Does Workplace Discrimination Impede Innovation? *

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Abstract

We identify a negative causal effect of workplace discrimination on corporate innovation, using the staggered adoption of U.S. state employment laws that prohibit discrimination based on sexual orientation and gender identity. We find a significant increase in patents and patent citations for firms headquartered in states that pass such laws relative to firms headquartered in states that do not. This result is more pronounced for firms that previously have not implemented pro-gay non-discrimination policies, for firms in states with a large homosexual population, and for firms in human capital-intensive industries. Overall, our findings support the view that inclusion inspires innovation.

Keywords: Innovation; Patents; Workplace Discrimination; Anti-discrimination Law; Sexual Orientation

JEL Classification: G38; J24; K31; M14; O31

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Abstract

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The best way to ensure the development of new ideas is through a diverse and inclusive workforce. Forbes Insights (2011)

1. Introduction

Anecdotal evidence suggests that workplace discrimination impedes corporate innovation. For example, in an opinion editorial in the Wall Street Journal, November 3, 2013, Tim Cook, Apple's CEO, urges Congress to support the Employment Non-Discrimination Act, arguing that workplace equality is important for business creativity. He states, "Embracing people's individuality is a matter of basic human dignity and civil rights. It also turns out to be great for the creativity that drives our business.[1]" Despite some circumstantial examples, there is little empirical evidence on how workplace discrimination influences corporate innovation. In this paper, we fill this gap and reveal a negative causal effect of workplace discrimination on firms' innovation.

As explained in Becker (1957) and Arrow (1973), workplace discrimination refers to unjustified actions taken against workers because of personal characteristics that are unrelated to their productivity. Such discriminatory tastes usually arise from prejudices held by employers and coworkers. In this regard, we expect that workplace discrimination impedes innovation for the following reasons.

Innovation requires teamwork and proactive employee participation. Discrimination in the workplace reduces workforce cohesion, lowers social ties and trust, and prevents cooperative participation in research activities, which may hinder knowledge spillovers and exchange of ideas among employees (Becker, 1957; Dougherty,

[1] http://www.wsj.com/articles/SB10001424052702304527504579172302377638002

1992; Van de Ven, 1986). On the other hand, an inclusive workplace can better engage employees with a variety of backgrounds and viewpoints, who can help companies to "think outside the box" by providing a wider range of perspectives and intellectual skills (Amason, 1996; Hong and Page, 2001; Watson et al., 1993). Moreover, considering that the long-term nature of innovation requires talented employees with long-term commitment, an inclusive and equal workplace can increase employee satisfaction and loyalty, and thus help firms recruit and retain talented people in the long term, which in turn fosters firms' innovation (Edmans, 2011; Holmstrom, 1989; Zingales, 2000).

We empirically examine the relation between workplace discrimination and innovation based on the staggered passage of U.S. state-level employment laws that prohibit discrimination based on sexual orientation and gender identity. We use the passage of these employment laws to capture an exogenous decrease in workplace discrimination (in particular, discrimination against homosexuals in the workplace). This setting is highly appealing from an empirical standpoint for two reasons. First, the motivation behind these laws centers around state courts' determination to address a persistent, widespread pattern of discrimination on the basis of sexual orientation and gender identity, and to reinforce the commitment to fairness and equal opportunity in the workplace. As these laws were not passed with the intention of promoting innovation, potential effects on innovation are likely to be an unintended consequence of these laws. Second, the staggered adoption of these laws in several U.S. states enables us to identify their effects in a difference-in-differences framework. Because multiple shocks affect different firms exogenously at different times, we can avoid the common identification difficulty faced by studies with a single shock: the potential biases and noise coinciding with the shock that directly affects corporate innovation (Roberts and Whited, 2012).

Using a panel of 58,009 U.S. public firms from 1976 to 2008 and a difference-in-differences approach, we show that an exogenous decrease in workplace discrimination subsequently leads to a significant increase in innovation outputs. On average, firms headquartered in states that pass this employment anti-discrimination law experience an increase in the number of patents by 8% and an increase in the number of patent citations by 11%, relative to firms headquartered in states that do not pass such a law.

The identifying assumption central to a causal interpretation of the difference-in-differences estimation is that treated and control firms share parallel trends prior to the law changes. Our tests show that their pre-treatment trends are indeed indistinguishable. Moreover, most of the impact of employment anti-discrimination laws on innovation occurs three years after the law enactment, which suggests a causal effect.

However, it is possible that the adoption of state anti-discrimination laws is triggered by local business conditions that in turn increase firms' innovation. To mitigate this concern, we additionally control for local business conditions such as state GDP, population, education, and political balance. Our inferences are largely unchanged. In further tests, we exploit the fact that economic conditions are likely to be similar in neighboring states, whereas the effects of anti-discrimination laws stop at state borders. This discontinuity in anti-discrimination laws allows us to difference away any unobserved confounding factors as long as they affect both the treated state and its neighbors. By comparing treated firms to their immediate neighbors, we can better identify how much of the observed innovation change is due to anti-discrimination laws rather than other shocks to local business conditions. When we difference away changes in local business conditions by focusing on treated and control firms closely located on either side of a state border, we continue to find a significant increase in firms' innovation after their states pass anti-discrimination laws, relative to their neighboring firms. These results indicate that the observed increase in innovation after the enactment of state anti-discrimination laws is not driven by local economic shocks.

To provide further evidence that the effects of anti-discrimination laws on innovation are indeed tied to workplace discrimination, we apply a double difference-in-differences approach to examine heterogeneous treatment effects. We find that the effects of anti-discrimination laws on corporate innovation are stronger for firms that previously did not implement pro-gay non-discrimination policies, for firms that are in states with a large homosexual population, and for firms that operate in human capital-intensive industries. These cross-sectional variations in the impacts of anti-discrimination laws on innovation further increase our confidence in the presence of a discrimination channel.

This paper provides at least four major contributions to the literature. First, our paper adds to the literature that examines the drivers of innovation. Current research on this topic has focused on factors such as incentive compensation for management (Manso, 2011), institutional ownership (Aghion et al., 2013), anti-takeover provisions (Atanassov, 2013), access to the equity market (Hsu et al., 2013), information environment (He and Tian, 2013), employees' job security (Acharya et al., 2014), etc. Although these studies enhance our understanding of the mechanisms that motivate firms to innovate, the role of firms' work environment is largely overlooked. This lack of evidence makes it difficult to fully understand the drivers of corporate innovation, given that innovative ideas arise usually when employees communicate, share ideas, and collaborate with their peers (Cross et al., 2007; Spender and Strong, 2012). Our paper helps to fill this gap by documenting an inclusive workforce as an important driver of innovation.

Second, our study sheds light on the real consequences of labor market discrimination. Since Becker's (1957) seminal work, the subject of labor market discrimination has been an important research area in the economics literature. While most studies on discrimination focus on documenting the existence of unfair treatment of women, minorities, and homosexuals in the workplace, the real economic cost of discrimination is relatively under-explored. Our paper suggests that discrimination in the labor market imposes significant costs on the economy by decreasing corporate innovativeness.

Third, our paper is broadly related to the literature on corporate social responsibility (CSR), in which non-discrimination employment policy is one of its main components. Despite the growing importance of CSR in U.S. firms' operations, the effect of CSR on firm performance is still under debate. One group of researchers argues that CSR results in positive effects because focusing on the interests of other stakeholders increases their willingness to support a firm's operation, which in turn increases the firm's performance (Deng et al., 2013; Jensen, 2001). In contrast, other groups of researchers believe that CSR is a wealth transfer from shareholders to other stakeholders and thus reduces firm performance (Cronqvist et al., 2009; Friedman, 1970; Pagano and Volpin, 2005). Our paper establishes a new channel through which CSR affects firm value. The findings in this paper show that CSR (in particular, an inclusive employment policy) is beneficial in the case of innovation, which requires heavy investment in human capital, and a tolerant and inclusive workforce (Holmstrom, 1989).

Lastly, our paper has important policy implications. Though Title VII of the U.S. Civil Rights Act of 1964 provides comprehensive nationwide protection from discrimination based on race, color, national origin, gender, and religion, adding sexual minorities to that list remains a controversial topic across the U.S. While more than 20 of the 50 U.S. states have offered full legal protections, legislators in the remaining states are still debating whether or not to follow suit, partially because the impacts of these anti-discrimination laws on the society and economy are still unclear. Our paper provides evidence that this legislation fosters creativity in the workplace.

The remainder of the paper is organized as follows. Section 2 develops our hypothesis. Section 3 reviews the background on sexual orientation discrimination. Section 4 describes our sample and key variable construction. Section 5 presents the empirical results. We conclude in Section 6.

2. Hypothesis Development

Becker (1957) formalizes how workers who are equally productive are treated differently because of the discriminatory tastes of employers and colleagues, and predicts that discrimination will lead to disputes and segregation in the workplace. There are at least three reasons that discrimination at a firm's workplace can impede the firm's innovation.

First, Van de Ven (1986), Dougherty (1992) and others show that the process of innovation is usually the development and implementation of new ideas by workers who, over time, interact and exchange ideas with their colleagues. Collaboration, open communication, and trust in the workplace play an important role in fostering firm innovativeness. The tension and lack of cooperation among employees caused by discrimination can significantly decrease the effectiveness of the innovation process.

Second, severe discrimination in the workplace prevents the inclusion of employees with heterogeneous backgrounds and thus is harmful to innovation, because innovation usually requires a wider range of perspectives and a greater variety of intellectual skills. Hong and Page (2001) construct a model of heterogeneous agents of bounded ability and analyze their individual and collective performance of finding solutions to difficult problems (such as searching for new cancer treatment or developing new software). Their model predicts that heterogeneous perspectives and heuristics among these individuals help lead to optimal solutions for these problems. From the perspective of psychology, Simonton (1999, pp. 207, 213) states that "creativity is favored by an intellect that has been enriched with diverse experiences and perspectives ... It is as if the mere exposure to different lifestyles and divergent values enables individuals to expand the range and originality of their ideational variations." Empirical studies on group decision-making also find that groups consisting of more diverse individuals produce higher quality and more innovative decisions than groups of homogenous individuals (Amason, 1996; Watson et al., 1993). Based on survey data of

Danish firms, Ostergaard et al. (2011) and Parrotta et al. (2014) find that a firm's patenting activity is positively associated with its workforce diversity.

Third, innovation is a long-term process, in which human capital, rather than physical capital, is particularly important (Zingales, 2000). Edmans (2011) finds that factors such as respect and fairness in the workplace increase employee satisfaction and contribute to firms' long-term success, especially for firms with high R&D and patenting activities. Discrimination, however, limits an organization's ability to fully benefit from the multifaceted talent pool, and significantly reduces its employee satisfaction, loyalty, and commitment (Sheridan, 1992; Sanchez and Brock, 1996; Ragins and Cornwell, 2001). The lack of commitment of talented employees is especially harmful to innovating firms, because R&D investment creates intangible knowledge stocks which are embedded in the employees' human capital, and firms lose such knowledge base when their employees leave (Campbell et al., 2012; Ganco et al., 2014).

In summary, the above discussion leads to our hypothesis that workplace discrimination impedes corporate innovation. It is also worth noting that, even if discrimination decreases a firm's competitiveness and is usually against the law, it could continue to persist in a firm's workplace as long as discriminatory employers and co-workers derive utility from indulging their prejudices. In equilibrium, the severity of workplace discrimination depends on the tradeoff of these "benefits" and costs. When an exogenous change in law increases the legal costs of discriminatory actions, we expect a decline in workplace discrimination, which subsequently enhances corporate innovation.

3. Background on Sexual Orientation Discrimination

People who have a homosexual orientation account for a nontrivial part of U.S. population. According to Gates (2011), a review conducted by Williams Institute at UCLA School of Law, approximately 3.5% (9 million) of American adults identify themselves as lesbian, gay, or bisexual. Moreover, 8.2% (19 million) of American adults have engaged in same-sex sexual activities at least once, and 11% (25.6 million) of American adults acknowledge at least some same-sex sexual attraction.

Discrimination on the basis of sexual orientation and gender identity is a widespread problem in the American workplace. Badgett et al. (2007) document a variety of studies showing that homosexual people experience various forms of discrimination, including denial of employment, workplace harassment, negative performance evaluations, denial of promotion, job termination, etc. In a June 2013 Pew Research Center survey of the American homosexual population, more than 20% of homosexual employees reported experiencing discrimination in the workplace.[2]

It is worth pointing out that, for sexual orientation discrimination to occur, one does not need to be open about his sexual orientation. This discrimination can be based on *perceived* sexual orientation or gender non-conformity. Barber (2002) and Diefenbach (2007) describe a variety of cases in which individuals are sexually harassed based on *perceived* sexual orientation (which is not necessarily the same as their actual sexual orientation). Wood-Nartker et al. (2007) and Sirin et al. (2004) provide examples of the degree to which individuals use cues like job titles and gender non-conformity as a way

[2] Pew Research Social & Demographic Trends, "A Survey of LGBT Americans," June 13, 2013. http://www.pewsocialtrends.org/2013/06/13/a-survey-of-lgbt-americans/#fn-17196-1.

to determine an individual's sexual orientation. As a result, sexual orientation discrimination in the workplace is applicable to not only homosexuals but also heterosexuals who are *perceived* by others as homosexuals.

Despite facing severe discrimination in society and in the labor market, some evidence suggests that homosexuals play an active role in high-tech industries. In October 2014, Tim Cook, CEO of Apple, became the first U.S. CEO of a public firm who openly admitted his gay identity. Other examples include Lisa Brummel (executive vice president of human resources of Microsoft), Jon Hall (executive director of Linus International), Madison Reed (co-founder of Facebook), Megan Smith (vice president for new business development of Google), Peter Thiel (co-founder of PayPal), etc. Further, using the U.S. census data, Florida (2003) describes homosexual population as a "creative class" and finds a positive association between the geographic concentration of homosexual population and high-tech industries.

Although the U.S. does not have any federal legislation that prohibits sexual orientation discrimination in the labor market, American homosexuals have sought and won legal protections against employment discrimination at the state level in the last few decades. In 1977, the District of Columbia became the first U.S. district to pass an anti-discrimination law that prohibits employment discrimination on the basis of sexual orientation (Human Rights Act of 1977). By the end of 2007, 20 states have since followed suit. Table 1 presents a detailed list of statewide non-discrimination legislations provided by the Human Rights Campaign.[3]

[3] The list of statewide employment laws is obtained from http://hrc-assets.s3-website-us-east-1.amazonaws.com//files/assets/resources/statewide_employment_10-2014.pdf.

These employment protections for homosexual employees have usually mirrored the earlier protections against workplace discrimination on the basis of race, gender, religion, national origin, and physical disability, and have allowed advocates to frame the sexual orientation protections as incremental additions to existing policies (see Klawitter and Flatt (1998) for more institutional details of these policies). Moreover, the adoption of sexual orientation anti-discrimination policies largely depends on skillful work by policy entrepreneurs, well-organized gay rights groups, and the absence of significant opposition groups (Haider-Markel and Meier, 2003). None of these factors seem to be directly related to corporate patenting activities, suggesting that these law changes are unlikely to be triggered by factors that drive corporate innovation.

Existing literature finds that these pro-gay anti-discrimination laws have significantly increased awareness of sexual orientation discrimination, improved living and working environment for homosexuals, and helped to create a level playing field for them (Button et al., 1995; Klawitter and Flatt, 1998). Gates (2009) finds a significant wage increase of same-sex couples following the passage of these laws (especially among those with a higher level of education), which suggests that these laws have noticeably reduced the workplace discrimination against homosexuals.

4. Sample Formation and Variable Construction

4.1 The Sample

We retrieve patent and patent citation data from the worldwide Patent Statistical Database (PATSTAT, April 2012) and financial information from Compustat. We then obtain the firm's headquarter information from Compustat, Compact Disclosure (which records headquarters' changes), and manually check any missing information.

We assume that firms produce zero patents if they are not matched with PATSTAT. Patents are included in the database only if they are eventually granted. Given the average of a two-year lag between patent application and patent grant, and that the latest year in the database is 2011, patents that were applied for in 2009 and 2010 may not appear in the database. Following the suggestion by Hall et al. (2001), we end our sample period in 2008.

We exclude the firms that are incorporated outside the U.S., and exclude firms in the financial industry (SIC codes 6000-6999) and utility industry (SIC codes 4900-4999) due to the differences in regulatory oversight for these industries. Following Bloom et al. (2013), we further drop firms that never filed a single patent during our entire sample period. Our final sample consists of 58,009 firm-year observations (4,915 unique firms) from 1976 to 2008.

It is worth mentioning that the quality of PASTAT database is at least as good as that of NBER patent database (which has been widely used in the innovation literature). Moshirian et al. (2014) compare the U.S. patent coverage in both databases, and find that they are generally comparable, except for a large decline in the number of patents from the NBER database over the 2002-2006 period. This difference is because many patents applications filed during this period were still under review and had not been granted by

2006 when the NBER database ends. However, the PATSTAT database does not suffer from this problem because it continues to include granted patents up to 2011.[4]

4.2 Innovation Variables

To assess the success of long-term investment in corporate innovation, we employ five innovation measures based on patent counts and patent citations. The use of patenting to measure a firm's innovativeness has been widely used in the literature since Scherer (1965) and Griliches (1981).

The first measure of innovation is the number of patents filed (and subsequently granted) by a firm in a given year. Our second measure of innovation is the sum of citation counts across all patents filed by the firm in a given year, which captures the significance of the patent outputs. Because citations are received for many years after a patent is created, patents created near the end of the sample period have less time to accumulate citations. To address this truncation bias, we follow the recommendations of Hall et al. (2001, 2005) and scale the citation count of each patent by the average citation count of all firms' patents that are filed in the same year.

Moreover, we employ citations per patent as the third measure of innovation to capture the patent's quality. Lastly, given that we are interested in determining whether or not workplace discrimination affects employees' productivity in innovative projects, we use patents and citations per employee as our last two innovation measures. Due to

[4] As a robustness check, we repeat our analysis based on the NEBR patent database over a shorter period from 1976 to 2003 (the suggested ending year of using NBER patent database by Hall et al. (2001)), and find that our inference is unchanged.

the high level of skewness of patent data, we use natural logarithms of the innovation variables.

4.3 Other Control Variables

We control for a vector of firm and industry characteristics that may affect a firm's innovation productivity, and these controls are motivated by prior literature (e.g., Fang et al., 2014; He and Tian, 2013). These variables include firm size, firm age, asset tangibility, leverage, cash holding, R&D expenditures, capital expenditures, ROA, Tobin's *Q*, and industry concentration (the Herfindahl index based on sales). Following Aghion et al. (2005), we also include the squared Herfindahl index in our regressions to mitigate non-linear effects of product market competition on innovation outputs. All explanatory variables are lagged by one year. To minimize the effect of outliers, we winsorize all variables at the 1st and 99th percentiles. Detailed variable definitions are provided in the Appendix.

4.4 Summary Statistics

Table 2 provides summary statistics. On average, firms in our sample have 11 patents filed (and subsequently granted) per year and receive 22 total citations and 0.76 citations per patent. After normalizing patents and patent citations by number of employees, we find that an average firm generates 5.89 patents and 17 citations per 1000 employees.

Our average sample firms have book value assets of $2.49 billion, hire more than 9,000 employees, and are 16 years old. They hold a sizeable amount of cash with a cash ratio of 20% of total assets. The average R&D and capital expenditure account for 7%

and 6% of total assets, respectively. The average firms are moderately levered with a book leverage ratio of 20%, and tangible assets account for 26% of total assets in the average firms. In terms of performance, sample firms perform well with an average ROA of 7% and Tobin's *Q* of 2.13.

5. Empirical Results

5.1 Visual Illustration

Figure 1 depicts the effects of the employment anti-discrimination laws on innovation in states that adopt the policy change relative to states that do not adopt the policy change. We follow Autor et al. (2006) and Acharya et al. (2014) in constructing this graph. The y-axis shows the logarithm of the number of patents or citations received to patents filed in a given year; the x-axis shows the time relative to the adoption of the anti-discrimination laws, ranging from five years prior to the adoption year (year 0) until ten years afterwards.

The plots demonstrate the point estimates of the coefficients β_n from the following regression:

$$Innovation_{i,t} = \alpha + \sum_{n=-5}^{10} \beta_n * Pass\_year_{s,t+n} + Year\ FE + \varepsilon_{i,t} \ , \qquad (1)$$

where *i* indexes firm, *s* indexes the state in which the firms' headquarters are located, and *t* indexes the year. $Pass\_year_{s,t+n}$ is a dummy variable indicating the year relative to the adoption of the anti-discrimination laws in state *s* and year *t*.[5] The two plots in Figure 1 correspond to the number of patents and citations, respectively, and they show the same

[5] For example, $Pass\_year_{s,\ t+1}$ takes the value of one in the first year after the adoption of anti-discrimination laws in state *s*, and zero otherwise.

pattern. Innovation increases significantly after the adoption of the employment anti-discrimination laws. For example, in the year prior to the law adoption, the β_{-1} coefficient is approximately 0.02 for patents, while in five years after the law adoption, the corresponding β_5 coefficient is more than six times as large (0.013). In terms of patent citations, the β_{-1} coefficient is approximately 0.08; in contrast, the corresponding β_5 coefficient is three times as large (0.25). Moreover, we observe that the greatest increase in innovation appears several years after the law adoption, suggesting that the passage of anti-discrimination laws has a persistent long-run effect.

5.2 Baseline Regression

Several U.S. state courts adopted the anti-discrimination laws in different years during the sample period. Thus, we can examine the before-after effect of the change in anti-discrimination laws in affected states (the treatment group) compared to the before-after effect in states in which such a change was not effected (the control group). This is a difference-in-differences test design in multiple treatment groups and multiple time periods as employed by Acharya et al. (2014), Atanassov (2013), Bertrand et al. (2004), and Imbens and Wooldridge (2009). We implement this test through the following regression:

$$Innovation_{i,t} = \alpha + \beta_1 Pass_{s,t-1} + \beta_2 Other\ Firm\ Characteristics_{i,t-1} + Firm\ FE + Year\ FE + Region \times Year\ FE + \varepsilon_{i,t}\ , \qquad (2)$$

where *i* indexes firm, *s* indexes the state in which the firms' headquarters are located, and *t* indexes the year. The dependent variable is a proxy for innovation performance. The variable *Pass* is a dummy variable that equals one if the employment anti-discrimination law is in place in state *s* in a given year, and zero otherwise. We include a set of control variables that may affect a firm's innovation output, as discussed in Section 4. The year fixed effects enable us to control for intertemporal technological shocks, as well as the fact that citations to patents applied for in later years would be, on average, lower than those in earlier years. Similarly, the firm fixed effects also allow us to control for time-invariant differences in patenting and citation practices across firms. Following Acharya et al. (2014), we also control for regional time trends through the interaction of region dummies with year dummies.[6] These interactions enable us to nonparametrically account for time-varying differences between geographic regions of the U.S. in corporate innovation and in the enactment of employment anti-discrimination laws. Given that our treatment is defined at the state level, we cluster standard errors by state.

The coefficient of interest in this model is the β_1 coefficient. As explained by Imbens and Wooldridge (2009), the employed fixed effects lead to β_1 being estimated as the *within-state* differences before and after the anti-discrimination law change as opposed to similar before-after differences in states that did not experience such a change during the same period.

It is helpful to consider an example. Suppose we want to estimate the effect of the anti-discrimination law passed in Minnesota in 1993 on innovation. We can subtract the number of innovations before the law adoption from the number of innovations after the law adoption for firms headquartered in Minnesota. However, economy-wide shocks may

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

occur at the same time and affect corporate innovations in 1993. To difference away such factors, we calculate the same difference in innovations for firms in a control state that does not adopt such a law. Finally, we calculate the difference between these two differences, which represents the incremental effect of the law change on firms in Minnesota compared to firms in the control state.

Table 3 presents the regression results. The coefficient estimates on the passage of employment anti-discrimination laws are positive and statistically significant in all columns. The dependent variable in column (1) is Ln(1+patents) and we find that the coefficient estimate on the *Pass* indicator is 0.076 and significant at the 5% level, suggesting a positive effect of the law change on corporate innovation. The economic magnitude is also sizeable: the adoption of anti-discrimination laws leads to an increase in the number of patents by approximately 7.9% ($= e^{0.076} - 1$).

Examining Ln(1+citations) as the dependent variable in column (2), we find that the coefficient on the *Pass* indicator is 0.106 and is significant at the 5% level, which implies that the adoption of anti-discrimination laws leads to an increase in the number of patent citations by approximately 11.2% ($= e^{0.106} - 1$).

The positive effects of anti-discrimination laws on the number of citations could be driven by either more patents or more citations per patent. To further examine the impact of each patent, we examine the number of citations per patent in column (3) and find that the law adoption has a significant and positive effect on citations per patent. These results indicate that the anti-discrimination law leads to an increase in not only the number of patents but also the impact of the patents.

In columns (4)-(5), we repeat our test using patents and citations scaled by the number of employees. The coefficients on the *Pass* indicator are 0.095 and 0.117, respectively, and both are significant at the 1% level. These results indicate that patents and citations per 1000 employees increase by approximately 9.96% and 12.41%, respectively, in states that adopt employment anti-discrimination laws as compared with states that do not. Therefore, employees' productivity in innovation increases significantly after employment anti-discrimination laws are adopted.

With regards to control variables, large firms, firms with large cash holdings, firms with high R&D expenditures, and firms with higher growth potential are more innovative. These results are broadly consistent with prior literature (e.g., Fang et al., 2014; He and Tian, 2013).

Taken together, these results indicate a negative casual effect of discrimination on innovation outputs in terms of both quantity and quality.

5.3 The Pre-treatment Trends

The validity of difference-in-differences estimation depends on the parallel trends assumption: absent the employment anti-discrimination laws, treated firms' innovation would have evolved in the same way as that of control firms. Table 4 presents the results that investigate the pre-trend between the treated group and control group. In particular, we define seven dummies, *Year −2*, *Year −1*, *Year 0*, *Year +1*, *Year +2*, *Year +3*, and *Year +4 and afterwards* to indicate the year relative to the enactment of the employment anti-discrimination laws. For example, year 0 indicates the year in which the law is enacted; year −2 indicates that it is 2 years before the law enactment; and year +2 indicates that it is 2 years after the law enactment. Then, we re-estimate Equation (2) by replacing the *Pass* indicator with the seven indicators above.

The coefficients on *Year −2* and *Year −1* indicators are especially important because their significance and magnitude indicate whether there is any difference in innovation between the treatment group and the control group prior to the adoption of employment anti-discrimination laws. The coefficients on both indicators are close to zero and not statistically significant across all five columns. These results suggest that the parallel trend assumption of the difference-in-differences approach is not violated.

The coefficients on *Year 0* and *Year +1* indicators are also small in magnitude and insignificant in all five columns. The impact of employment anti-discrimination laws starts to show up two years after the enactment: the coefficients on *Year +2* indicator become significantly positive for patents per 1000 employees (column (4)) and citations per 1000 employees (column (5)). The coefficients on *Year +4 and afterwards* are more than twice as large as the coefficients on the *Year 0* indicator for all five innovation measures, indicating that it takes a few years to reveal the full impact of employment anti-discrimination laws on corporate innovation. This is understandable given that innovation is usually a long-term process. This result is also consistent with the pattern illustrated in Figure 1.

Overall, Table 4 shows that the treated group and the control group share a similar trend in innovation prior to the law changes, thus supporting the parallel trends assumption associated with the difference-in-differences estimation. Moreover, Table 4 also indicates that most of the impact of anti-discrimination laws on innovation occurs three years *after* they are passed, which suggests a causal effect.

5.4 Confounding Local Business Conditions

Location is one important common factor that likely induces an association between the passing of anti-discrimination laws and corporate innovation. Specifically, corporations with the strongest innovation performance are concentrated in California, New York, New Jersey, Massachusetts, Connecticut, Illinois, and Texas. Of these seven states, six (all but Texas) are "liberal" states, where the combination of general attitudes and state policies are much more likely to give rise to active anti-discrimination policies than in more conservative states. This geographic effect would tend to induce correlations between the passing of anti-discrimination laws and corporate innovation.

In this section, we implement two tests to address this issue. In our first test, we additionally control for a set of observable state characteristics in the regression. In our second test, we difference away unobservable local business conditions by focusing on treatment firms that are on one side of a state border and their neighboring control firms on the other side of the state border. In both tests, we continue to find a significant increase in innovation after the adoption of anti-discrimination laws.

Table 5 presents our first test. In addition to our usual set of explanatory variables used in Table 3, we also account for various time-varying, state-level variables in our regressions. We control for the political balance in a given state (measured as the ratio of Republican to Democrat state representatives in the House of Representatives). Further, since richer and larger states may have the resources to provide a higher level of innovation and may also be more likely to pass anti-discrimination legislation, we include the logarithm of real GDP in a state. We additionally control the logarithm of annual state population. Further, investment in education is another factor that may lead to differences in patenting. Therefore, we also control for a state's intellectual resources using the number of degree-granting institutions of higher education, as well as the enrollment in institutions of higher education. Data on both state GDP and population are collected from the U.S. Bureau of Economic Analysis. Information regarding the number of colleges, college enrollment, and political balance is obtained from the annual Statistical Abstracts from the U.S. Census Bureau.

We find that the adoption of anti-discrimination laws continues to have a positive and (statistically and economically) significant impact on corporate innovation. Compared to Table 3, the coefficient on the *Pass* dummy becomes a little smaller in columns (1) and (2), but gets bigger in columns (3)-(5). Also, we find that more colleges in a state are (weakly) positively associated with innovation quality in column (3). Other state-level variables have no significant impact on corporate innovation, probably because we have already controlled for *Region* × *Year FE* in the regression.

Although the above test accounts for *observable* local business conditions, some unobservable local economic shocks may be associated with both the passage of anti-discrimination laws and corporate innovation. In our second test, we exploit the discontinuity of anti-discrimination laws and examine the innovation change in the treatment firms on the state border relative to their neighboring control firms. The logic is as follows. Suppose that anti-discrimination laws are driven by unobserved changes in local business conditions, and that it is these changes (not the anti-discrimination laws) that spur corporate innovation in reality. Then both firms in treated states and their neighbors in untreated states just across the state border would spuriously appear to react to the law changes, because economic conditions, unlike state laws, have a tendency to spill across state borders (Heider and Ljungqvist, 2014). In this case, the change in innovation in treated firms should be no different from that in the neighboring control firms that are located just across the state border.

To examine this possibility, we match each treated firm to a control firm that is in the same industry, is in an adjacent state without passing the anti-discrimination law, and is closest to the treated firm in distance. Obviously, treated firms may not necessarily share the same local economic condition with its "closest" control firm if the treated firm is in the middle of a large state. To alleviate this concern, we further require that the distance between the treated firm and its matched untreated firm be within 50 miles.[7] If the distance between the treated firm and its closest control firm is more than 50 miles, we drop this pair from our sample. By doing so, we increase our confidence that our treated firm and control firm are truly close to each other geographically and thus face similar local economic shocks. Then, we re-estimate Equation (2) by focusing on this sub-sample of firms across the state border. We also include a pair fixed effect for each pair of treated firms and neighboring control firms.

Table 6 presents the results. Restricting our sample to the pairs of neighboring treated and control firms reduces the sample to 7,617 firm-year observations; yet, we still find positive and significant coefficients (at the 1% level) on the *Pass* indicator in all five

[7] As a robustness check, we also require the distance between the treated firm and control firm to be within 10, 20, 30, or 100 miles, and our inferences are unchanged.

columns (except for column (1)). Taking column (2) for example (where patent citations is the dependent variable), the coefficient on *Pass* is 0.140 and is significant at the 1% level, indicating that the number of patent citations increases by approximately 15% in the treated firms relative to untreated firms in the same industry located just on the other side of the state border. The point estimate is even slightly larger than that reported in our baseline regression in column (2) of Table 3. Overall, these results suggest that unobserved local confounds are unlikely to drive our results.

5.5 Double Difference-in-differences Tests

To provide further evidence that the effects of anti-discrimination laws on innovation are indeed tied to discrimination, in this subsection we implement double difference-in-differences tests to examine the heterogeneous treatment effects.

First, if the enhanced innovation after the law enactment is due to decreased discrimination in the workplace, we expect this treatment effect to be stronger in firms that do not have pro-gay non-discrimination policies prior to the treatment. We obtain the information on firm-level pro-gay non-discrimination policies from the Kinder, Lydenberg, Domini Research & Analytics (KLD) ratings database, which covers approximately 650 companies that have comprised the Domini 400 Social SM Index and the S&P 500 index since 1991 and more than 3,000 companies that have comprised the Russell 3000 index since 2003. The KLD database provides an indicator variable to flag whether or not a firm has a pro-gay non-discrimination policy in a given year, and this policy indicates that the company has implemented notably progressive policies toward its gay and lesbian employees.

We re-estimate Equation (2) by replacing the *Pass* indicator with *Pass* × *Pro-gay* and *Pass* × *Non-pro-gay* indicators. The *Pro-gay* indicator takes the value of one if the firm has a pro-gay non-discrimination policy prior to the passage of employment non-discrimination law, and zero otherwise. Similarly, the *Non-pro-gay* indicator is defined as (1− *Pro-gay*). Table 7 presents the results.[8]

The coefficients on *Pass* × *Pro-gay* are not significantly different from zero, while the coefficients on *Pass* × *Non-pro-gay* are positive and significant across all five columns. This result indicates that the effect of employment non-discrimination laws on corporate innovation is significant for firms that previously had not adopted pro-gay non-discrimination policies, whereas it is virtually absent in firms that had done so.

Furthermore, the impact of anti-discrimination laws on corporate innovation may also depend on the state's homosexual population. *Ex ante*, there could be two different views on how a state's homosexual population is related to the treatment effect. On one hand, if there are a large number of homosexual people in a state, then homosexual employees are likely to account for a sizable part of a firm's workforce and, thus, the treatment effect is likely to be more pronounced. On the other hand, a large homosexual population in a state indicates friendliness of the state towards homosexual people in the first place; for this reason, the treatment effect should be less pronounced. We empirically examine these two views by obtaining the information on a state's homosexual population from the 2005 American Community Survey.[9] We define the

[8] Because KLD database starts in 1991, the sample in Table 7 is smaller than that in Table 3.

[9] Earlier survey information on the homosexual population is also available in the Census 1990 and Census 2000 data. The 2005 American Community Survey may provide a more accurate estimation of the homosexual population because more homosexual people have been willing to identify themselves in recent years (Gates, 2006).

High gay population state indicator as taking the value of one for the top ten states with the largest percentage of population that is gay, lesbian, or bisexual, and zero otherwise.[10] Then, *Low gay population state* is defined as (1− *High gay population state*). We re-estimate Equation (2) by replacing the *Pass* indicator with *Pass* × *High gay population state* and *Pass* × *Low gay population state* indicators.

As reported in Table 8, the coefficients on *Pass* × *High gay population state* are positive and significant at the 1% level across all five columns, while the coefficients on *Pass* × *Low gay population state* are usually not significant and much smaller in magnitude. For example, in column (1) (where the dependent variable is the patent number), the coefficient on *Pass* × *High gay population state* is 0.116 and significant at the 1% level; in contrast, the coefficient on *Pass* × *Low gay population state* is only 0.034 and not significantly different from zero.

Lastly, considering that discrimination affects productivity associated with human capital, not physical capital, the treatment effects should be stronger for firms that rely more on human capital. Following prior research (e.g., Coff, 2002; Younge et al., 2014), we measure human capital intensity as the number of knowledge workers as a proportion of all workers. We obtain data on employment levels from the Occupational Employment Statistics (OES) survey from the Bureau of Labor Statistics. Based on the OES occupational codebook, we define knowledge workers to be those with an occupational code below 50,000. This definition includes occupations such as managers, scientists, engineers, computer programmers, IT professionals, and so forth. The OES provides data

[10] The top ten states (and district) with the largest percentage of homosexual people is District of Columbia, New Hampshire, Massachusetts, Maine, California, Colorado, Vermont, New Mexico, Minnesota, and Florida.

on the breakdown of the total number of workers employed in each three-digit SIC industry. From the OES data, we calculate the proportion of the total workforce being knowledge workers for a given three-digit SIC industry, and then assign that measure to each focal firm in our sample. We then define the *High human capital intensity* indicator as one if the proportion of knowledge workers among all workers is above the sample median, and zero otherwise. Then, the *Low human capital intensity* indicator is defined as (1− *High human capital intensity*). We re-estimate Equation (2) by replacing the *Pass* indicator with *Pass* × *High human capital intensity* and *Pass* × *Low human capital intensity* indicators.

Table 9 presents the results. The coefficients on *Pass* × *High human capital intensity* are positive and significant at the 1% level across all five columns, while the coefficients on *Pass* × *Low human capital intensity* are virtually zero. For example, in column (2) (where the dependent variable is patent citations), the coefficient on *Pass* × *High human capital intensity* is 0.237 and significant at the 1% level, while the coefficient on *Pass* × *Low human capital intensity* is only -0.048 and not significantly different from zero.

Taken together, the effects of anti-discrimination laws on corporate innovation are much stronger for firms that previously have not had pro-gay non-discrimination policies, for firms in a state with a large homosexual population, and for firms in human capital-intensive industries. These results suggest that workplace discrimination is indeed the mechanism through which a state's anti-discrimination law influences corporate innovation.

6. Conclusions

In this paper, we investigate the effect of workplace discrimination on business success from the perspective of innovation, and find that workplace discrimination has a negative casual effect on corporate innovation. We exploit various exogenous shocks from state anti-discrimination laws that prohibit discrimination based on sexual orientation and gender identity, and study the changes in corporate innovation following these law changes. Using a difference-in-differences approach, we find a significant increase in firms' patents and patent citations following the law changes, relative to firms in states that do not pass such laws. We further find that the impact of anti-discrimination laws on corporate innovation is more pronounced when the firms previously did not have a pro-gay non-discrimination policy in place, when the state has a large homosexual population, and when the firms rely more on human capital. Overall, our findings are consistent with the view that an equal and inclusive workforce fosters creativity and innovation.

Our paper provides important implications not only for technology firms' hiring strategies, but also for public policies aimed at fostering innovation. Our results suggest that policies aimed to promote equal employment can have real economic effects in terms of improving corporate innovation. This finding is particularly timely and relevant because of the on-going consideration of federal legislation to ban sexual orientation discrimination in the workplace (the Employment Non-Discrimination Act).

Lastly, although our paper focuses on discrimination against homosexuals (for identification purposes), the same economic mechanisms apply for other types of discrimination in the workplace, such as discrimination on the basis of gender, race, ethnic background, age, etc. Examining the policies that aim to reduce these types of discrimination and create a more inclusive workplace could be an interesting area for future research.

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Appendix: Variable Definitions

Variable	*Definition*
Measures of Innovation Output	
LnPat	Natural logarithm of one plus firm's total number of patents filed (and subsequently granted).
LnCit	Natural logarithm of one plus firm's total number of citations received on the firm's patents filed. To adjust the citation count, each patent's number of citations is divided by the average citation count of all patents applied in the same year.
LnCit/pat	Natural logarithm of one plus firm's average number of citations received on the firm's patents filed. If the firm filed no patents in that year, the missing value of average citation counts is set to zero.
LnPat/emp	Natural logarithm of one plus firm's total number of patents filed (and subsequently granted), scaled by the number of the firm's employees.
LnCit/emp	Natural logarithm of one plus firm's total number of citations received on the firm's patents filed (and subsequently granted), scaled by the number of the firm's employees.
Firm Characteristics	
Cash	Cash and marketable securities normalized by the book value of total assets.
Firm size	Natural logarithm of the number of employees.
Leverage	Total debt normalized by the book value of total asset.
R&D	R&D expenditures normalized by the book value of total assets. If R&D expenditures variable is missing, we set the missing value to zero.
Capex	Capital expenditures normalized by the book value of total assets.
ROA	Return on assets, measured as operating income normalized by the book value of total assets.
Firm age	Number of years since the firm's first appearance in CRSP.
Tobin's Q	Market value of equity plus book value of assets minus book value of equity minus balance sheet deferred taxes, normalize by the book value of total assets.
Tangible	Property, plant & equipment normalized by the book value of total assets.
Hindex	Herfindahl index is the sum of squared sales-based market shares of all firms in a three-digit SIC industry.
Pro-gay	An indicator variable that takes the value of one if the company has implemented notably progressive policies toward its gay and lesbian employees, and zero

	otherwise.
Non-pro-gay	1−Pro-gay.
High human capital intensity	An indicator variable that takes the value of one for the firm whose proportion of knowledge workers among all workers is above the sample median, and zero otherwise.
Low human capital intensity	1− High human capital intensity.
State Characteristics	
Pass	An indicator variable that takes the value of one if a state has adopted the employment law which prohibits discrimination based on sexual orientation and gender identity in a given year, and zero otherwise.
Ln(State GDP)	Natural logarithm of annual state GDP.
Ln(Population)	Natural logarithm of a state's population.
Ln(Colleges)	Natural logarithm of the number of degree-granting institutions of higher education in a given state.
Ln(Enrollment)	Natural logarithm of enrollment in institutions of higher education in a given state.
Political balance	The ratio of Republican-to-Democrat representatives in the Lower House (House of Representatives) for a given state.
High gay population state	An indicator variable that takes the value of one for the top ten states with the largest percentage of population that is gay, lesbian, or bisexual, and zero otherwise.
Low gay population state	1− High gay population state.

Table 1: List of the Passages of State Employment Anti-discrimination Laws

This table reports the year when each state adopted state-level employment anti-discrimination laws that prohibit discrimination based on sexual orientation and gender identity, from 1976 to 2007.

State	Law	Year
District of Columbia	D.C. CODE 1-2512	1977
Wisconsin	WIS. STAT. 111.32 (13m)	1982
Massachusetts	MASS. GEN. LAWS ch. 151B, 3 (6)	1989
Connecticut	CONN. GEN. STAT. 46a-81a	1991
Hawaii	HAW. REV.STAT. 378-1	1991
Vermont	1 VT. STAT.ANN. 143	1991
California	CAL. GOV. CODE 12940	1992
New Jersey	N.J. STAT. 10:5-5 (hh)	1992
Minnesota	MINN.STAT. 363A.03 subd. 44	1993
Rhode Island	R.I. GEN. LAWS 28-5-6 (7)	1995
New Hampshire	N.H. REV. STAT. ANN. 354-A:2 (XIV-c)	1998
Nevada	NEV.REV.STAT. 613.310 (6)	1999
Maryland	MD CODE, STATE GOV'T, 20-606	2001
New Mexico	N.M. STAT. 28-1-2 (P)	2003
New York	N.Y. EXEC. LAW 292 (27)	2003
Maine	ME. REV. STAT. ANN. Tit. 5 4553 (9-C)	2005
Illinois	775 ILCS 5/1-102 (O-1)	2006
Washington	WASH.REV.CODE 49.60.040 (15)	2006
Colorado	COLO.REV.STAT. 24-34-401 (7.5)	2007
Iowa	IOWA CODE 216.2 (14)	2007

Table 2: Summary Statistics

The sample consists of 58,009 firm-year observations from 1976-2008. We obtain patent information from PATSTAT and financial information from Compustat. Definitions of all variables are provided in the Appendix. All dollar values are in 2008 dollars. All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	N	Mean	SD	P1	Median	P99
Patents	58009	11.05	87.64	0	0	183
Citations	58009	22.42	193.97	0	0	360
Citations per patent	58009	0.76	1.45	0	0	6.45
Patents per 1000 employees	58009	5.89	24.43	0	0	100
Citations per 1000 employees	58009	17.03	92.89	0	0	317.8
Cash	58009	0.20	0.23	0.001	0.10	0.90
Firm assets ($b)	58009	2.49	15.54	0.003	0.19	39.13
Number of employees in 1000s	58009	9.48	41.17	0.01	1.06	127.8
Firm age	58009	16.37	15.67	1	11	72
Tobin's Q	58009	2.13	1.97	0.433	1.45	11.64
ROA	58009	0.07	0.22	-0.926	0.12	0.40
Leverage	58009	0.20	0.18	0	0.17	0.84
Tangible	58009	0.26	0.18	0.01	0.22	0.80
R&D	58009	0.07	0.11	0	0.03	0.52
Capex	58009	0.06	0.06	0.002	0.05	0.29
H-index	58009	0.18	0.15	0.04	0.14	0.79

Table 3: Effect of Employment Anti-discrimination Laws on Innovation

This table reports the difference-in-differences tests that examine the impacts of employment anti-discrimination laws on corporate innovation. The indicator variable *Pass* takes the value of one if a state has adopted the employment law which prohibits discrimination based on sexual orientation and gender identity in a given year, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics based on standard errors clustered by state are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Pass	0.076**	0.106**	0.025**	0.095***	0.117***
	(2.25)	(2.60)	(2.40)	(3.46)	(3.69)
Cash	0.224***	0.330***	0.142***	0.405***	0.562***
	(3.97)	(5.69)	(7.35)	(6.41)	(8.40)
Firm size	0.186***	0.214***	0.039***	-0.029**	-0.019
	(7.90)	(7.94)	(6.41)	(-2.14)	(-1.14)
Ln(Firm age)	-0.015	-0.011	0.014**	-0.003	0.015
	(-0.84)	(-0.57)	(2.46)	(-0.18)	(0.95)
Tobin's Q	0.016***	0.018***	0.004**	0.006	0.008
	(5.75)	(5.33)	(2.64)	(1.19)	(1.41)
Leverage	-0.022	0.055	0.015	-0.067*	0.025
	(-0.55)	(1.02)	(0.74)	(-1.71)	(0.42)
R&D	0.227*	0.360***	0.172***	0.729***	0.921***
	(1.88)	(2.71)	(4.78)	(5.33)	(6.08)
Capex	0.042	0.107	0.092*	0.189*	0.196
	(0.49)	(1.04)	(1.75)	(1.72)	(1.62)
Tangible	-0.158*	-0.251**	-0.027	-0.059	-0.108
	(-1.85)	(-2.62)	(-0.64)	(-0.53)	(-0.98)
ROA	-0.008	0.018	0.027	0.040	0.046
	(-0.21)	(0.36)	(1.14)	(0.77)	(0.66)
H-index	-0.282	-0.465	-0.182**	-0.234	-0.378*
	(-0.92)	(-1.35)	(-2.23)	(-1.33)	(-1.91)
H-index^2	0.639*	0.861**	0.220**	0.351*	0.495**
	(1.84)	(2.25)	(2.49)	(1.75)	(2.54)
Constant	0.765***	0.884***	0.381***	0.698***	0.797***
	(6.91)	(8.41)	(12.90)	(8.41)	(9.85)
Observations	58009	58009	58009	58009	58009
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Region × Year FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.751	0.726	0.405	0.571	0.620

Table 4: Testing for Pre-treatment Trends and Reversals

This table investigates the pre-treatment trends between the treated group and control group. The indicator variables *Year −2*, *Year −1*, *Year 0*, *Year +1*, *Year +2*, *Year +3*, and *Year +4 and afterwards*, indicate the year relative to the adoption of the state employment law that prohibits discrimination based on sexual orientation and gender identity. For example, the *Year +1* indicator takes the value of one if it is one year after a state adopts the employment law, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics based on standard errors clustered by state are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Year −2	0.034	0.055	0.007	0.022	0.037
	(1.15)	(1.27)	(0.33)	(0.77)	(1.00)
Year −1	0.027	0.059	0.012	0.031	0.052
	(0.86)	(1.47)	(0.68)	(0.94)	(1.53)
Year 0 (event year)	0.055	0.054	0.020	0.068	0.054
	(1.33)	(1.01)	(0.83)	(1.58)	(1.09)
Year +1	0.051	0.064	0.013	0.068*	0.078
	(1.32)	(1.26)	(0.74)	(1.74)	(1.58)
Year +2	0.043	0.076	0.017	0.090***	0.104***
	(1.00)	(1.65)	(0.86)	(2.93)	(2.90)
Year +3	0.070	0.082*	0.024	0.104***	0.124***
	(1.67)	(1.68)	(1.51)	(3.38)	(3.58)
Year +4 and afterwards	0.122***	0.172***	0.041***	0.133***	0.166***
	(2.72)	(3.12)	(3.02)	(3.86)	(4.32)
Cash	0.224***	0.329***	0.142***	0.405***	0.561***
	(3.98)	(5.71)	(7.34)	(6.42)	(8.41)
Firm size	0.186***	0.214***	0.039***	-0.029**	-0.019
	(7.94)	(7.98)	(6.42)	(-2.15)	(-1.14)
Ln(Firm age)	-0.015	-0.011	0.014**	-0.004	0.015
	(-0.88)	(-0.61)	(2.48)	(-0.20)	(0.93)
Tobin's Q	0.015***	0.018***	0.004**	0.006	0.008
	(5.67)	(5.23)	(2.59)	(1.17)	(1.38)
Leverage	-0.022	0.055	0.015	-0.067*	0.025
	(-0.55)	(1.02)	(0.74)	(-1.70)	(0.42)
R&D	0.222*	0.352***	0.170***	0.724***	0.914***
	(1.86)	(2.68)	(4.72)	(5.32)	(6.08)
Capex	0.042	0.107	0.092*	0.189*	0.196
	(0.49)	(1.04)	(1.76)	(1.73)	(1.63)
Tangible	-0.157*	-0.250**	-0.027	-0.058	-0.107
	(-1.84)	(-2.61)	(-0.64)	(-0.52)	(-0.97)
ROA	-0.008	0.016	0.027	0.039	0.045
	(-0.23)	(0.33)	(1.12)	(0.75)	(0.64)
H-index	-0.280	-0.462	-0.181**	-0.233	-0.376*
	(-0.91)	(-1.34)	(-2.23)	(-1.34)	(-1.92)

H-index^2	0.638*	0.859**	0.220**	0.351*	0.494**
	(1.85)	(2.26)	(2.49)	(1.77)	(2.57)
Constant	0.765***	0.884***	0.381***	0.698***	0.797***
	(6.85)	(8.30)	(12.91)	(8.36)	(9.84)
Observations	58009	58009	58009	58009	58009
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Region × Year FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.751	0.727	0.405	0.571	0.620

Table 5: Controlling for State-level Characteristics

This table reports the difference-in-differences tests that examine the impacts of employment anti-discrimination laws on corporate innovation, controlling for state-level characteristics. The indicator variable *Pass* takes the value of one if a state has adopted the employment law which prohibits discrimination based on sexual orientation and gender identity in a given year, and zero otherwise. Ln(State GDP) is the natural logarithm of annual real state GDP. Ln(Population) is the natural logarithm of a state's population. Ln(Colleges) is the natural logarithm of the number of degree-granting institutions of higher education in a given state. Ln(Enrollment) is the natural logarithm of enrollment in institutions of higher education in a given state. Political balance is the ratio of Democrat-to-Republican representatives in the Lower House (House of Representatives) for a given state. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics based on standard errors clustered by state are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Pass	0.072**	0.100**	0.027**	0.098***	0.122***
	(2.24)	(2.55)	(2.32)	(3.51)	(3.65)
Ln(State GDP)	-0.042	0.002	-0.008	-0.119	-0.073
	(-0.42)	(0.01)	(-0.17)	(-1.31)	(-0.64)
Ln(Population)	0.138	0.090	-0.082	0.099	0.028
	(1.06)	(0.46)	(-1.18)	(0.87)	(0.16)
Ln(Colleges)	0.007	0.037	0.043*	0.016	0.064
	(0.11)	(0.51)	(1.78)	(0.23)	(0.82)
Ln(Enrollment)	-0.104	-0.133	0.044	-0.003	-0.029
	(-0.83)	(-0.91)	(0.98)	(-0.03)	(-0.23)
Political balance	-0.022	-0.031	-0.001	0.007	0.011
	(-0.91)	(-1.00)	(-0.12)	(0.35)	(0.45)
Cash	0.226***	0.333***	0.143***	0.403***	0.559***
	(3.99)	(5.76)	(7.46)	(6.35)	(8.34)
Firm size	0.188***	0.216***	0.038***	-0.030**	-0.020
	(7.87)	(7.86)	(6.28)	(-2.19)	(-1.20)
Ln(Firm age)	-0.016	-0.011	0.015**	-0.003	0.016
	(-0.91)	(-0.62)	(2.46)	(-0.16)	(1.00)
Tobin's Q	0.016***	0.018***	0.004***	0.006	0.008
	(5.71)	(5.31)	(2.69)	(1.19)	(1.43)
Leverage	-0.021	0.056	0.015	-0.065*	0.027
	(-0.54)	(1.05)	(0.79)	(-1.68)	(0.45)
R&D	0.228*	0.360***	0.173***	0.727***	0.918***
	(1.89)	(2.72)	(4.84)	(5.30)	(6.07)
Capex	0.046	0.115	0.098*	0.198*	0.207*
	(0.54)	(1.13)	(1.86)	(1.78)	(1.68)
Tangible	-0.151*	-0.244**	-0.028	-0.068	-0.120
	(-1.78)	(-2.57)	(-0.65)	(-0.60)	(-1.08)
ROA	-0.007	0.017	0.027	0.038	0.043
	(-0.19)	(0.35)	(1.14)	(0.74)	(0.61)

H-index	-0.260	-0.425	-0.170**	-0.231	-0.372*
	(-0.84)	(-1.22)	(-2.06)	(-1.29)	(-1.83)
H-index^2	0.612*	0.826**	0.219**	0.348*	0.494**
	(1.75)	(2.13)	(2.42)	(1.70)	(2.47)
Constant	-0.313	0.079	1.329**	0.541	1.125
	(-0.28)	(0.05)	(2.50)	(0.55)	(0.77)
Observations	58009	58009	58009	58009	58009
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Region × Year FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.752	0.727	0.405	0.570	0.620

Table 6: Treated Firms and Neighboring Control Firms across State Border

This table examines whether the effect of employment anti-discrimination laws on innovation is confounded by unobserved changes in local business conditions. For each treated firm, we match to a control firm that is in the same industry, in a neighboring state without adopting the anti-discrimination law, and closest in distance. The indicator variable *Pass* takes the value of one if a state has adopted the employment law which prohibits discrimination based on sexual orientation and gender identity in a given year, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics based on standard errors clustered by state are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Pass	0.047	0.140***	0.077***	0.125***	0.206***
	(1.60)	(4.11)	(5.34)	(3.83)	(5.37)
Cash	0.297***	0.548***	0.242***	0.875***	1.187***
	(4.57)	(6.60)	(5.85)	(8.92)	(9.87)
Firm size	0.469***	0.516***	0.096***	0.113***	0.146***
	(41.65)	(39.67)	(20.15)	(10.41)	(11.67)
LnAge	0.098***	0.072***	0.002	-0.013	-0.031
	(4.70)	(2.97)	(0.20)	(-0.58)	(-1.15)
Tobin's Q	0.026***	0.018***	-0.005	-0.030***	-0.044***
	(4.89)	(2.60)	(-1.60)	(-3.22)	(-3.87)
Leverage	-0.216***	-0.158*	-0.080**	-0.394***	-0.385***
	(-3.15)	(-1.83)	(-2.04)	(-4.55)	(-3.47)
RD/assets	1.701***	2.193***	0.557***	2.617***	3.173***
	(12.22)	(12.61)	(6.61)	(11.41)	(11.25)
CAPEX	1.428***	2.312***	0.860***	1.209***	1.832***
	(4.98)	(6.82)	(5.34)	(3.28)	(4.14)
Tangible	-0.198*	-0.407***	-0.084	-0.568***	-0.709***
	(-1.78)	(-3.18)	(-1.48)	(-4.19)	(-4.61)
ROA	-0.243***	-0.265***	-0.104**	-0.021	-0.181
	(-3.32)	(-2.84)	(-2.22)	(-0.18)	(-1.27)
Hindex	-0.878**	-1.436***	-0.404***	0.632**	0.248
	(-2.48)	(-3.66)	(-2.93)	(2.41)	(0.84)
HindexSQ	1.566***	2.194***	0.446**	-0.704**	-0.436
	(3.00)	(3.81)	(2.50)	(-2.17)	(-1.23)
Constant	-1.635***	-1.635***	-0.084	-0.090	-0.087
	(-12.89)	(-10.71)	(-1.45)	(-0.77)	(-0.59)
Observations	7617	7617	7617	7617	7617
Year FEs	Yes	Yes	Yes	Yes	Yes
Pair FEs	Yes	Yes	Yes	Yes	Yes
Region × year FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.698	0.666	0.312	0.427	0.466

Table 7: Heterogeneous Treatment Effects based on Firms' Pro-gay Policy

This table reports the double difference-in-differences tests that examine the relative impacts of employment anti-discrimination laws on innovation in firms with and without pre-existing firm-level pro-gay policies. The indicator variable *Pro-gay* takes the value of one if a firm has a pro-gay policy prior to the enactment of the employment anti-discrimination law, and zero otherwise. *Non-pro-gay* is (1− *Pro-gay*). The indicator variable *Pass* takes the value of one if a state has adopted the employment law which prohibits discrimination based on sexual orientation and gender identity in a given year, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics based on standard errors clustered by state are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Pass × Pro-gay	0.116	0.357	0.129	0.053	0.129
	(0.72)	(1.25)	(1.22)	(1.57)	(0.89)
Pass × Non-pro-gay	0.118**	0.165**	0.047**	0.084**	0.079*
	(2.23)	(2.50)	(2.02)	(2.54)	(1.80)
Cash	0.280***	0.284**	0.002	0.192***	0.159*
	(2.82)	(2.07)	(0.04)	(2.75)	(1.87)
Firm size	0.274***	0.302***	0.038	-0.085***	-0.111***
	(6.95)	(6.84)	(1.64)	(-2.75)	(-3.55)
Ln(Firm age)	-0.015	-0.128*	-0.078**	-0.064**	-0.119***
	(-0.28)	(-1.73)	(-2.26)	(-2.06)	(-3.65)
Tobin's Q	0.029**	0.036*	0.009	0.001	0.012
	(2.22)	(1.99)	(1.49)	(0.07)	(0.64)
Leverage	-0.155	-0.036	0.012	-0.211***	-0.027
	(-1.54)	(-0.24)	(0.15)	(-2.83)	(-0.18)
R&D	0.299	0.816	0.337	0.117	0.841
	(0.85)	(1.52)	(1.46)	(0.26)	(1.56)
Capex	0.248	0.192	-0.078	0.409*	0.422
	(0.52)	(0.24)	(-0.24)	(1.75)	(0.64)
Tangible	0.008	-0.053	0.059	0.071	-0.024
	(0.03)	(-0.12)	(0.40)	(0.44)	(-0.09)
ROA	0.120	0.236	0.100	-0.080	0.106
	(0.63)	(1.34)	(1.53)	(-0.37)	(0.44)
H-index	1.409	2.336**	0.896***	0.575	0.970*
	(1.66)	(2.36)	(3.01)	(1.62)	(1.76)
H-index^2	-0.257	-1.227	-0.800***	-0.004	-0.378
	(-0.34)	(-1.32)	(-3.24)	(-0.01)	(-0.69)
Constant	0.664**	0.843**	0.431***	1.079***	1.335***
	(2.56)	(2.34)	(3.16)	(6.44)	(7.25)
Observations	8613	8613	8613	8613	8613
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Region × Year FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.870	0.848	0.510	0.850	0.846

Table 8: Heterogeneous Treatment Effects based on States' Gay Population

This table reports the double difference-in-differences tests that examine the relative effects of employment anti-discrimination laws on corporate innovation in difference states based on the population that is gay, lesbian, and bisexual. The indicator variable *High gay population state* takes the value of one for the top ten states with the largest percentage of population that is gay, lesbian, or bisexual, and zero otherwise. *Low gay population state* is (1− *High gay population state*). The indicator variable *Pass* takes the value of one if a state has adopted the employment law which prohibits discrimination based on sexual orientation and gender identity in a given year, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics based on standard errors clustered by state are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Pass × High gay population state	0.116*** (2.77)	0.164*** (3.17)	0.035** (2.65)	0.130*** (3.53)	0.174*** (3.72)
Pass × Low gay population state	0.034 (0.77)	0.048 (0.79)	0.014 (0.97)	0.057** (2.24)	0.062* (1.72)
Cash	0.222*** (3.97)	0.328*** (5.77)	0.142*** (7.36)	0.404*** (6.43)	0.560*** (8.49)
Firm size	0.186*** (7.91)	0.214*** (7.94)	0.039*** (6.40)	-0.030** (-2.19)	-0.020 (-1.19)
Ln(Firm age)	-0.016 (-0.91)	-0.012 (-0.67)	0.014** (2.46)	-0.004 (-0.24)	0.014 (0.88)
Tobin's Q	0.016*** (5.72)	0.018*** (5.30)	0.004** (2.64)	0.006 (1.19)	0.008 (1.39)
Leverage	-0.022 (-0.56)	0.055 (1.02)	0.015 (0.74)	-0.067* (-1.72)	0.025 (0.41)
R&D	0.226* (1.88)	0.359*** (2.71)	0.172*** (4.80)	0.729*** (5.35)	0.919*** (6.14)
Capex	0.042 (0.49)	0.108 (1.04)	0.092* (1.74)	0.189* (1.72)	0.197 (1.62)
Tangible	-0.159* (-1.86)	-0.252** (-2.64)	-0.027 (-0.64)	-0.059 (-0.53)	-0.109 (-0.99)
ROA	-0.008 (-0.22)	0.017 (0.35)	0.027 (1.14)	0.039 (0.77)	0.046 (0.65)
H-index	-0.270 (-0.88)	-0.448 (-1.30)	-0.179** (-2.20)	-0.224 (-1.28)	-0.360* (-1.84)
H-index^2	0.627* (1.82)	0.844** (2.22)	0.217** (2.47)	0.342* (1.72)	0.478** (2.49)
Constant	0.769*** (6.85)	0.892*** (8.40)	0.382*** (13.03)	0.700*** (8.36)	0.806*** (10.03)
Observations	58009	58009	58009	58009	58009

Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Region × Year FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.751	0.726	0.405	0.571	0.620

Table 9: Heterogeneous Treatment Effects based on Human Capital Intensity

This table reports the double difference-in-differences tests that examine the relative effects of employment anti-discrimination laws on corporate innovation in different industries based on the human capital intensity. The indicator variable *High human capital intensity* takes the value of one for the firms whose proportion of knowledge workers among all workers is above the sample median, and zero otherwise. *Low human capital intensity* is (1− *High human capital intensity*). The indicator variable *Pass* takes the value of one if a state has adopted the employment law which prohibits discrimination based on sexual orientation and gender identity in a given year, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics based on standard errors clustered by state are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Pass × High human	0.151***	0.237***	0.065***	0.154***	0.227***
capital intensity	(3.28)	(4.64)	(5.04)	(3.15)	(4.70)
Pass × Low human	-0.016	-0.048	-0.020	0.023	-0.010
capital intensity	(-0.44)	(-1.12)	(-1.51)	(0.82)	(-0.34)
Cash	0.216***	0.324***	0.139***	0.403***	0.557***
	(3.76)	(5.55)	(7.13)	(6.76)	(8.97)
Firm size	0.194***	0.224***	0.041***	-0.026*	-0.017
	(8.11)	(8.19)	(6.48)	(-1.80)	(-0.93)
Ln(Firm age)	-0.025	-0.023	0.012**	-0.009	0.009
	(-1.21)	(-1.06)	(2.07)	(-0.46)	(0.54)
Tobin's Q	0.016***	0.018***	0.004**	0.005	0.008
	(5.37)	(5.26)	(2.56)	(1.01)	(1.40)
Leverage	-0.023	0.053	0.013	-0.063	0.029
	(-0.54)	(0.93)	(0.63)	(-1.57)	(0.47)
R&D	0.217*	0.328**	0.158***	0.721***	0.875***
	(1.73)	(2.26)	(4.03)	(5.00)	(5.55)
Capex	0.040	0.104	0.097*	0.166	0.170
	(0.43)	(0.94)	(1.84)	(1.38)	(1.28)
Tangible	-0.189**	-0.269***	-0.037	-0.078	-0.118
	(-2.12)	(-2.74)	(-0.91)	(-0.73)	(-1.12)
ROA	-0.018	0.007	0.025	0.040	0.045
	(-0.50)	(0.15)	(1.07)	(0.73)	(0.63)
H-index	-0.284	-0.459	-0.168*	-0.262	-0.390**
	(-0.94)	(-1.33)	(-1.96)	(-1.57)	(-2.06)
H-index^2	0.689**	0.917**	0.228**	0.413**	0.559***
	(2.01)	(2.35)	(2.34)	(2.40)	(3.09)
Constant	0.783***	0.898***	0.388***	0.708***	0.803***
	(6.89)	(8.49)	(12.74)	(8.12)	(9.62)
Observations	58009	58009	58009	58009	58009

Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Region × Year FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.746	0.723	0.404	0.570	0.620

Figure 1: Effect of the Passage of Employment Anti-discrimination Laws on Innovation

This figure shows a visual difference-in-differences examining the effects of employment anti-discrimination laws on patent and citation counts in adopting states, relative to non-adopting states, from 5 years prior to the laws' passage (Year 0) to 10 years afterwards.