharya et al. (2014), Figure 2 plots the effects of state-level smoke-free laws on corporate innovation in legislating states, using the difference-in-differences specification specified below, relative to non-legislating states, from 9 years prior to the passage of smoke-free laws (Year 0) to 9 years afterward. We choose such a 19-year window because our sample period spans 19 years over 1997–2015. In particular, Figure 2 plots point estimates of the coefficients $\beta_n's$ from running the following regression: $\mathrm{INNOVATION}_{ist} = \alpha + \beta_{\mathrm{BEFORE}\,-3} \times \mathrm{EVENT\_YEAR}_{st}^{\mathrm{BEFORE}\,-3} + \beta_{-3} \times \mathrm{EVENT\_YEAR}_{st}^{-3} + \beta_{-2} \times \mathrm{EVENT\_YEAR}_{st}^{-2} + \beta_{-1} \times \mathrm{EVENT\_YEAR}_{st}^{-1} + \beta_0 \times \mathrm{EVENT\_YEAR}_{st}^{0} + \beta_1 \times \mathrm{EVENT\_YEAR}_{st}^{1} + \beta_2 \times \mathrm{EVENT\_YEAR}_{st}^{2} + \beta_3 \times \mathrm{EVENT\_YEAR}_{st}^{3} + \beta_{\mathrm{AFTER}\,3} \times \mathrm{EVENT\_YEAR}_{st}^{\mathrm{AFTER}\,3} + \mathrm{FIRM\_FE} + \mathrm{REGION\_YEAR\_FE} + \varepsilon_{ist}$. Innovation denotes the natural log of PATENT or CITATION of firm *i* in state *s* in year *t*. *n* denotes the year relative to the passage of smoke-free laws. For example, $\mathrm{EVENT\_YEAR}_{st}^{\mathrm{BEFORE}\,-3}$ denotes an indicator variable that equals 1 if firm *i* in year *t* that ranges from Year −9 to Year −4 of smoke-free laws and 0 otherwise. $\mathrm{EVENT\_YEAR}_{st}^{-3}$ denotes an indicator variable that equals 1 if firm *i* in year *t* that is in Year −3 of smoke-free laws and 0 otherwise. $\mathrm{EVENT\_YEAR}_{st}^{2}$ denotes an indicator variable that equals 1 if firm *i* in year *t* that is in Year 2 of smoke-free laws and 0 otherwise.

FIGURE 2 (continued)

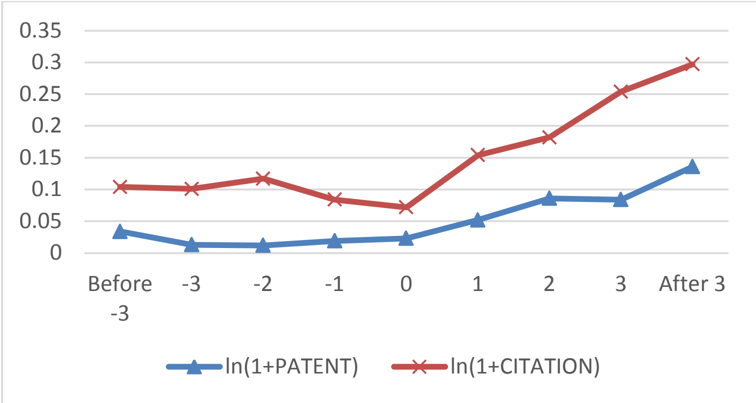


TABLE 1

List of States Legislating Smoke-Free Laws

Table 1 lists the years when different states adopted smoke-free laws that ban smoking in the workplace.

State	Law	Effective Year
Delaware	DEL. CODE ANN. tit. 16 § 2903(e)	2002
South Dakota	S.D. CODIFIED LAWS § 22-36-2 & 22-36-4	2002
Florida	FLA. STAT. ANN. § 386.204	2003
New York	N.Y. PUB. HEALTH LAW §§ 1399-n and 1399-o	2003
Massachusetts	Mass. Gen. Laws 270, § 22 (b)(2)	2004
Montana	MONT. CODE ANN. § 50-40-104	2005
North Dakota	N.D. CENT. CODE § 23-12-10 (1)	2005
Rhode Island	R.I. Gen. Laws § 23-20.10-4	2005
Washington	WASH. REV. CODE §§ 70.160.020, -.030	2005
Arkansas	ARK. CODE ANN. § 20-27-1804 (b)(1)	2006
Colorado	COLO. REV. STAT. ANN. § 25-14-204 (1)(k)(I)	2006
District of Columbia	D.C. CODE ANN. § 7-742 (2)	2006
Hawaii	HAW. REV. STAT. ANN. § 328J-4	2006
Nevada	NEV. REV. STAT. ANN. § 202.2483 (1)	2006
New Jersey	N.J. REV. STAT. § 26:3D-58	2006
Ohio	OHIO REV. CODE ANN. § 3794.02 (a)	2006
Utah	UTAH CODE ANN. § 26-38-8	2006
Arizona	ARIZ. REV. STAT. ANN. § 36-601.01 (b)	2007
Louisiana	LA. REV. STAT. ANN. § 40:1300.256 (a)(3)	2007
Minnesota	MINN. STAT. §§ 144.413 (1)(b) & 144.414 (1)	2007
Tennessee	TENN. CODE ANN. § 39-17-1803 (a)(2)	2007
New Mexico	N.M. STAT. ANN. § 24-16-4 (A)	2007
Illinois	410 ILL. COMP. STAT. ANN. §§ 82/10 & 82/15	2008
Iowa	IOWA CODE ANN. § 142D.3	2008
Maryland	Md. HEALTH-GENERAL Code Ann. § 24-504	2008
Pennsylvania	35 PA. CONS. STAT. ANN. §§ 637.2 and 637.3(a)	2008
Maine	ME. REV. STAT. ANN. tit. 22, § 1580-A	2009
Nebraska	NEB. REV. STAT. §§ 71-5724 and 71-5729	2009
Oregon	OR. REV. STAT. §§ 433.835 and 433.845	2009
Vermont	VT. STAT. ANN. tit. 18, § 1421	2009
Kansas	KAN. STAT. ANN. §§ 21-4009 and 21-4010	2010
Michigan	MICH. COMP. LAWS ANN. §§ 333.12601 and 333.12603	2010
Wisconsin	WIS. STAT. § 101.123	2010
Indiana	IND. CODE. ANN. § 7.1-5-12-4	2012

TABLE 2

Summary Statistics

The sample consists of 36,337 firm-year observations over the period 1997–2015, obtained from merging the Compustat database with the USPTO PatentsView database. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	Mean	Std. Dev.	P25	Median	P75
PATENT	31.21	95.07	2	4	16
CITATION	518.03	1484.51	12.38	60.35	274.77
PATENT_PER_EMPLOYEE	18.92	36.67	1.29	5.03	18.35
CITATION_PER_EMPLOYEE	426.46	1164.21	6.92	49.34	267.52
EMPLOYEE (thousands)	8.69	22.87	0.21	0.98	5.34
CASH	26.93%	26.26%	5.08%	17.75%	42.66%
RD	11.68%	19.08%	0.32%	4.53%	14.19%
RD_MISSING	0.20	0.40	0	0	0
ROA	1.11%	33.82%	-3.02%	10.20%	17.85%
PPE	43.15%	33.58%	17.56%	34.08%	60.19%
LEVERAGE	18.95%	21.33%	0.33%	13.29%	29.97%
CAPEX	5.34%	6.51%	1.65%	3.32%	6.36%
TOBIN_Q	2.40	2.09	1.20	1.69	2.73
H_INDEX	0.09	0.07	0.05	0.06	0.10
FIRM_AGE	21.02	15.68	9	16	29
STATE_GDP (trillion $)	0.76	0.63	0.26	0.48	1.20
STATE_POPULATION (million)	16.30	12.31	6.12	11.57	26.48
STATE_UNEMPLOYMENT	5.90%	1.99	4.61	5.41	6.68
STATE_RD_EXPENDITURES	2.92%	1.33	1.79	2.60	4.04
DEMOCRAT_GOVERNOR	0.44	0.50	0	0	1.00
STATE_COLLEGE_DEGREE	34.57%	5.45%	30.54%	35.10%	39.52%
STATE_SMOKER	18.07%	4.14%	14.67%	18.01%	21.57%
BUSINESS_COMBINATION	0.91	0.29	1	1	1
GOOD_FAITH	0.38	0.48	0	0	1

TABLE 3

The Timing of Adopting Smoke-Free Laws: The Duration Model

Table 3 estimates a Weibull hazard model where the "failure event" is the adoption of smoke-free laws in a given U.S. state. The sample consists of all U.S. states over our sample period with treated states dropped from the sample once they have adopted smoke-free laws. AVG_ln(1+PATENT) is the average ln(1+PATENT) across all firms headquartered in a state. AVG_ln(1+CITATION) is the average ln(1+CITATION) across all firms headquartered in a state. AVG_ln(1+PATENT_PER_EMPLOYEE) is the average ln(1+PATENT_PER_EMPLOYEE) across all firms headquartered in a state. AVG_ln(1+CITATION_PER_EMPLOYEE) is the average ln(1+CITATION_PER_EMPLOYEE) across all firms headquartered in a state. All independent variables are at the state level. Variable definitions are provided in the Appendix. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 3 (continued)

Variable	1	2	3	4
AVG_ln(1+PATENT)	0.012 (0.379)			
AVG_ln(1+CITATION)		0.115 (0.183)		
AVG_ln(1+PATENT_PER_EMPLOYEE)			0.145 (0.500)	
AVG_ln(1+CITATION_PER_EMPLOYEE)				0.172 (0.231)
ln(STATE_GDP)	0.753 (1.825)	1.090 (1.789)	0.884 (1.756)	1.082 (1.719)
ln(STATE_POPULATION)	-0.927 (1.955)	-1.291 (1.909)	-1.078 (1.890)	-1.290 (1.834)
STATE_UNEMPLOYMENT	-5.799 (11.947)	-6.886 (11.971)	-6.124 (12.023)	-7.124 (12.143)
STATE_RD_EXPENDITURES	13.564 (14.902)	12.674 (15.622)	12.859 (15.095)	12.152 (15.864)
DEMOCRAT_GOVERNOR	0.102 (0.422)	0.101 (0.417)	0.095 (0.423)	0.100 (0.416)
STATE_COLLEGE_DEGREE	-0.914 (5.767)	-1.153 (5.757)	-1.168 (5.854)	-1.404 (5.800)
STATE_SMOKER	-9.474 (8.707)	-8.537 (8.632)	-8.890 (9.058)	-8.258 (8.745)
BUSINESS_COMBINATION	0.409 (0.454)	0.317 (0.446)	0.401 (0.418)	0.346 (0.424)
GOOD_FAITH	-0.771 (0.807)	-0.846 (0.817)	-0.813 (0.793)	-0.836 (0.786)
Constant	0.573 (10.212)	1.770 (9.943)	1.112 (9.876)	1.653 (9.598)
No. of obs.	650	650	650	650
χ^2	7.44	7.45	7.44	7.65

TABLE 4

The Effect of State-Level Smoke-Free Laws on Corporate Innovation

Table 4 examines the effect of state-level smoke-free laws on corporate innovation using the difference-in-differences specification in equation (1). Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 4 (continued)

Variable	ln(1+PATENT) 1	ln(1+CITATION) 2	ln(1+PATENT_ PER_EMPLOYEE) 3	ln(1+CITATION_ PER_EMPLOYEE) 4
SMOKE_FREE	0.071***	0.138**	0.090***	0.148**
	(0.026)	(0.056)	(0.033)	(0.061)
FIRM_SIZE	0.265***	0.418***	-0.048*	0.109***
	(0.030)	(0.046)	(0.024)	(0.040)
CASH	0.262***	0.553***	0.490***	0.770***
	(0.047)	(0.120)	(0.090)	(0.166)
RD	0.038	0.149	0.193**	0.244
	(0.058)	(0.120)	(0.085)	(0.151)
RD_MISSING	-0.063**	-0.094	-0.077*	-0.131
	(0.026)	(0.070)	(0.045)	(0.082)
ROA	-0.047	-0.075	-0.040	-0.074
	(0.049)	(0.074)	(0.053)	(0.082)
PPE	0.024	-0.004	0.007	-0.012
	(0.042)	(0.084)	(0.038)	(0.067)
LEVERAGE	-0.100**	-0.292***	-0.279***	-0.499***
	(0.038)	(0.080)	(0.045)	(0.090)
CAPEX	-0.134	-0.051	-0.205	-0.292
	(0.099)	(0.240)	(0.166)	(0.299)
TOBIN_Q	-0.004	0.007	-0.001	0.019**
	(0.003)	(0.006)	(0.005)	(0.008)
H_INDEX	0.259	0.181	0.214	0.389
	(0.441)	(0.859)	(0.418)	(0.884)
H_INDEX^2	0.030	0.416	-0.043	-0.275
	(0.705)	(1.304)	(0.788)	(1.533)
ln(FIRM_AGE)	-0.014	-0.126	-0.176***	-0.488***
	(0.042)	(0.108)	(0.060)	(0.128)

Variable	ln(1+PATENT) 1	ln(1+CITATION) 2	ln(1+PATENT_ PER_EMPLOYEE) 3	ln(1+CITATION_ PER_EMPLOYEE) 4
ln(STATE_GDP)	-0.045	0.097	-0.085	-0.014
	(0.215)	(0.433)	(0.156)	(0.368)
ln(STATE_POPULATION)	0.046	-0.101	0.079	-0.006
	(0.218)	(0.440)	(0.160)	(0.377)
STATE_UNEMPLOYMENT	-0.367	0.134	-0.226	1.374
	(0.987)	(2.052)	(1.208)	(2.171)
STATE_RD_EXPENDITURES	0.367	-1.526	-1.278	-4.043
	(1.378)	(3.027)	(1.346)	(3.079)
DEMOCRAT_GOVERNOR	-0.008	-0.005	0.005	0.003
	(0.015)	(0.032)	(0.018)	(0.035)
STATE_COLLEGE_DEGREE	-0.392	-0.794	0.293	0.081
	(0.391)	(0.767)	(0.386)	(0.831)
STATE_SMOKER	-0.255	-1.003	-0.792	-1.835
	(0.552)	(1.282)	(0.630)	(1.607)
BUSINESS_COMBINATION	-0.043	-0.166*	-0.142***	-0.306*
	(0.033)	(0.084)	(0.052)	(0.153)
GOOD_FAITH	0.041	0.156	0.080	0.180
	(0.047)	(0.108)	(0.059)	(0.129)
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
Constant	1.479	4.339**	1.758**	4.854***
	(0.974)	(1.902)	(0.740)	(1.744)
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.826	0.701	0.647	0.592

TABLE 5

Robustness Checks

Table 5 reports different robustness checks on the effect of state-level smoke-free laws on corporate innovation using the difference-in-differences specification in equation (1). In Panel A, we exclude the states of California and Massachusetts. In Panel B, we only count the number of patents (citations) by inventors located in the headquarters state. In Panel C, we drop the requirement that firms have at least 1 patent during our sample period. In Panel D, we include all three types of smoke-free laws. Panels E and F examine the effect of state-level smoke-free laws on corporate innovation using alternative innovation measures. Panel G includes ENDA. All the control variables used in Table 4 are also included in this regression (except that we do not include RD, RD_MISSING as the control variables in column 4 of Panel F) but unreported for brevity. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 5 (continued)

Variable	ln(1+PATENT) 1	ln(1+CITATION) 2	ln(1+PATENT_ PER_EMPLOYEE) 3	ln(1+CITATION_ PER_EMPLOYEE) 4
Panel A. Excluding the States of California and Massachusetts				
SMOKE_FREE	0.067**	0.123*	0.063**	0.090*
	(0.031)	(0.063)	(0.028)	(0.051)
Other controls		Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	24,812	24,812	24,812	24,812
Adj. R^2	0.827	0.697	0.628	0.573
Panel B. Limiting to Inventors Located in the Headquarters State				
SMOKE_FREE	0.043*	0.097*	0.054*	0.111*
	(0.023)	(0.053)	(0.032)	(0.062)
Other controls		Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.808	0.693	0.641	0.599
Panel C. Including Firms without Any Patent during Our Sample Period				
SMOKE_FREE	0.043***	0.093***	0.059**	0.106**
	(0.014)	(0.034)	(0.022)	(0.045)
Other controls		Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	73,724	73,724	73,724	73,724
Adj. R^2	0.861	0.774	0.724	0.687

TABLE 5 (continued)

Panel D. Including All Three Smoke-Free Laws

SMOKE_FREE	0.078***	0.136**	0.102***	0.151**
	(0.027)	(0.057)	(0.031)	(0.062)
SMOKE_FREE_S	0.080	-0.003	0.111*	0.041
	(0.062)	(0.098)	(0.062)	(0.107)
SMOKE_FREE_D	-0.042	-0.103	0.001	-0.046
	(0.047)	(0.101)	(0.040)	(0.096)
Other controls	Same as Table 4			
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.826	0.701	0.647	0.592

	ln(1 + PATENT_ PER_RD)	ln(1 + CITATION_ PER_RD)	ln(1 + CITATION_ PER_PATENT)	ln(1+CITATION_ YEAR)
Variable	1	2	3	4
Panel E. Using Alternative Innovation Measures Based on Patents and Citations				
SMOKE_FREE	0.033***	0.094**	0.071*	0.075**
	(0.011)	(0.038)	(0.036)	(0.033)
Other controls	Same as Table 4			
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.523	0.565	0.479	0.771

TABLE 5 (continued)

Variable	ln(1 + ORIGINALITY) 1	ln(1 + GENERALITY) 2	ln(1 + PATENT_VALUE) 3	RD 4
Panel F. Using Alternative Innovation Measures: Other Measures				
SMOKE_FREE	0.050**	0.068***	0.325***	0.003*
	(0.019)	(0.023)	(0.116)	(0.002)
Other controls		Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.835	0.753	0.653	0.785

Variable	ln(1+PATENT) 1	ln(1+CITATION) 2	ln(1+PATENT_ PER_EMPLOYEE) 3	ln(1+CITATION_ PER_EMPLOYEE) 4
Panel G. Controlling for ENDA				
SMOKE_FREE	0.067**	0.122**	0.078**	0.117*
	(0.028)	(0.058)	(0.035)	(0.059)
ENDA	0.020	0.075	0.059	0.145**
	(0.028)	(0.052)	(0.035)	-0.063
Other controls		Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.826	0.701	0.647	0.592

TABLE 6

Pre-Treatment Trends

Table 6 examines whether there are any pre-treatment trends in corporate innovation of firms located in legislating states (the treated firms) relative to firms located in non-legislating states (the control firms). The indicator variables YEAR_BEFORE3, YEAR_BEFORE2, YEAR_BEFORE1, YEAR_0, YEAR_1, YEAR_2, and YEAR_3_AND_AFTER, indicate the year relative to the year of smoke-free laws' passage (Year 0). For example, the indicator variable, YEAR_1, takes the value of 1 if it is 1 year after a state passes such laws, and 0 otherwise. All the control variables used in Table 4 are also included in this regression but unreported for brevity. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6 (continued)

Variable	ln(1+PATENT) 1	ln(1+CITATION) 2	ln(1+PATENT_ PER_EMPLOYEE) 3	ln(1+CITATION_ PER_EMPLOYEE) 4
YEAR_BEFORE3	-0.013	0.018	0.027	0.070
	(0.025)	(0.047)	(0.025)	(0.049)
YEAR_BEFORE2	-0.014	0.038	0.059	0.107
	(0.025)	(0.050)	(0.039)	(0.065)
YEAR_BEFORE1	-0.005	0.009	0.041	0.052
	(0.029)	(0.051)	(0.036)	(0.061)
YEAR_0	0.003	0.001	0.064	0.078
	(0.030)	(0.055)	(0.043)	(0.070)
YEAR_1	0.033	0.087	0.096*	0.136*
	(0.032)	(0.055)	(0.048)	(0.069)
YEAR_2	0.066*	0.116	0.155***	0.179**
	(0.034)	(0.072)	(0.042)	(0.073)
YEAR_3_AND_AFTER	0.091**	0.201***	0.132***	0.253***
	(0.037)	(0.074)	(0.035)	(0.074)
Other controls	Same as Table 4			
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.826	0.701	0.647	0.592

TABLE 7

Controlling for Unobservable Local Economic Conditions

Table 7 examines whether the effect of state-level smoke-free laws on corporate innovation is confounded by unobservable changes in local economic conditions using a sample of treated firms (located in legislating states) and close-by control firms (located in non-legislating states) across the state's border. For each treated firm, we match it to a control firm that is in the same industry, in a neighboring state without such laws, and closest in total assets in the year of such laws' passage. We further require the distance between the treated and control firms to be within 100 miles. All the control variables used in Table 4 are also included in this regression but unreported for brevity. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ln(1+PATENT)	ln(1+CITATION)	ln(1+PATENT_ PER_EMPLOYEE)	ln(1+CITATION_ PER_EMPLOYEE)
Variable	1	2	3	4
SMOKE_FREE	0.105*	0.375***	0.074	0.327**
	(0.058)	(0.107)	(0.094)	(0.133)
Other controls		Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	1,966	1,966	1,966	1,966
Adj. R^2	0.814	0.676	0.594	0.504

TABLE 8

Heterogeneous Treatment Effects

Table 8 examines heterogeneous treatment effects of state-level smoke-free laws on corporate innovation by varying a state's enforcement of smoke-free laws and by varying a state's pre-existing level of tobacco controls, using a difference-in-difference-in-differences specification. Panel A focuses on state-level enforcement of smoke-free laws. Panel B focuses on state-level pre-existing tobacco controls. All the control variables used in Table 4 are also included in this regression but unreported for brevity. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 8 (continued)

Variable	ln(1 + PATENT) 1	ln(1 + CITATION) 2	ln(1 + PATENT_PER_ EMPLOYEE) 3	ln(1 + CITATION_PER_ EMPLOYEE) 4
Panel A. Treatment Effects by Varying State-Level Enforcement of Smoke-Free Laws				
SMOKE_FREE × MORE_QUIT_SMOKING (a)	0.193***	0.383***	0.190**	0.284*
	(0.042)	(0.133)	(0.085)	(0.165)
SMOKE_FREE × LESS_QUIT_SMOKING (b)	0.063**	0.123**	0.083**	0.139**
	(0.026)	(0.054)	(0.032)	(0.058)
MORE_QUIT_SMOKING	-0.064**	-0.157**	-0.044	-0.087
	(0.027)	(0.075)	(0.052)	(0.097)
Other controls		Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.826	0.701	0.647	0.592
F-statistic of the test: (a) = (b)	14.39***	5.40**	2.77	1.09
Panel B. Treatment Effects by Varying State-Level Pre-Existing Tobacco Controls				
SMOKE_FREE × LOW_PREEXISTING_ TOBACCO_CONTROL (a)	0.102***	0.172***	0.133***	0.208***
	(0.031)	(0.062)	(0.031)	(0.056)
SMOKE_FREE × HIGH_PREEXISTING_ TOBACCO_CONTROL (b)	0.023	0.057	-0.002	0.001
	(0.029)	(0.066)	(0.042)	(0.077)
HIGH_PREEXISTING_ TOBACCO_CONTROL	0.035*	0.097*	0.105***	0.181**
	(0.019)	(0.050)	(0.037)	(0.070)
Other controls		Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337
Adj. R^2	0.826	0.701	0.647	0.592
F-statistic of the test: (a) = (b)	5.99**	3.11*	12.89***	10.53***

TABLE 9

The Effect of Smoke-Free Laws on Local Residents' Health Conditions

Table 9 examines the effect of state-level smoke-free laws on local residents' health conditions. The sample consists of 1,830,905 individuals who have at least 4 years' college education over the period 1997–2015, obtained from the BRFSS. In Columns 1 and 2, we reported ordered logistic regression results, where the dependent variable is HEALTH_SCORE. The health score ranges from 1 to 5, corresponding to the overall health condition being "poor," "fair," "good," "very good," and "excellent." In columns 3 and 4, we report logistic regression results, where the dependent variable GOOD_HEALTH, an indicator variable that takes the value of 1 if the overall health conditions are "very good" or "excellent," and 0 otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9 (continued)

Variable	HEALTH_SCORE 1	HEALTH_SCORE 2	GOOD_HEALTH 3	GOOD_HEALTH 4
SMOKE_FREE	0.017*	0.021**	0.016*	0.020**
	(0.009)	(0.010)	(0.009)	(0.009)
ln(AGE)		-0.801***		-0.946***
		(0.018)		(0.019)
MALE		-0.067***		-0.077***
		(0.006)		(0.007)
WHITE		0.373***		0.471***
		(0.026)		(0.030)
ln(STATE_GDP)	0.001	-0.037	0.017	-0.030
	(0.043)	(0.049)	(0.046)	(0.052)
ln(STATE_POPULATION)	0.350**	0.288*	0.405***	0.329**
	(0.154)	(0.158)	(0.154)	(0.157)
STATE_UNEMPLOYMENT	0.455	0.829**	0.379	0.877*
	(0.315)	(0.395)	(0.397)	(0.516)
STATE_RD_EXPENDITURES	0.684	0.845	0.193	0.324
	(0.865)	(0.956)	(0.879)	(1.027)
DEMOCRAT_GOVERNOR	0.003	0.016	0.003	0.019
	(0.005)	(0.010)	(0.005)	(0.012)
STATE_COLLEGE_DEGREE	0.557***	0.271	0.548***	0.196
	(0.166)	(0.212)	(0.184)	(0.257)
STATE SMOKER	0.029	-0.577**	-0.074	-0.762***
	(0.264)	(0.265)	(0.291)	(0.281)
BUSINESS_COMBINATION	0.151***	0.154***	0.167***	0.172***
	(0.028)	(0.028)	(0.032)	(0.034)
GOOD_FAITH	-0.234***	-0.253***	-0.195***	-0.215***
	(0.032)	(0.032)	(0.031)	(0.031)
STATE_FE	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes
Constant			-5.636**	-0.554
			(2.223)	(2.191)
No. of obs.	1,830,905	1,830,905	1,830,905	1,830,905
Pseudo R^2	0.004	0.011	0.006	0.021

TABLE 10

Inventor Productivity and Labor Productivity

Table 10 examines the effect of state-level smoke-free laws on measures for inventor productivity and labor productivity in general using the difference-in-differences specification in equation (1). The unit of analysis is firm-year observation. In Panel A, the dependent variables include measures of inventor productivity. We calculate all variables only based on patents produced by inventors who have stayed in the same firm and in the same state over the sample period to ensure that their output and productivity are not affected by other factors. In Panel B, the dependent variable is labor productivity. All the control variables used in Table 4 are also included in this regression but unreported for brevity. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 10 (continued)

Panel A. Inventor Output and Productivity

Variable	ln(1 + PATENT)	ln(1 + CITATION)	ln(1 + PATENT_PER_ EMPLOYEE)	ln(1 + CITATION_ PER_EMPLOYEE)	ln(1 + PATENT_ PER_INVENTOR)	ln(1 + CITATION_ PER_INVENTOR)
	1	2	3	4	5	6
SMOKE_FREE	0.058**	0.130**	0.065***	0.147***	0.014*	0.061*
	(0.024)	(0.053)	(0.019)	(0.046)	(0.007)	(0.033)
Other controls				Same as Table 4		
FIRM_FE	Yes	Yes	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	36,337	36,337	36,337	36,337	36,337	36,337
Adj. R^2	0.815	0.678	0.559	0.524	0.337	0.417

Panel B. Labor Productivity

	LABOR_PRODUCTIVITY
SMOKE_FREE	0.039**
	(0.017)
Other controls	Same as Table 4
FIRM_FE	Yes
REGION_YEAR_FE	Yes
No. of obs.	34,910
Adj. R^2	0.408

TABLE 11

Inventor Relocation

Table 11 examines the effect of state-level smoke-free laws on inventor relocation and the difference in inventor productivity. Panel A employs a difference-in-differences specification at the state-year level to examine inventor relocation into and out of legislating states. The unit of analysis is state-year observation. Panel B compares inventor-level productivity between newly arrived and departed inventors. Newly arrived inventors are those who came from other states within 3 years after their destination state adopted smoke-free laws. Departed inventors are those who moved to other states within 3 years after their home state adopted smoke-free laws. The unit of analysis is at the inventor level Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 11 (continued)

Variable	ln(1+INFLOW_FROM_STATES_ WITHOUT_SMOKE_FREE_LAWS) 1	ln(1+OUTFLOW_TO_STATES_ WITHOUT_SMOKE_FREE_LAWS) 2	ln(1+NET_INFLOW_FROM_STATES_ WITHOUT_SMOKE_FREE_LAWS) 3	ln(1+INFLOW_FROM_STATES_WITH_ SMOKE_FREE_LAWS) 4	ln(1+OUTFLOW_TO_STATES_WITH_ SMOKE_FREE_LAWS) 5	ln(1+NET_INFLOW_FROM_STATES_ WITH_SMOKE_FREE_LAWS) 6
Panel A. State-Level Inventor Relocation						
SMOKE_FREE	0.112**	-0.023	0.892**	-0.087	-0.099	0.093
	(0.045)	(0.064)	(0.384)	(0.196)	(0.069)	(0.329)
ln(STATE_GDP)	0.070	-0.120	1.238	-3.692***	-1.362***	-0.610
	(0.295)	(0.299)	(1.225)	(0.825)	(0.253)	(1.621)
ln(STATE_POPULATION)	0.299	1.941***	-12.349***	5.836*	2.744***	-0.704
	(0.458)	(0.501)	(3.693)	(2.927)	(0.596)	(3.835)
STATE_UNEMPLOYMENT	-1.177	1.577	-15.345	4.358	-0.218	21.205*
	(2.017)	(1.662)	(12.377)	(7.082)	(2.223)	(12.009)
STATE_RD_EXPENDITURES	-2.189	-6.397**	-16.438	18.923	0.366	10.459
	(2.668)	(3.032)	(26.618)	(11.295)	(3.892)	(16.924)
DEMOCRAT_GOVERNOR	0.035	-0.006	0.346	0.137	0.046	0.111
	(0.035)	(0.035)	(0.237)	(0.092)	(0.035)	(0.173)
STATE_COLLEGE_DEGREE	-0.063	0.593	-7.120	-0.291	1.007	2.890
	(0.662)	(0.705)	(4.989)	(2.297)	(0.853)	(4.783)
STATE_SMOKER	-0.996	-0.819	-9.826	-4.261	1.486	-8.354
	(1.234)	(1.480)	(9.487)	(4.227)	(1.771)	(7.472)
BUSINESS_COMBINATION	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped
GOOD_FAITH	-0.064	0.044	-0.655	-0.235	0.612***	-1.100***
ln(STATE_GDP)	(0.073)	(0.079)	(0.592)	(0.289)	(0.111)	(0.315)
STATE_FE	Yes	Yes	Yes	Yes	Yes	Yes
REGION_YEAR_FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.319	-25.111***	176.558***	-42.494	-23.346***	16.477
	(7.137)	(7.292)	(56.040)	(45.745)	(8.294)	(61.979)
No. of obs.	950	950	950	950	950	950
Adj. R^2	0.963	0.954	0.417	0.874	0.937	0.456

TABLE 11 (continued)

Panel B. Productivity of Newly Arrived and Departed Inventors

	Newly Arrived Inventors		Departed Inventors		Test of Differences	
Variable	Mean 1	Median 2	Mean 3	Median 4	*t*-Test (1) – (3)	Wilcoxon Test (2) – (4)
Total # of patents by the inventor over the sample period	14.81	9	14.13	8	0.67***	1***
Total # of patent citations received by the inventor over the sample period	300.28	98.36	283.02	89.83	17.26**	8.53***