Does Workforce Diversity Pay? Evidence from Corporate Innovation*

Huasheng Gao
Nanyang Business School
Nanyang Technological University
S3-B1A-06, 50 Nanyang Avenue, Singapore 639798
65.6790.4653
hsgao@ntu.edu.sg

Wei Zhang
School of Finance
Shanghai University of Finance and Economics
777 Guoding Road, Shanghai, China, 200433
21.6590.4273
zhangwei@mail.shufe.edu.cn

This version: July, 2014

Abstract

We examine the impacts of workforce diversity on business success from the perspective of corporate innovation. Our baseline results reveal that firms with greater workforce diversity generate more patents and patent citations. To establish causality, we apply an instrumental variable approach and use a difference-in-differences test based on the multiple exogenous shocks from the adoption of state-level employment law that prohibits discrimination based on sexual orientation and gender identity. Our identification strategies suggest a positive causal effect of workforce diversity on firm innovation. Overall, our findings are consistent with the view that a diverse and inclusive workforce provides a greater range of perspectives and ideas that spur innovation.

Keywords: Innovation; Patents; Citations; Workforce Diversity

JEL Classification: O31; J24; K31; M14

---

* We are grateful for the helpful comments from Simba Chang, Paul Hsu, Chuan Yang Hwang, Chishen Wei, Ting Xu, Le Zhang and the seminar participants in Nanyang Technological University. Gao acknowledges financial support from the Tier One research grant provided by the Ministry of Education of Singapore. All errors are our own.

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

1. Introduction

The United States, once "white-dominant," is increasingly multi-racial, multi-lingual, and multi-ethnic. Over the last few decades, immigrants from Latin America, Asia, and elsewhere have greatly expanded the population of minority residents. In 1900, only one in eight residents of the U.S. claimed non-European origins; in the 2000s, three in ten. By 2050, people of color are projected to equal non-Hispanic whites in numbers (Passel and Cohn 2008; U.S. Census Bureau 2004). Moreover, female participation in the labor force is increasing as well. In 1970, fewer than 40% of women were in the labor force, while this number reached close to 50% in 2010.[1] Thus, the impact of workforce diversity on American society and economy has emerged as an important question for both academicians and policy-makers. In this paper, we investigate this question from the perspective of corporate innovation.

There are two opposing views concerning the effect of workforce diversity on corporate innovation. On one hand, diversity creates communication barriers, 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 and therefore impede corporate innovation (Becker 1957; Lazear 1999; Williams and O'Reilly 1998; Zajac et al. 1991). Under this view, firms with greater workforce diversity are expected to be less innovative (innovation impeding hypothesis).

[1] http://www.dol.gov/wb/factsheets/QS-womenwork2010.htm

On the other hand, diversity may also bring substantial benefits to corporate innovation. Employees with a variety of backgrounds may provide diverse perspectives, valuable ideas, and problem-solving abilities, which facilitates the achievement of optimal creative solutions and innovation (Berliant and Fujita 2011; Drach-Zahavy and Somech 2001). 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 diverse perspectives and heuristics among these individuals help lead to optimal solutions for these problems. 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). This line of literature predicts that firms with greater workforce diversity are more innovative (innovation fostering hypothesis).

We empirically evaluate these two competing views based on a large sample of U.S. public firms. We use the number of patents granted to a firm and the number of future citations received by patents to assess the success of long-term investment in corporate innovation. The use of patenting to measure a firm's innovativeness has been widely used in the literature since Scherer (1965) and Griliches (1981).

Our baseline tests show a positive relation between corporate workforce diversity and innovativeness. This relation is both statistically and economically significant and is robust to using alternative measures of innovation outputs. A one-standard-deviation increase in workforce diversity leads to approximately a 26% increase in number of patents and 31% increase in number of patent citations.

While the baseline results are consistent with the view that workforce diversity fosters corporate innovation, an important concern is that workforce diversity could be endogenous. Unobservable firm characteristics correlated with both firm workforce diversity and innovation may bias the results, leading to a concern of omitted variables. Moreover, innovative firms are more likely to be successful and to attract people from diverse backgrounds, resulting in a reverse causality concern. To establish causality, we use two different identification strategies.

Our first identification strategy is to construct a set of instrumental variables and apply the two-stage least squares (2SLS) regression analysis. In particular, we construct two instruments for firms' workforce diversity: the state-level abnormal interracial marriage rate (a proxy for local racial segmentation) and the state-level abnormal male-female salary gap that is not explained by observable workers' characteristics (a proxy for local gender discrimination). Our results from 2SLS confirm the positive relation between workforce diversity and innovation.

Our second identification strategy is to rely on a natural experiment: the passage of a state-level employment law that prohibits discrimination based on sexual orientation and gender identity. Using a difference-in-differences approach, we show that an exogenous increase in workforce diversity subsequently leads to a significant increase in innovation outputs. A key advantage of this identification strategy is that multiple shocks affect different firms exogenously at different times. This avoids the common identification difficulty faced by studies with a single shock: the potential omitted variables coinciding with the shock that directly affect corporate innovation. Overall, our identification test results suggest that corporate workforce diversity has a positive causal effect on firm innovation.

This paper provides at least four major contributions to the literature. First, our research contributes to the ongoing debate over whether diversity hinders or promotes economic growth. Existing evidence generally suggests that diversity hinders economic growth. For example, Easterly and Levin (1997) examine cross-country difference in economic growth and find that diversity increases polarization, facilitates competitive rent seeking between groups, and eventually impedes economic growth. Alesina and La Ferrara (2002) and Glaeser et al. (2000) find that diversity decreases trust in an organization, as people often distrust members of other ethnic groups and prefer interacting in homogeneous communities. This lack of trust usually leads to poor economic development (La Porta et al. 1997; Temple and Johnson 1998). Our paper, however, provides new micro-evidence on the bright side of diversity in terms of fostering innovation.

Second, our paper is broadly related to the literature on corporate social responsibility (CSR), in which corporate diversity is one of its major dimensions. 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 argue 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, corporate workforce diversity) is beneficial in the case of innovation, which requires heavy investment in human capital, and a tolerant and inclusive workforce (Holmstrom 1989).

Third, 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 economic literature. While most of the 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 fills this gap and suggests that discrimination in the labor market imposes significant costs on the economy by decreasing corporate innovativeness.

Lastly, our paper also adds to the literature that examines the drivers of innovation. Current research on this topic has focused on factors such as incentive compensation for top management (Manso 2010), institutional ownership (Aghion et al. 2013), anti-takeover provisions (Atanassov 2013), access to the equity market (Gao et al. 2014; Hsu et al. 2013), firms' information environment (He and Tian 2014), 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' workforce composition is largely overlooked.[2] This absence 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). Our paper helps to fill this gap by documenting workforce diversity as an important driver of innovation.

[2] Based on survey data of Danish firms, Ostergaard et al. (2011) find that a firm's likelihood of introducing a new product or service is positively associated with its employee diversity in gender and education, but negatively associated with age diversity, and has no significant relation with ethnic diversity. However, also based on Danish firms, Parrotta et al. (2014) find that a firm's patenting activity is positively associated with ethnic diversity and has no robust association with education and demographic diversity. Unlike our study, these two papers provide little evidence on the *causal* relation between workforce diversity and innovation. Moreover, they did not investigate patent citations or any other quality variables of innovation; thus, they did not investigate whether or not workforce diversity plays a role in the *quality* of innovation.

The remainder of the paper is organized as follows. Section 2 describes our sample and key variable construction; Section 3 presents the baseline regression results; Section 4 presents the identification tests. We conclude in Section 5.

2. Sample Formation and Variable Construction

2.1 The Sample

We obtain the measure of corporate workforce diversity 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 since 1991 and more than 3,000 companies that have comprised the Russell 3000 since 2003. Firms' financial information is obtained from Compustat. We retrieve patent and patent citation data from the worldwide Patent Statistical Database (PATSTAT, April 2012), and match corporations in Patstat with those in the KLD/Compustat database using propriety name-matching software.

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. We also 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. After undertaking the dataset construction described above, we have a total of 2,823 corporations. However, about half of these corporations never applied for a single patent during the entire sample period. Retaining them in the data adds noise as there is variation among these firms in diversity, but they all have the same value of the patent and citation counts – zero. Following Bloom et al. (2013), we drop firms that never filed a single patent during our entire sample period. Therefore, our final sample consists of 8,834 firm-year observations (1,419 unique firms) from 1992 to 2008.

2.2 Diversity Measures

KLD measures a firm's workforce diversity across several dimensions. Each dimension is associated with positive (i.e., strength) and negative (i.e., concern) indicators. If the firm conducts a good deed (a harm) listed as a strength (concern) indicator, it gains (loses) one point. Its potential strengths include (1) a woman/minority CEO, (2) woman/minority promotion, (3) a number of board seats held by women and minorities, (4) good work and life benefits, (5) women and minorities as subcontractors, (6) employment of the disabled, (7) pro-gay non-discrimination policies, and (8) "other strengths." A corporation that satisfies the threshold for all eight items would earn a score of 8 for strengths. Potential concerns include (1) involvement in affirmative action issues, (2) no female representation on the board or in senior executive positions, and (3) "other concerns." A firm that triggers concerns in all three areas would lose 3 points.

The diversity score for a firm is the sum of item scores along the diversity dimensions, based on the computation of its strength and concern indicators. Thus, the net score for diversity (strengths and concerns) could be anything from 8 to −3. A higher value indicates greater workforce diversity.[3]

[3] It is worth pointing out that the total number of strength and concern indicators may vary over time. To address this issue, we follow Deng et al. (2013) and construct an adjusted diversity score. In particular, we first count the number of strength and concern indicators for each year, and then divide the strength and concern scores for each firm by the respective number of strength and concern indicators. Then, the adjusted diversity score is the difference between the adjusted strength and concern scores. In untabulated tests, we find that the raw diversity score and adjusted diversity score are highly correlated (the correlation coefficient is 0.93) and using adjusted diversity score gives almost the same results as using the raw diversity score.

2.3 Innovation Variables

In this paper, we employ five innovation measures based on patent counts and patent citations. The first measure of innovation is the number of patents filed (and subsequently granted) by a firm in a given year.

As patents vary widely in their technological and economic importance, simple patent counts may not capture innovation success accurately. One measure of the importance of a patent is its citation count. However, due to the finite length of the sample, citations suffer from a time truncation bias. 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 adjust the citation count of each patent. Each patent's citation count is scaled by the average citation count of all firms' patents that are filed in the same year. Thus, our second measure of innovation is the sum of adjusted citation counts across all patents filed by the firm in a given year.

As a robustness check, we also 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 workforce diversity affects employees' productivity in innovative projects, we use patents and citations per employee as our last two innovation measures. Due to the high level of skewness of patent data, we use natural logarithms of the innovation variables.

2.4 Other Control Variables

We control for a vector of firm and industry characteristics that may affect a firm's future innovation productivity, and these controls are motivated by 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. Detailed variable definitions are provided in the Appendix.

2.5 Summary Statistics

To minimize the effect of outliers, we winsorize all variables at the 1st and 99th percentiles. Table 1 provides summary statistics. On average, firms in our sample have 45 patents filed (and subsequently granted) per year and receive 99 citations. Moreover, on average, firms have book value assets of $9.2 billion, a cash ratio of 20%, an R&D ratio of 5.7%, an ROA of 11.9%, a tangible asset ratio of 25.1%, a leverage of 19.9%, a capital expenditure ratio of 5.2%, a Tobin's *Q* of 2.36, and are 26 years old since first appearing on CRSP.

Table 2 shows the results of our univariate tests. We group firms into two categories: high-diversity firms and low-diversity firms, based on the sample median value of their diversity score. The average number of patents in high-diversity firms is 88.7, which is four times as large as that in low diversity-firms (22 patents). High-diversity firms, on average, receive199.6 patent citations, which is about 4.3 times as large as that in low-diversity firms (45.9 citations). At the median, high-diversity firms have 5 patents and receive 11 citations and 0.89 citations per patent, while low-diversity firms have 2 patents and receive 3 citations and 0.66 citations per patent. These differences are all significant at the 1% level. Further scaling the patents and citations by the number of employees, we find that the median firm in the high-diversity group has 0.67 patents and 2.93 citations per 1000 employees, while the median firm in the low-diversity group has only 0.41 patents and 1.77 citations per 1000 employees. The difference is also significant at the 1% level. These results support the innovation fostering hypothesis, which states that corporate workforce diversity increases innovation.

3. Baseline Regression Results

To assess how diversity affects innovation, we estimate various forms of the following model using the ordinary least squares (OLS) model:

$$Innovation_{i,t} = \alpha + \beta_1 Diversity_{i,t-1} + \beta_2 Other\ Firm\ Characteristics_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon, \quad (1)$$

where *i* indexes firm and *t* indexes time. The dependent variables are the measures of firms' innovation outcome. We take a one-year lag of all independent variables to explain innovation in year *t*. We include several firm and industry characteristics that may affect a firm's innovation output, as discussed in Section 2.

The main specification incorporates year fixed effects and two-digit SIC industry fixed effects to account for macroeconomic factors and time-invariant unobservable industry characteristics on firms' innovation productivity.[4] Also, as our regressions use firm-level time series and cross-sectional data, the standard errors are clustered by firm to correct for heteroskedasticity and serial correlation.

[4] A useful approach to dealing with unobserved heterogeneity is to use firm fixed effects. However, this method relies entirely on the within-firm variation for identification of coefficients, and will remove a lot of the "legitimate" variation in the data. This problem is particularly severe when the treatment variable (the diversity variable in our case) has little within-firm variation, because the firm fixed effects will absorb most of the cross-sectional variation of the diversity score and underestimate the explanatory power of diversity. In our sample, a firm's workforce diversity tends to be sticky over time. The correlation coefficient of a firm's diversity and its lagged diversity is 0.90, and 78.5% of firm-year observations have the same diversity score as their previous year. For this reason, we do not control for firm fixed effects in our baseline regression. However, we include firm fixed effects in the difference-in-differences tests in Section 4.2.

The dependent variable in column (1) of Table 3 Panel A is Ln(1+patents) and we find that the coefficient estimate on the diversity score is 0.193 and significant at the 1% level, suggesting a positive association between a firm's diversity and its innovation output. The economic magnitude is also sizeable: a one point increase in the diversity score leads to a 21% ($= e^{0.193} - 1$) increase in the number of patents.

Examining Ln(1+citations) as the dependent variable in column (2), we find that the coefficient on the diversity score is 0.227 and is significant at the 1% level, which implies that an increase in the diversity score by one point leads to an increase of citations by 25% ($= e^{0.227} - 1$).[5]

The positive association between diversity and 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). We find that greater diversity is associated with more citations per patent. Taken together, these results indicate that, as compared to the firms with low diversity, firms with greater diversity produce a larger number of patents and their patents are of higher impact.

In columns (4) and (5) of Table 3 Panel A, we scale the number of patents and citations by the number of employees to measure the employee productivity in innovation, respectively. The coefficient estimates of the diversity score are still positive and significant at the 1% level in both columns. These results indicate that a diverse labor force is positively associated with employee productivity in innovation.

[5] Given that the standard deviation of the diversity score is 1.19, a one-standard-deviation increase in the workforce diversity leads to, approximately, a 26% ($= e^{0.193\times1.19} - 1$) increase in number of patents and 31% ($= e^{0.227\times1.19} - 1$) increase in number of patent citations.

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

The diversity measure we use in Panel A is a combined measure of corporate workforce diversity across several different dimensions, including woman/minority CEO, woman/minority promotion, woman/minority director, good work and life benefits, woman/minority subcontractors, employment of the disabled, and pro-gay non-discrimination policies. A natural question is: how do these individual factors influence corporate innovation? In Panel B, we re-estimate Panel A by replacing the overall diversity score with each of the above individual factors, respectively. We find that all these factors (except for woman/minority director) have a significant and positive association with innovation measures.

Overall, the empirical evidence in Table 3 supports the innovation fostering hypothesis that a more diverse labor force increases corporate innovativeness.

4. Identification Tests

After establishing a robust positive relation between diversity and firm innovation, we next address the identification problem. It is possible that innovative companies are successful and thus can afford extensive and expensive diversity programs, and are more attractive to employees with diverse background (a reverse causality concern). It is also possible that some omitted variables drive both the firm's diversity and innovation (an omitted variable concern). For example, an open-minded CEO is more likely to foster innovative investment projects while supporting the rights of homosexual employees. Thus, the positive relation between corporate diversity and innovation is spuriously driven by CEO open-mindedness, which is unobservable in the data.

In this section, we address potential endogeneity concerns by adopting two different identification strategies. Section 4.1 presents the first identification strategy that constructs two instrumental variables for diversity and runs two-stage least squares(2SLS) regressions. Section 4.2 presents our second identification strategy that uses a difference-in-differences approach by exploiting a natural experiment: changes in state employment laws prohibiting discrimination based on sexual orientation and gender identity.

4.1 Instrumental Variable Approach

We perform 2SLS regression analyses using a racial segmentation index and male-female wage gap as two instrumental variables for a firm's diversity score. Following Levine et al. (2014), we develop a racial segmentation index based on the accumulated stock of interracial marriages using the 2000 Census data of population.[6] The Census sample provides the largest microdata set containing detailed marriage and demographic information in the U.S. We exploit this dataset to construct information on the abnormal rate of racial intermarriage in each state. Based on all married whites and blacks between the ages of 18 and 65 (approximately 1.6 million of couples), we estimate the following regression:

$$Racially\ mixed\ couple = \alpha + \beta_1 Husband\ Age + \beta_2 Husband\ Education + \beta_3 Wife\ Age + \beta_4 Wife\ Education + \beta_5 Random\ Interracial\ Marriate\ Rate + \beta_6 Proportion\ of\ Blacks\ among\ Married\ Couples + \varepsilon. \quad (2)$$

[6] The Census data of population is collected once every 10 years. We choose data from the year 2000 because it is in the middle of our sample period.

The dependent variable takes the value of one if it is a racially mixed couple, and zero otherwise. We control for the husband and wife's age and education. The random interracial marriage rate is calculated as $2P\times(1-P)$, where P is the proportion of blacks among the married couples. The ε term is the unexplained component of intermarriage. For a given state s, we then take an average ε of couples in this state, denoted as $\overline{\varepsilon_s}$. Then, for each state, we compute its racial segmentation index as $100\times[-\overline{\varepsilon_s}+Max(\overline{\varepsilon_s})]$, where $Max(\overline{\varepsilon_s})$ denotes the maximum value of $\overline{\varepsilon_s}$ across all U.S. states. By doing so, the state with the biggest $\overline{\varepsilon_s}$ will have a zero value of racial segmentation index and the state with the smallest $\overline{\varepsilon_s}$ will have the highest value of racial segmentation index. We interpret large values of the racial segmentation index as an indicator of severe racial segmentation. The intuition is: if African Americans only marry other African Americans and white Americans only marry other white Americans, then these two races are socially segmented; in contrast, if these two groups commonly marry each other, it indicates that they are socially integrated.[7] Levine et al. (2014) show that firms in areas of high racial segmentation have strong racial discrimination and pay significantly less to their black workers. Given that a firm's diversity policy may be influenced by its local racial preference, we expect the racial segmentation index to be negatively associated with a firm's diversity score (i.e., when there is a strong local racial segmentation, the firms in this area are less likely to have high racial diversity), thus satisfying the relevance requirement of instrumental variables. However, to the extent that the construction of the racial index variable is based on the individual resident's marriage decision, this variable is unlikely to have a direct effect on an individual firm's innovation performance other than through the channel of diversity, satisfying the exclusion condition of instrumental variables.

[7] In an untabulated analysis, we extend white-black mixed marriage to white-nonwhite mixed marriage and our inference is unchanged.

Our second instrumental variable is the male-female wage gap, which is the state-level hourly wage gap between men and women based on an American Community Survey 2000 sample (371,618 unique workers). For each state, we run the following regression:

$$Hourly\ wage = \alpha + \beta_1 Male\ indicator + \beta_2 Worker\ Age + \beta_3 Worker\ Education + \beta_4 Annual\ Working\ Hours + \ \beta_5 Worker\ Race + \beta_5 Industry\ FE + \varepsilon. \quad (3)$$

The dependent variable is the worker's hourly wage. We control for worker's age, education, annual hours of work, race, and industry fixed effects. The variable of interest is the β_1 coefficient, which measures the male-female wage disparity that is not explained by the observable worker's characteristics. Existing literature suggests that a larger gender wage gap that is not explained by observable workers' characteristics (at least partially) indicates a higher level of gender discrimination (see, for example, Blinder 1973; Mincer and Polachek 1974; Oaxaca 1973). Therefore, we expect this variable to be negatively correlated with our sample firms' diversity. There is no reason to believe, however, that the state-level gender pay gap could have a direct effect on an individual firm's innovation performance, except via its effect on a firm's diversity.

As reported in Table 4 Panel A, the top five states with least severe racial segmentation are District of Columbia, Hawaii, Alaska, California, and Maryland; the top five states with most severe racial segmentation are Idaho, Arkansas, Wyoming, North Dakota, and Alabama. In Panel B, the top five states with least gender discrimination are West Virginia, Maryland, Vermont, New Mexico, and District of Columbia; the top five states with most gender discrimination are Connecticut, Missouri, Georgia, New Hampshire, and Colorado. We then obtain the firm's headquarter information from Compact Disclosure, following Pirinsky and Wang (2006), and use the state-level racial and gender discrimination in the firm's headquarters as two instrumental variables.[8]

To provide additional support for our choice of instruments, we perform the following two tests in each of the 2SLS regressions: (1) a Cragg-Donald (1993) instrument relevance test to confirm the relevance of the instrumental variables (i.e., high correlations between the instrumental variables and diversity score), and (2) a Sargan (1958) overidentification test to examine the exogeneity of the instrumental variables (i.e., no significant correlations between the instrumental variables and the error terms in the innovation regressions).

In Table 4 Panel C, we report the results from the 2SLS regressions. The first-stage regression results are reported in column (1), and the second-stage regression results are reported in columns (2)-(6). In column (1), we use the diversity score as the dependent variable and the two instrumental variables discussed above, firm and industry characteristics, and industry and year fixed effects as the independent variables. As expected, both instrumental variables (racial segmentation index and gender pay gap) have negative coefficients and both coefficients are significant at the 1% level. The F-statistics for first-stage Cragg-Donald test is 47.67; the p-value is less than 0.001, rejecting the null hypothesis that the instruments are weak. This result confirms the relevance of our instrumental variables.

In column (2), we use the number of patents as the dependent variable; we use the predicted diversity score and other firm and industry characteristics as the independent variables. The p-value of the overidentification test is 0.97, which fails to reject the null hypothesis that the instrumental variables are valid. In other words, our two instrumental variables pass the Sargan

[8] Breschi (2008) and Howells (1990) show that firms usually locate their R&D facilities close to the company's headquarters and do not disperse them geographically.

overidentification test. We find that the coefficient estimate on the predicted diversity score is still positive and significant at the 1% level, indicating that workforce diversity increases a firm's patenting activity.

In columns (3)-(6), we estimate the 2SLS regressions using the number of citations, citations per patent, patents per employee, and citations per employee as the dependent variables, respectively. In all four columns, our two instrumental variables pass the Sargan overidentification test and we find positive and significant coefficient estimates on the predicted diversity score.

Overall, the regression results reported in Table 4 show that the positive relationship between workforce diversity and innovation is robust to addressing the endogeneity concern. The results support the innovation fostering hypothesis that a firm's workforce diversity contributes to its successful patenting.

4.2 Difference-in-Differences Test

Our second identification strategy is to use the natural experiment created by the passage of employment laws that prohibit discrimination based on sexual orientation and gender identity by several U.S. states since the 1970s (see Table 5 for a detailed list[9]). This setting is highly appealing from an empirical standpoint for two reasons. First, the motivation behind the passage of these laws centered around state courts' determination to address a persistent, widespread pattern of discrimination on the bases of sexual orientation and gender identity by employers, 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 our outcomes of interest are likely to be an unintended consequence of the passage of these laws.

[9] The list of statewide employment laws is obtained from http://www.hrc.org/files/assets/resources/employment_laws_1-2014.pdf

Second, the staggered adoption of these laws in several U.S. states enables us to identify their effects in a difference-in-differences framework.

Figure 1 depicts the effects of the employment anti-discrimination laws on innovation in states that adopted the policy change relative to states that did 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:

$$Innovation_{i,t} = \alpha + \sum_{n=-5}^{10} \beta_n * Pass\_year_{s,t+n} + Year\ FE + \varepsilon_{i,t} \ , \qquad (4)$$

where *i* indexes firm and s indexes the state in which firms' headquarters are located, and *t* indexes the year. $Pass\_year_{s,t+n}$ is a variable indicating the year relative to the adoption of the anti-discrimination laws in state *s* and year *t*.[10] The two plots in Figure 1 correspond to patents and citations, respectively, and they show the same pattern. Innovation increases after the adoption of the employment anti-discrimination laws. Moreover, the greatest increase in innovation appears several years afterwards, suggesting that the passage of anti-discrimination laws has a persistent long-run effect.

We investigate whether or not the passage of these employment anti-discrimination laws in the U.S. leads to greater corporate innovation. Several U.S. state courts adopted the anti-discrimination laws in different years during the sample period. Thus, we can examine the

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

before-after effects 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), Bertrand et al. (2004), and Imbens and Wooldridge (2009). We implement this test through the following regression:

$$Innovation_{i,t} = \alpha + \beta_1 Pass_{s,t-1} + \beta_2 Other\ Firm\ Characteristics_{i,t-1} + Firm\ FE + Year\ FE + \varepsilon_{i,t}\ , \quad (5)$$

where *i* indexes firm and *s* indexes the state in which firms' headquarters are located, and *t* indexes the year. Similar to the main specification, 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. We include a set of control variables that may affect a firm's innovation output, as we discussed in Section 3. 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.

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. Results are reported in Table 5. Since the difference-in-differences regression analysis does not require KLD diversity data, our tests are conducted over a larger sample of 58,016 firm-years with 4,915 firms from 1976 to 2008. However, we find both quantitatively and qualitatively similar results using the 1992-2008 KLD sample.

Remarkably, the coefficient estimates on the passage of employment anti-discrimination laws are positive and statistically significant in all columns. Columns (1) and (2) show that the passage of employment anti-discrimination laws leads to an increase in firm-level innovation as measured by both patents and citations. In addition to being statistically significant, the economic magnitude of the employment anti-discrimination laws on innovative corporate activity is also sizeable. In particular, we find that the adoption of anti-discrimination laws leads to an increase in the annual number of patents and citations by 12.3% ($= e^{0.116} - 1$) and 15.3% ($= e^{0.142} - 1$), respectively, compared to firms located in states that did not pass anti-discrimination laws.

In column (3), we perform our tests replacing the dependent variable with citations per patent. We find that the passage of employment anti-discrimination laws also has a positive and significant impact on corporate innovation quality. In columns (4)-(5), we repeat our test using patents and citations scaled by the number of employees. We find that patents and citations per 1,000 employees increase by, respectively, 11.0% and 13.7% 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.

However, one important common factor that likely induces an association between the passing of these anti-discrimination laws and corporate innovation is location. Specifically, corporations which have the strongest innovation performance are concentrated in two areas: California and the north Atlantic region of New York, New Jersey, Massachusetts and

Connecticut. The other two states that show a high level of corporate innovation are 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 diversity 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 Table 7, in addition to our usual set of explanatory variables, 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. 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 in a given state, 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 taken from the annual Statistical Abstracts from the U.S. Census Bureau.

We find that smaller state GDP, larger population and more colleges in a state are positively associated with innovation. Further, a higher ratio of Republican to Democrat state representatives in the House of Representatives has a negative impact on innovation by firms. Importantly, we find that the adoption of anti-discrimination laws continues to have a positive and (statistically and economically) significant impact on corporate innovation.

Taken together, these results indicate a positive casual effect of corporate diversity on innovation outputs in terms of both quantity and quality, which supports our innovation fostering hypothesis.

5. Conclusions

The concept of diversity was originally created to justify the inclusion of people who were traditionally excluded from schools, universities, corporations, and other kinds of organizations. As the U.S. workforce continues to grow more diverse, the effects of diversity on economic outcomes are an increasingly important issue. In this paper, we investigate this question from the perspective of corporate innovation. Based on a large sample of U.S. public firms, we find that firms of greater workforce diversity generate a larger number of patents and patents with greater impacts. To establish causality, we use an instrumental variable approach and a difference-in-differences approach. Our identification tests reveal a positive causal effect of workforce diversity on firm innovation. Overall, our findings are consistent with the view that diversity has a positive effect on business success, because it allows companies to “think outside the box” by bringing previously excluded groups inside the box. This process provides a wider range of perspectives and a greater variety of intellectual skills, thus enhancing a company's 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 of people of different gender, race, and sexual orientation can have real economic effects in terms of improving corporate innovation.

Reference

Acharya, Viral, Ramin Baghai, and Krishnamurthy Subramanian, 2014. Wrongful discharge laws and innovation, *Review of Financial Studies 27*, 301–346.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, 2005. Competition and innovation: An inverted-U relationship, *Quarterly Journal of Economics* 120, 701–728.

Aghion, Philippe, John Van Reenen, and Luigi Zingales, 2013. Innovation and institutional ownership, *American Economic Review* 103, 277–304.

Alesina, Alberto, and Eliana, La Ferara, 2002. Who trusts others? *Journal of Public Economics* 85, 207–234.

Alesina, Alberto, and Eliana, La Ferara, 2005. Ethnic diversity and economic performance, *Journal of Economic Literature* 43, 762–800.

Amason, Allen, 1996. Distinguishing the effects of functional and dysfunctional conflict on strategic decision making: Resolving a paradox for top management teams, *Academy of Management Journal* 39, 123–148.

Atanassov, Julian, 2013. Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting, *Journal of Finance* 68, 1097–1131.

Autor, David, John J. Donohue, III and Stewart Schwab, 2006. The costs of wrongful-discharge laws, *Review of Economics and Statistics* 88, 211–231.

Beck, Gary, 1957. The economics of discrimination. Chicago: University of Chicago Press.

Berliant, Marcus, and Masahisa Fujita, 2011. The dynamics of knowledge diversity and economic growth, *Southern Economic Journal* 4, 856–884.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, 2004. How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics* 119, 249–75.

Blinder, Alan, 1973. Wage discrimination: Reduced form and structural estimates, *Journal of Human Resources* 8, 436–55.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, 2013. Identifying technology spillovers and product market rivalry, *Econometrica* 81, 1347–1393.

Breschi, Stefano, 2008. Innovation-specific agglomeration economies and the spatial clustering of innovative firms. *Handbook of Research on Innovation and Clusters*, 167–92. Ed. C. Karlsson. Cheltenham: Edward Elgar Publishing.

Cragg, John, and Stephen Donald, 1993. Testing identifiability and specification in instrumental variable models, *Econometric Theory* 9, 222–240.

Cross, Rob, Andrew Hargadon, Salvatore Parise, and Robert Thomas, 2007. Together we innovate, *Sloan Management Review*, R6.

Cronqvist, Henrik, Fredrik Heyman, Mattias Nilsson, Helena Svaleryd, and Jonas Vlachos, 2009. Do entrenched managers pay their workers more? *Journal of Finance* 64, 309–339.

Deng, Xin, Jun-koo Kang, and Buen Sin Low, 2013. Corporate social responsibility and stakeholder value maximization: Evidence from mergers, *Journal of Financial Economics* 110, 87–109.

Drach-Zahavy, Anat, and Anit Somech, 2001. Understanding team innovation: The role of team processes and structures, *Group Dynamic Theory Research Practice* 5, 111–123.

Easterly, Wiliam, and Ross Levine, 1997. Africa’s growth tragedy: Policies and ethnic divisions, *Quarterly Journal of Economics* 112, 1203–1250.

Fang, Vivian, Xuan Tian, and Sheri Tice, 2013. Does stock liquidity enhance or impede firm innovation? *Journal of Finance* forthcoming.

Gao, Huasheng, Po-Hsuan Hsu, and Kai Li, 2014. Public equity markets and corporate innovation strategies: Evidence from private firms, Nanyang Technological University working paper.

Glaeser, Edward, David Laibson, Jos Scheinkman, and Christine Soutter, 2000. Measure trust, *Quarterly Journal of Economics* 115, 811–846.

Griliches, Zvi, 1981. Market value, R&D, and patents. *Economics Letters* 7, 183–167.

Friedman, Milton, 1970. The social responsibility of business is to increase its profits. *New York Times Magazine,* September 13, 1970,

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, 2001. The NBER patent citation data file: Lessons, insights and methodological tools, Unpublished working paper.

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, 2005. Market value and patent citations, *RAND Journal of Economics* 36, 16–38.

He, Jie, and Tian Xuan, 2013. The dark side of analyst coverage: The case of innovation, *Journal of Financial Economics* 109, 856–878.

Holmstrom, Bengt, 1989. Agency costs and innovation, *Journal of Economic Behavior and Organization* 12, 305–327.

Hong, Lu, and Scott Page, 2001. Problem solving by heterogeneous agents, *Journal of Economic Theory* 97, 123–163.

Howells, Jeremy, 1990. The location and organization of research and development: New horizons. *Research Policy* 19, 133–146.

Hsu, Po-Hsuan, Xuan Tian, and Yan Xu, 2014. Financial development and innovation: Cross-country evidence, *Journal of Financial Economics* 112, 116–135.

Imbens, Guido, and Jeffrey Wooldridge, 2009. Recent developments in the econometrics of program evaluation, *Journal of Economic Literature* 47, 5–86.

Jensen, Michael, 2001. Value maximization, stakeholder theory, and the corporate objective function, *Journal of Applied Corporate Finance* 14, 8–21.

La Porta, Rafael, Florencio Lopez-De-Silanes, Andrei Shleifer, and Robert Vishny, 1997. Trust in large organizations, *American Economic Review* papers and proceedings 87, 354–358.

Lazear, Edward, 1999. Globalizations and the market for team-mates, *Economic Journal* 109, 15–40.

Lerner, Josh, and Julie Wulf, 2007. Innovation and incentives: Evidence from corporate R&D, *Review of Economics and Statistics* 89, 634–644.

Levine, Ross, Alexey Levkov, and Yona Rubinstein, 2014. Bank deregulation and racial inequality in America, *Critical Finance Review* 3, 1–48.

Manso, Gustavo, 2011. Motivating innovation, *Journal of Finance* 66, 1823–1860.

Mincer, Jacob and Solomon Polachek, 1974. Family investments in human capital: Earnings of women, *Journal of Political Economy* 82, 76–108.

Oaxaca, Ronald, 1973. Male-female wage differentials in urban labor markets, *International Economic Review* 14, 693–709.

Ostergaard, Christian, Bram Timmermans, and Kari Kristinsson, 2011. Does a different view create something new? The effect of employee diversity on innovation, *Research Policy* 40, 500–509.

Pagano, Marco, and Paolo Volpin, 2005. Managers, workers, and corporate control, *Journal of Finance* 60, 841–868.

Passel, Jeffrey, and D' Vera Cohn, U.S. population projections: 2005-2050, Pew Research Center Report.

Parrotta, Pierpaolo, Dario Pozzoli, and Mariola Pytlikova, 2014. The nexus between labor diversity and firm's innovation, *Journal of Population Economics* 27, 303–364.

Pirinsky, Christo, and Qinghai Wang, 2006, Does corporate headquarters location matter for stock returns? *Journal of Finance* 61, 1991–2015.

Sargan, John, 1958. The estimation of economic relationships with instrumental variables, *Econometrica* 26, 393– 415.

Scherer, F. M., 1965. Firm size, market structure, opportunity, and the output of patented inventions, *American Economic Review* 55, 1097–1125.

Temple, Jonathan, and Paul Johnson, 1998. Social capability and economic growth, *Quarterly Journal of Economics* 113, 965–990.

Watson, Warren, Kamalesh Kumar, and Larry Michaelsen, 1993. Cultural diversity's impact on interaction process and performance: comparing homogenous and diverse task groups, *Academy of Management* 36, 590–602.

William, Katherine, and Charles O'Reilly, 1998. Demography and diversity in organizations: A review of 40 years of research, *Research in Organizational Behavior* 20, 77–140.

Zajac, Edward, Brian Golden, and Stephen Shortell, 1991. New organizational forms for enhancing innovation: The case of internal corporate joint ventures, *Management Science* 37, 170–184.

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	
Diversity	Sum of diversity scores. It is the net score for diversity based on the computation of strength and concern indicators.
Woman/minority CEO	An indicator variable that takes the value of one if the company's chief executive officer is a woman or a member of a minority group, and zero otherwise.
Woman/minority promotion	An indicator variable that takes the value of one if the company has made notable progress in the promotion of women and minorities, and zero otherwise.
Woman/minority director	An indicator variable that takes the value of one if women, minorities, and/or the disabled hold four seats or more (with no double counting) on the board of directors, or one-third or more of the board seats if the board numbers less than 12, and zero otherwise.
Good work and life benefits	An indicator variable that takes the value of one if the company has outstanding employee benefits or other programs addressing work/life concerns, and zero otherwise.
Woman/minority subcontractors	An indicator variable that takes the value of one if the company does at least 5% of its subcontracting, or otherwise has a demonstrably strong record on purchasing or contracting, with women- and/or minority-owned businesses, and zero otherwise.
Employment of the disabled	An indicator variable that takes the value of one if the company has implemented innovative hiring programs for the disabled, or otherwise has a superior reputation as an employer of the disabled, and zero otherwise.
Pro-gay non-	An indicator variable that takes the value of one if the company has implemented

discrimination policy	notably progressive policies toward its gay and lesbian employees, and zero otherwise.
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 to 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.
State Characteristics	
Racial segmentation index	State-level abnormal white-black interracial marriage rate. Based on all married blacks and whites in the Census 2000 dataset, we first regress the interracial marriage indicator on the husband's age, the husband's education, the wife's age, the wife's education, the random interracial marriage rate, and the percentage of blacks among married couples. We then take the average of the residual from the regression in each state and a more negative value of these residual indicates higher racial segmentation. The racial segmentation index is constructed by normalizing these state-level average residuals so that the state with the highest average residuals to have zero value for the racial segmentation index and the state with the lowest state-level average residuals to have the highest value for the racial segmentation index. A higher value of racial segmentation index indicates a higher level of racial segmentation.
Male–female wage gap	State-level hourly wage gap between men and women, using American Community Survey 2000 sample. For each state, we run regression of hourly wage on male dummy, controlling for age, education, annual hours of work, race and industry fixed effects. The estimates on male dummy are used as the measure of the abnormal male-female wage disparity that is not explained by observable worker characteristics. A higher value indicates a higher level of gender discrimination.
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 (in millions).
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 (in thousands).
Political balance	The ratio of Republican-to-Democrat representatives in the Lower House (House of Representatives) for a given state; this variable is not available for the state of Nebraska, as it has a nonpartisan legislature whose members are elected without party designation.

Table 1. Summary Statistics

The sample consists of 8,834 firm-year observations from 1992-2008, obtained from KLD/Patsat/Compustat merged databases. The sample firms are required to have at least one patent over the entire sample period. 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	8834	45.1	211.2	0	2	836
Citations	8834	99.1	476.0	0	5	1685
Citations per patent	8834	1.04	1.36	0	0.75	6.05
Patents per 1000 employees	8834	5.4	15.2	0	0.47	76.9
Citations per 1000 employees	8834	46.2	172.7	0	2.12	744.9
Diversity	8834	0.35	1.19	-1	0	4
Cash	8834	0.20	0.22	0.001	0.11	0.87
Firm assets ($b)	8834	9.20	34.68	0.06	1.78	125.8
Number of employees in 1000s	8834	24.49	72.34	0.09	6.50	307.4
Firm age	8834	26.38	21.08	2	20	81
Tobin's Q	8834	2.36	1.53	0.86	1.83	8.10
ROA	8834	0.12	0.13	-0.45	0.13	0.40
Leverage	8834	0.20	0.18	0	0.18	0.76
Tangible	8834	0.25	0.19	0.01	0.20	0.83
R&D	8834	0.06	0.08	0	0.03	0.39
Capex	8834	0.05	0.04	0.004	0.04	0.22
H-index	8834	0.18	0.17	0.03	0.12	0.92

Table 2. Univariate Tests

The sample consists of 8,834 firm-year observations from 1992-2008, obtained from KLD/Patsat/Compustat merged databases. The sample firms are required to have at least one patent over the entire sample period. Definitions of all variables are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. We divide the full sample into high-diversity firms and low-diversity firms based on the sample median of diversity. P-values of the t-test and the Wilcoxon z-test of the differences in innovation measures between high-diversity firms and low-diversity firms are reported in the last two columns. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	High-diversity firms		Low-diversity firms		Test of differences	
	Mean (1)	Median (2)	Mean (3)	Median (4)	*t*-test (1) – (3)	Wilcoxon *z*-test (2) – (4)
Patents	88.7	5	22.0	2	0.000***	0.000***
Citations	199.6	11	45.9	3	0.000***	0.000***
Citations per patent	1.10	0.89	1.01	0.66	0.001***	0.000***
Patents per 1000 employees	5.35	0.67	5.39	0.41	0.538	0.000***
Citations per 1000 employees	44.3	2.93	47.2	1.77	0.775	0.000***

Table 3: The Effect of Diversity on Innovation

The sample consists of 8,834 firm-year observations from 1992-2008, obtained from KLD/Patsat/Compustat merged databases. The sample firms are required to have at least one patent over the entire sample period. The dependent variables are various measures of innovation outputs. In Panel A, we examine the effect of overall KLD diversity score. In Panel B, we examine the effect of each individual factor that comprises the overall KLD diversity score. Definitions of all variables 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 firm are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Overall Diversity Score

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Diversity	0.193***	0.227***	0.020***	0.088***	0.105***
	(12.11)	(12.25)	(4.13)	(9.07)	(8.37)
Cash	1.165***	1.596***	0.297***	0.890***	1.399***
	(10.19)	(11.16)	(6.70)	(9.12)	(10.94)
Firm size	0.455***	0.505***	0.041***	-0.058***	-0.061***
	(29.10)	(27.48)	(8.04)	(-5.70)	(-4.58)
Ln (Firm age)	0.051**	-0.007	-0.035***	-0.037***	-0.074***
	(2.34)	(-0.25)	(-4.64)	(-2.59)	(-4.02)
Tobin's Q	0.021	0.043***	0.005	-0.027**	-0.002
	(1.62)	(2.69)	(0.99)	(-2.33)	(-0.16)
Leverage	0.099	0.276**	0.042	-0.006	0.155
	(1.09)	(2.38)	(1.18)	(-0.08)	(1.62)
R&D	4.574***	6.242***	1.264***	4.161***	6.055***
	(14.71)	(16.28)	(10.70)	(15.17)	(17.30)
Capex	3.276***	4.143***	0.696***	1.592***	2.289***
	(6.90)	(7.22)	(3.90)	(4.63)	(5.06)
Tangible	0.011	-0.222	-0.148***	0.022	-0.095
	(0.08)	(-1.29)	(-2.96)	(0.26)	(-0.83)
ROA	0.629***	0.562***	0.143**	0.396***	0.061
	(3.99)	(2.88)	(2.32)	(2.70)	(0.33)
H-index	0.472	-0.359	-0.288***	-0.515***	-1.239***
	(1.55)	(-1.01)	(-2.99)	(-3.08)	(-5.71)
H-index^2	0.144	1.010**	0.434***	0.669***	1.384***
	(0.44)	(2.52)	(3.87)	(3.87)	(5.95)
Constant	-1.425***	-1.152***	0.464**	-0.023	0.202
	(-6.53)	(-3.80)	(2.55)	(-0.21)	(1.04)
Observations	8834	8834	8834	8834	8834
Year FEs	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.415	0.388	0.192	0.381	0.442

Panel B: Individual Diversity Factor

	(1) LnPat	(2) LnCit	(3) LnCit/pat	(4) LnPat/emp	(5) LnCit/emp
Woman/minority CEO	0.164**	0.153*	-0.001	0.102*	0.064
	(2.21)	(1.76)	(-0.06)	(1.84)	(0.93)
Woman/minority promotion	0.185***	0.221***	0.027**	0.080***	0.085***
	(4.82)	(4.86)	(2.21)	(3.20)	(2.62)
Woman/minority director	0.007	-0.007	-0.027	-0.025	-0.057
	(0.11)	(-0.09)	(-1.46)	(-0.78)	(-1.35)
Good work and life benefits	0.510***	0.587***	0.031*	0.181***	0.209***
	(7.57)	(7.76)	(1.86)	(5.58)	(5.01)
Woman/minority subcontractors	0.665***	0.769***	0.097***	0.259***	0.333***
	(7.25)	(7.52)	(4.77)	(6.59)	(6.56)
Employment of the disabled	0.880***	0.923***	0.094***	0.366***	0.413***
	(7.25)	(6.90)	(3.61)	(6.39)	(5.72)
Pro-gay non-discrimination policy	0.690***	0.799***	0.065***	0.366***	0.434***
	(14.69)	(14.31)	(4.42)	(12.67)	(11.52)
Other controls			Same as Panel A		

Table 4: Instrumental Variables Approach

The sample consists of 8,834 firm-year observations from 1992-2008, obtained from KLD/Patsat/Compustat merged databases. The sample firms are required to have at least one patent over the entire sample period. All continuous variables are winsorized at the 1st and 99th percentiles. Robust t-statistics based on standard errors clustered by firm are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Panels A and B present the racial segmentation index and gender wage gap across U.S. states, respectively. Panel C presents the regression results of 2SLS using racial segmentation index and gender wage gap as two instrumental variables.

Panel A: Racial Segmentation Index by State

1. District of Columbia	0	26. North Carolina	0.058
2. Hawaii	0.01	27. Oklahoma	0.058
3. Alaska	0.033	28. Pennsylvania	0.058
4. California	0.037	29. Texas	0.058
5. Delaware	0.044	30. Kentucky	0.059
6. Maryland	0.044	31. Minnesota	0.059
7. New Jersey	0.045	32. New Hampshire	0.059
8. Nevada	0.046	33. South Dakota	0.059
9. New York	0.046	34. Wisconsin	0.059
10. Virginia	0.046	35. Indiana	0.06
11. Washington	0.047	36. Kansas	0.06
12. Colorado	0.048	37. Maine	0.06
13. Nebraska	0.05	38. Iowa	0.061
14. Arizona	0.051	39. Missouri	0.061
15. Florida	0.051	40. Tennessee	0.061
16. New Mexico	0.051	41. West Virginia	0.061
17. Connecticut	0.052	42. Mississippi	0.062
18. Massachusetts	0.052	43. Alabama	0.063
19. Oregon	0.053	44. Louisiana	0.063
20. Ohio	0.054	45. Montana	0.063
21. Illinois	0.055	46. North Dakota	0.063
22. Michigan	0.055	47. South Carolina	0.063
23. Rhode Island	0.055	48. Utah	0.063
24. Vermont	0.055	49. Wyoming	0.064
25. Georgia	0.057	50. Arkansas	0.065
		51. Idaho	0.065

Panel B: Gender Wage Gap by State

1. West Virginia	2.82	26. North Dakota	7.28
2. Maryland	2.99	27. Rhode Island	7.29
3. Vermont	3.71	28. Hawaii	7.44
4. New Mexico	3.89	29. Iowa	7.48
5. District Of Columbia	4.02	30. Minnesota	7.55
6. Idaho	4.31	31. Illinois	7.59
7. Arkansas	4.67	32. Pennsylvania	7.8
8. Montana	4.83	33. Wisconsin	7.88
9. Kansas	5.09	34. Louisiana	8.43
10. Nevada	5.22	35. Arizona	8.5
11. South Dakota	5.46	36. Michigan	8.66
12. Kentucky	5.49	37. Massachusetts	9.07
13. Alaska	5.63	38. New York	9.13
14. Texas	5.67	39. Delaware	9.21
15. Indiana	5.7	40. Nebraska	9.59
16. South Carolina	5.85	41. New Jersey	9.95
17. Oklahoma	5.97	42. Virginia	10.2
18. North Carolina	6.22	43. Wyoming	10.29
19. Alabama	6.3	44. Tennessee	10.3
20. Washington	6.33	45. Ohio	10.52
21. Florida	6.47	46. California	10.73
22. Oregon	6.94	47. Colorado	11.15
23. Maine	6.96	48. New Hampshire	11.19
24. Mississippi	7.13	49. Georgia	12.23
25. Utah	7.2	50. Missouri	12.94
		51. Connecticut	14.57

Panel C: 2SLS Regression

	First Stage	Second Stage				
	(1)	(2)	(3)	(4)	(5)	(6)
	Diversity	LnPat	LnCit	LnCit/pat	LnPat/emp	LnCit/emp
Diversity		1.992***	2.251***	0.382***	1.426***	1.598***
		(8.63)	(8.49)	(6.40)	(8.68)	(8.27)
Racial segmentation index	-15.799***					
	(-9.76)					
Male-female wage gap	-0.022***					
	(-3.99)					
Cash	0.616***	-0.145	0.120	0.032	-0.075	0.317
	(7.09)	(-0.57)	(0.41)	(0.49)	(-0.41)	(1.48)
Firm size	0.360***	-0.200**	-0.232**	-0.091***	-0.546***	-0.605***
	(36.67)	(-2.30)	(-2.31)	(-4.04)	(-8.80)	(-8.30)
Ln(Firm age)	0.106***	-0.121***	-0.200***	-0.069***	-0.163***	-0.215***
	(6.64)	(-2.90)	(-4.16)	(-6.41)	(-5.48)	(-6.14)
Tobin's Q	0.049***	-0.069***	-0.058**	-0.013**	-0.093***	-0.077***
	(5.19)	(-2.87)	(-2.10)	(-2.13)	(-5.41)	(-3.78)
Leverage	0.023	0.088	0.260	0.038	-0.006	0.148
	(0.32)	(0.54)	(1.40)	(0.90)	(-0.05)	(1.09)
R&D	1.486***	1.535**	2.828***	0.654***	1.882***	3.521***
	(6.49)	(2.37)	(3.80)	(3.91)	(4.09)	(6.50)
Capex	-1.030***	4.944***	6.030***	1.037***	2.799***	3.649***
	(-2.78)	(5.75)	(6.10)	(4.66)	(4.57)	(5.06)
Tangible	0.216**	-0.240	-0.509*	-0.200***	-0.150	-0.294
	(1.97)	(-0.96)	(-1.78)	(-3.11)	(-0.85)	(-1.41)
ROA	0.298**	0.069	-0.065	0.031	-0.032	-0.413*
	(2.46)	(0.24)	(-0.20)	(0.43)	(-0.16)	(-1.75)
H-index	-0.049	0.683	-0.123	-0.244*	-0.348	-1.051**
	(-0.22)	(1.33)	(-0.21)	(-1.84)	(-0.95)	(-2.45)
H-index^2	-0.445*	0.796	1.746**	0.564***	1.149***	1.917***
	(-1.71)	(1.35)	(2.57)	(3.69)	(2.73)	(3.88)
Constant	0.055	0.558	1.079	0.863***	1.447***	1.842***
	(0.18)	(0.82)	(1.38)	(4.90)	(2.98)	(3.23)
Observations	8819	8819	8819	8819	8819	8819
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Durbin-Wu-Hausman chi2 test p-value		<0.001	<0.001	<0.001	<0.001	<0.001
First-stage Cragg and Donald F-statistic	47.67***					
Overidentification test p-value		0.970	0.980	0.750	0.190	0.440
Adjusted R2	0.340	0.157	0.231	0.401	0.230	0.122

Table 5: List of the Passages of State Employment Anti-discrimination Laws

This table reports the year when each state adopted the state-level employment anti-discrimination laws that prohibit discrimination based on sexual orientation and gender identity, from 1976 to 2008.

State	Year	Number of firms affected
District of Columbia	1977	2
Wisconsin	1982	27
Massachusetts	1989	106
Connecticut	1991	64
Hawaii	1991	1
Vermont	1991	0
California	1992	322
New Jersey	1992	97
Minnesota	1993	86
Rhode Island	1995	5
New Hampshire	1998	14
Nevada	1999	13
Maryland	2001	36
New Mexico	2003	1
New York	2003	141
Maine	2005	2
Illinois	2006	80
Washington	2006	47
Colorado	2007	34
Iowa	2007	7

Table 6: Effect of the Passage of Employment Anti-discrimination Laws on Innovation

The sample consists of 58,016 firm-year observations from 1976-2008, obtained from Patstat/Compustat merged databases. The sample firms are required to have at least one patent over the entire sample period. All continuous variables are winsorized at the 1st and 99th percentiles. 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. 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	0.116***	0.142***	0.016**	0.110***	0.137***
	(8.90)	(8.62)	(2.07)	(7.12)	(7.31)
Cash	0.238***	0.346***	0.143***	0.415***	0.574***
	(9.01)	(9.66)	(7.46)	(9.29)	(10.66)
Firm size	0.189***	0.218***	0.040***	-0.027***	-0.016*
	(30.04)	(28.29)	(11.37)	(-3.57)	(-1.77)
Ln(Firm age)	-0.004	0.000	0.014***	0.002	0.023**
	(-0.49)	(0.02)	(2.94)	(0.25)	(2.08)
Tobin's Q	0.016***	0.018***	0.004***	0.006	0.008
	(7.67)	(6.22)	(2.61)	(1.56)	(1.64)
Leverage	-0.027	0.048	0.011	-0.073**	0.018
	(-1.25)	(1.64)	(0.69)	(-2.20)	(0.43)
R&D	0.240***	0.372***	0.177***	0.752***	0.942***
	(4.00)	(4.32)	(3.77)	(6.09)	(6.32)
Capex	0.017	0.083	0.087*	0.171*	0.179
	(0.26)	(0.98)	(1.84)	(1.72)	(1.52)
Tangible	-0.142***	-0.236***	-0.026	-0.045	-0.098
	(-3.19)	(-4.30)	(-0.99)	(-0.80)	(-1.51)
ROA	-0.008	0.016	0.028	0.042	0.049
	(-0.35)	(0.51)	(1.58)	(0.94)	(0.91)
H-index	-0.323***	-0.509***	-0.189***	-0.268***	-0.419***
	(-2.76)	(-3.61)	(-2.95)	(-2.77)	(-3.58)
H-index^2	0.678***	0.898***	0.226***	0.391***	0.535***
	(5.21)	(5.75)	(3.29)	(3.99)	(4.46)
Constant	0.651***	0.780***	0.334***	0.564***	0.668***
	(20.21)	(19.82)	(17.82)	(16.30)	(16.30)
Observations	58016	58016	58016	58016	58016
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.749	0.725	0.404	0.569	0.619

Table 7: Robustness Test for the Effect of Anti-discrimination Laws on Innovation after Controlling for State-level Characteristics

The sample consists of 58,016 firm-year observations from 1976-2008, obtained from Patstat/Compustat merged databases. The sample firms are required to have at least one patent over the entire sample period. All continuous variables are winsorized at the 1st and 99th percentiles. 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 logarithm of annual real state GDP (in millions). Ln(Population) is the logarithm of a state's population (in million). Ln(Colleges) is the logarithm of the number of degree-granting institutions of higher education in a given state. Ln(Enrollment) is the logarithm of enrollment in institutions of higher education in a given state (in thousands). Political balance is the ratio of Democrat-to-Republican representatives in the Lower House (House of Representatives) for a given state. 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	0.113***	0.135***	0.020**	0.117***	0.141***
	(8.66)	(8.17)	(2.54)	(7.30)	(7.28)
Ln(State GDP)	-0.173***	-0.184***	-0.093***	-0.313***	-0.298***
	(-3.08)	(-2.70)	(-2.91)	(-5.17)	(-4.18)
Ln(Population)	0.249***	0.284***	0.034	0.346***	0.330***
	(3.33)	(3.10)	(0.77)	(4.01)	(3.29)
Ln(Colleges)	0.083***	0.085**	0.033*	0.063	0.082*
	(2.61)	(2.12)	(1.72)	(1.61)	(1.74)
Ln(Enrollment)	-0.140***	-0.172***	0.028	-0.085	-0.108
	(-2.76)	(-2.75)	(0.93)	(-1.44)	(-1.54)
Political balance	-0.023**	-0.041***	0.006	0.012	0.000
	(-2.11)	(-2.99)	(0.94)	(0.95)	(0.02)
Cash	0.238***	0.346***	0.144***	0.411***	0.568***
	(9.02)	(9.65)	(7.48)	(9.18)	(10.53)
Firm size	0.190***	0.219***	0.039***	-0.029***	-0.017*
	(30.09)	(28.28)	(11.01)	(-3.76)	(-1.94)
Ln(Firm age)	-0.006	-0.002	0.014***	0.002	0.023**
	(-0.74)	(-0.19)	(3.00)	(0.26)	(2.11)
Tobin's Q	0.016***	0.018***	0.004***	0.006	0.008*
	(7.66)	(6.23)	(2.58)	(1.53)	(1.65)
Leverage	-0.025	0.050*	0.013	-0.068**	0.022
	(-1.14)	(1.71)	(0.83)	(-2.04)	(0.54)
R&D	0.239***	0.373***	0.177***	0.744***	0.935***
	(3.98)	(4.32)	(3.77)	(6.02)	(6.27)
Capex	0.031	0.101	0.094**	0.190*	0.198*
	(0.47)	(1.19)	(1.99)	(1.90)	(1.66)
Tangible	-0.141***	-0.237***	-0.029	-0.061	-0.116*
	(-3.16)	(-4.30)	(-1.10)	(-1.07)	(-1.78)
ROA	-0.007	0.016	0.028	0.039	0.043

	(-0.30)	(0.49)	(1.55)	(0.87)	(0.80)
H-index	-0.300**	-0.465***	-0.177***	-0.264***	-0.407***
	(-2.56)	(-3.30)	(-2.77)	(-2.71)	(-3.45)
H-index^2	0.650***	0.858***	0.223***	0.383***	0.524***
	(5.00)	(5.50)	(3.26)	(3.90)	(4.36)
Constant	-0.705	-0.797	0.608*	-0.870	-0.623
	(-1.23)	(-1.12)	(1.79)	(-1.26)	(-0.77)
Observations	57595	57595	57595	57595	57595
Year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.750	0.726	0.404	0.569	0.619

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 the 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.