

ORIGINAL ARTICLE

Pay Transparency and Inventor Productivity: Evidence From State-Level Pay Secrecy Laws

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Abstract

We examine the role of pay transparency in inventor productivity by exploiting the staggered adoption of state-level pay secrecy laws, which enhance pay transparency in the workplace. We find a significant increase in inventor productivity of firms located in states that have passed such laws relative to firms elsewhere. This relation is more pronounced for firms in states with lower levels of pre-existing pay transparency. We further show that pay secrecy laws promote inventor productivity by motivating inventors—especially minority inventors—to exert more effort, enhancing the diversity of inventor teams, and encouraging all inventors to pursue promotions.

1 | Introduction

The recent legal and regulatory environment of the U.S. has increasingly committed to pay transparency—making each employee's salary more observable to other employees within the company (Trotter et al. 2017; Heisler 2021).¹ Although there is a growing literature on the impact of pay transparency on reducing wage gaps (e.g., Kim 2015; Baker et al. 2023), little is known about the real effects of pay transparency on productivity. Analyzing these effects is important because there are concerns that enhanced pay transparency can reduce job satisfaction, increase turnover among star employees, and thus decrease productivity (Card et al. 2012; Mas 2017). In this article, we fill this gap in the literature by proposing an identification strategy to examine the effect of pay transparency on productivity with respect to technological innovation.

It is well-known that firms commonly use “pay secrecy rules and practices”—contracts and internal rules prohibiting or strongly discouraging employees from disclosing their wages to coworkers (Gely and Bierman 2003; Bierman and Gely 2004; Edwards 2005).² Such pay secrecy rules and practices have been criticized for their effect on pay discrimination (Kim 2013, 2015; Baker et al. 2023; Cullen and Perez-Truglia 2022) and have resulted in many prominent lawsuits.³ Our tests exploit the staggered passage of pay secrecy laws by various U.S. states since the 1980s, which has enhanced pay transparency by prohibiting firms from implementing pay secrecy rules and practices. We find that the adoption of pay secrecy laws indeed mitigates pay differentials between minority employees and their counterparts, which supports the effectiveness of these laws.

Our literature review suggests that enhanced pay transparency may encourage or discourage inventors, an important class of

employees in today's knowledge-based economy, for different reasons. Several arguments support a positive effect. First, pay transparency reduces the uncertainty of compensation that inventors expect from their efforts, which could motivate them to invest more in human capital and to work harder (Hsieh et al. 2019; Cullen and Perez-Truglia 2022). This incentive could be stronger among minority inventors (Kim 2015). Second, pay secrecy laws could increase the diversity of a firm's inventor teams and thus enhance their productivity, considering that the combination of diversified backgrounds and knowledge sources usually results in higher-quality innovation (Drach-Zahavy and Somech 2001; Hong and Page 2001; Berliant and Fujita 2011; Yang et al. 2022). Finally, when senior colleagues' compensation becomes more visible, inventors working for firms with higher expected promotion raises may exert more effort to pursue promotions.

On the other hand, there are also arguments suggesting a negative effect of pay transparency associated with pay secrecy laws. The potential disclosure of inventors' compensation may increase their chances of being recruited by competing firms, which reduces affected firms' incentives in innovation investment (Kim and Marschke 2005; Hitz and Werner 2012). Moreover, the enactment of pay secrecy laws may result in a large number of renegotiations or lawsuits, which require management teams' time as well as energy and likely distract them from innovation activities (Gao and Zhang 2019; Bennedsen et al. 2022). Finally, once some inventors find that they are underpaid, they may decide to exert less effort ("quiet quitting"), or they may work hard to attract external offers and eventually leave their current firms (Akerlof and Yellen 1990; Danziger and Katz 1997).

Using a panel of U.S. public firms with patent records from 1976 to 2017 and employing a staggered difference-in-differences approach, we show that the adoption of pay secrecy laws is associated with a significant increase in firms' inventor output scaled by their number of inventors, even when controlling for R&D input. We use patents' forward citations to capture the quality of innovation output so as to avoid weak patent concerns (Lemley and Sampat 2012; Picard and van Pottelsberghe de la Potterie 2013; Lei and Wright 2017). On average, firms headquartered in states that have adopted pay secrecy laws increase their numbers of patents and corresponding forward citations per inventor by 1.5% and 2.1%, respectively, relative to firms headquartered in other states. More importantly, we find that such increases occur two years after the passage of pay secrecy laws, which mitigates concerns of reverse causality. We also find similar increases in these firms' patent value, generality, and originality (Trajtenberg et al. 1997; Hsu et al. 2014; Kogan et al. 2017). On the other hand, we do not find a significant increase in R&D input after the adoption of pay secrecy laws, which confirms that our findings are due to enhanced productivity rather than increased investment in technological innovation.

Our use of the staggered passage of pay secrecy laws is appealing for three reasons. First, the motivation behind promoting pay secrecy laws is to reduce the wage gender/race gap. Given that these laws were not passed with the primary intention to enhance innovation, their effect on inventor productivity is likely an unintended consequence. Second, because multiple exogenous shocks affect different firms at different times, we can better avoid a common identification challenge faced by studies with a

single shock: the potential noise coinciding with the shock that directly affects the explained variable. Finally, due to staggered policy changes, a state can be in both the treatment group and the control group at different times, which helps mitigate concerns about any large differences between the two groups.

We also implement an extensive list of tests to investigate the validity of our difference-in-differences analysis, and we find that a state's passage of pay secrecy laws is unrelated to pre-existing levels and trends of local firms' inventor productivity, which mitigates the concern about omitted variables. Additionally, an important assumption behind a causal interpretation of the difference-in-differences estimates is that the treated firms and control firms share parallel trends with respect to inventor productivity before the adoption of these laws; that said, we show that the pre-treatment trends in inventor productivity are indeed indistinguishable between these two groups of firms. Moreover, we move the passage years from the actual event years to 3 to 5 years before and do not find a significant coefficient in a sample of treated firms in the pre-event years and control firms across all years. Furthermore, when we implement stacked difference-in-differences estimates following Gormley and Matsa (2011), Deshpande and Li (2019), and Cengiz et al. (2019), we find consistent results. More importantly, we also find consistent difference-in-differences estimates using a propensity score-matched sample to ensure homogeneous treated and control firms. In sum, these collective analyses support a causal interpretation of our main results.

We perform several robustness checks on our main findings. We exclude firms headquartered in California and Michigan—two states that adopted pay secrecy laws around the beginning of our sample period—as well as firms headquartered in New Hampshire, Connecticut, and Oregon, for these three latter states adopted pay secrecy laws around the end of our sample period. Moreover, we control for not-to-compete covenants, as well as control for state-specific pre-trends that reflect state-level progressiveness or openness and may affect inventor productivity. Finally, we use a number of alternative measures of innovation output in our analysis. When we perform these robustness checks, the positive relation between pay secrecy laws and inventor productivity remains.

To provide further evidence that the effect of pay secrecy laws on inventor productivity is indeed tied to pay transparency, we show that the effect of pay secrecy laws is stronger for states with higher pre-existing pay secrecy in the workplace and for firms with higher ratios of minority inventors, who are more vulnerable to pay secrecy practices. These results further increase our confidence that the positive impact of pay secrecy laws on innovation is likely due to pay transparency.

In the second part of this article, we investigate possible mechanisms through which pay secrecy laws enhance inventor productivity. We first show that, in an inventor-year panel, inventors' productivity significantly increases with pay secrecy laws, which confirms our firm-level results and highlights the role of inventors' motivation. More importantly, such a relation is stronger among minority inventors. Second, we show that inventor teams become more diversified after pay secrecy laws have been adopted and that patents produced by more diversified teams are of higher quality. Finally, we find that the positive

relation between pay secrecy laws and inventor productivity is more pronounced in firms with higher expected promotion raises. In summary, our mechanism tests provide further evidence for the effect of pay secrecy laws on inventor productivity.

Our empirical analysis responds to increasing concerns about pay discrimination and productivity.⁴ Although pay discrimination occurs in workplaces globally, it is empirically challenging to establish the causality between pay discrimination and employee performance, even when compensation data is available (Heckman 1998). In this study, we propose a new difference-in-differences framework to draw a causal inference for the negative impact of discriminatory compensation on productivity in innovation activities. Our empirical evidence thus has implications for both economic growth and human capital.

This study also adds to the growing literature that examines the real effects of pay secrecy laws and, more broadly, pay transparency. Although there exists an extensive list of studies showing that pay secrecy laws or laws related to pay transparency effectively reduce pay gaps,⁵ the real effects of pay transparency on productivity are still underexplored. Our use of patent data enables us to appropriately measure productivity at both firm and inventor levels, and our novel evidence shows that pay transparency fosters inventors' productivity and teamwork. In addition, our findings that diversified inventor teams are more likely to be formed after the passage of pay secrecy laws and that such teams produce more valuable patents offer new insights to the literature on workplace diversity.⁶

Moreover, this study is related to the literature that analyzes compensation design and its impact on firm-level innovation. This literature stream has focused on aspects such as pay-for-performance sensitivity, subjective vs. objective performance evaluations, and long-term compensation plans (e.g., Lerner and Wulf 2007; Hall and Lerner 2010; Ederer and Manso 2011; Manso 2011). Extending this stream, our article provides evidence that the transparency of compensation schemes—in addition to the compensation schemes themselves—is an important driver of corporate innovation and inventor productivity.

2 | Pay Secrecy Laws

2.1 | Institutional Background

The National Labor Relations Act (NLRA) of 1935 provides the earliest legal protection on pay secrecy matters. In Section 7, the Act protects non-supervisory employees who are covered by the Act from employer retaliation if they discuss their wages or working conditions with their colleagues as part of a concerted activity to improve them (U.S. Department of Labor 2016). Nevertheless, in the same document, the U.S. Department of Labor also highlighted that the NLRA did *not* solve the pay transparency issue because it did not address all situations in which employers prohibit or discourage employees from discussing their wages with their colleagues. Pay secrecy rules and practices appear frequently in the workplace as firms may use contracts and internal rules to prohibit employees from disclosing their wages to coworkers (Gely and Bierman 2003; Bierman and Gely 2004; Edwards 2005).⁷

As a reaction to the insufficient protection and enforcement of transparent compensation, specific state laws have been introduced since the 1980s to mitigate pay secrecy rules and to enhance pay transparency. For example, Michigan passed a law in 1982 that prohibited employers from: (1) requiring as a condition of employment non-disclosure by an employee of his or her wages; (2) requiring an employee to sign a waiver or other document that purports to deny an employee the right to disclose his or her wages; or (3) discharging, formally disciplining, or otherwise discriminating against an employee for job advancement on the basis of having disclosed his or her wages. In 1984, California passed a similar law. More recently, the following seven states passed similar laws between 2000 and 2016 (U.S. Department of Labor 2016): Illinois (2003), Vermont (2005), Colorado (2009), Maine (2009), Louisiana (2013), New Jersey (2013), Minnesota (2014), New Hampshire (2015), Connecticut (2015), and Oregon (2016). We map these states in Figure 1 and provide the details of these laws in Appendix A. These laws are known as pay secrecy laws because they aim to eliminate or mitigate pay secrecy rules and practices. These laws have been effective. For example, Kim (2015) reports that the adoption of pay secrecy laws increases female workers' total compensation by 3% and reduces gender pay gaps by more than 5% for female workers with a college education. Our later analysis in Section 2 also suggests that these laws mitigate pay gaps by 3% in terms of the hourly wages of scientists and engineers.

As pointed out by Kim (2013, 2015), the political motivation for passing these state laws is to close the wage gap. Feminist activists and legislators claim that once pay is no longer a secret, women will be able to discover gender pay gaps for themselves and subsequently take action to reduce such gaps.⁸ Opponents of such legislation argue that such laws may result in three types of costs. First, it may cause some social discomfort, inasmuch as the legislation challenges social norms in the U.S. regarding pay secrecy. Second, it could increase costs to employers if more employees (falsely) file suits. Third, after they learn what their co-workers earn, employees who are paid below the average may become disgruntled, whereas employees paid above the average may not necessarily become more satisfied (Card et al. 2012). The passage of state pay secrecy laws depends on the relative power between the two sides in each state at a given time. For example, after several failed attempts, Maine successfully passed its pay secrecy law in December 2009 because: (i) Congress passed the Lilly Ledbetter Fair Pay Act in early 2009; (ii) Ledbetter's legal case caused great public outrage regarding the gender pay gap; and (iii) Republican female senators Susan Collins and Olympia Snowe, both from Maine, were important supporters of this act (Ramachandran 2012; Kim 2015). In summary, a state's adoption of pay secrecy laws certainly depends on some political factors, such as a legislator's support, the existence of influential decision-makers, and public opinion towards pay secrecy itself.

To the best of our knowledge, these factors seem largely unrelated to inventors or innovative firms. Moreover, it is unlikely that the majority of firms will lobby or influence the passage of pay secrecy laws because managers are generally unwilling to adopt a transparent pay policy before the passage of state-level pay secrecy laws for the following reasons. First, pay secrecy policies that maintain a lack of transparency and prevent disclosure of salary information help reinforce the power of managers (Lawler

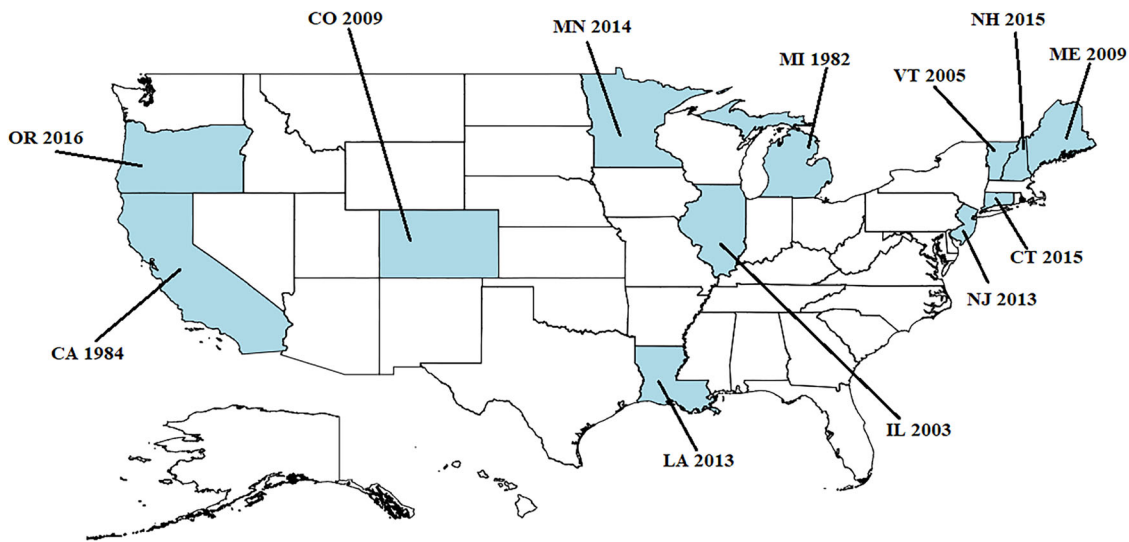


FIGURE 1 | A map of states legislating pay secrecy laws.

This figure presents the states that passed pay secrecy laws (in shaded areas) and their passage years. The legislating states include Michigan (1982), California (1984), Illinois (2003), Vermont (2005), Colorado (2009), Maine (2009), Louisiana (2013), New Jersey (2013), Minnesota (2014), Connecticut (2015), New Hampshire (2015), and Oregon (2016). The details of pay secrecy laws in each state are provided in Appendix A.

1992; Rosenfeld 2017). Second, as discussed in Gely and Bierman (2003) and Bierman and Gely (2004), pay secrecy practices are legally feasible and have established a social norm for firms and managers; as a result, managers might follow such social norms and peer practices because they may be risk averse and wish to avoid peer pressure. For example, when all firms practice pay secrecy, they may prevent employees from leaving for better paying jobs (Danziger and Katz 1997; Colella et al. 2007). Finally, although pay secrecy policies may benefit firms' profits and operations, they also come with costs in other dimensions, such as adding administrative costs because employees may feel unfairly treated and frequently request reevaluation.

On the other hand, we do not rule out the possibility that some managers and firms may be aware of the benefits of transparency in pay and thus may voluntarily adopt transparent pay policies to encourage innovative performance. In fact, the existence of such firms would make it difficult for us to find any relation between pay secrecy laws and innovation in our empirical analysis.

2.2 | Evidence on the Effectiveness of Pay Secrecy Laws

In this section, we examine the effectiveness of pay secrecy laws. Considering that these laws were initially adopted to reduce wage gaps between minority employees and their counterparts, we expect that, if these laws are effective, we will observe a reduction in wage gaps following the adoption of these laws.

Given that our article focuses on corporate innovation and inventors, we examine the salaries of scientists and engineers. We use the 1990 Census Bureau occupational classification system to categorize scientists and engineers as follows: engineers, mathematical and computer scientists, natural scientists, engineering and related technologists and technicians, and science

technicians.⁹ We use their hourly salaries and other variables from the IPUMS-CPS-ASEC (Flood et al. 2018) database to estimate the following ordinary least squares regression for the following employee-year panel:

$$\begin{aligned} \ln(\text{Hourly wage})_{jst} = & \alpha_0 + \alpha_1 \text{Transparency}_{st} \times \text{Minority}_j \\ & + \alpha_2 \text{Transparency}_{st} + \alpha_3 \text{Minority}_j \\ & + \alpha_4 X_{jst} + \delta_s + \gamma_l + \theta_t + \varepsilon_{jst}, \end{aligned} \quad (1)$$

in which $\ln(\text{Hourly wage})_{jst}$ denotes the natural logarithm of hourly wages received by employee j in industry/occupation l in state s in year t . The indicator variable Transparency_{st} takes the value of one if pay secrecy laws are passed in state s in year t , and zero otherwise. The indicator variable Minority_j takes the value of one if employee j is not a white male, and zero otherwise. X_{jst} denotes the set of time-varying control variables,¹⁰ δ_s denotes state fixed effects, γ_l denotes industry fixed effects (in Table 2 column 1) or occupation fixed effects (in Table 2 column 2), and θ_t denotes year fixed effects. Given that our treatment is defined at the state level, we cluster standard errors by location state (Atanassov 2013; Acharya et al. 2014; Png 2017a, 2017b). We provide the summary statistics of related variables in Panel A of Table 1.

The coefficient of interest in Equation (1) is α_1 for the interaction term, which captures the relation between the passage of pay secrecy laws and minority employees' salaries (as compared to majority employees' salaries). As reported in Table 2, the coefficients on the interaction terms $\text{Transparency} \times \text{Minority}$ are positive and significant in both columns, which is consistent with the expectation that pay secrecy laws significantly increase salaries for minority scientists and engineers relative to other scientists and engineers.¹¹ This finding suggests that these laws mitigate pay gaps by 3 percentage points in terms of the hourly wages of scientists and engineers. The economic

TABLE 1 | Summary statistics.

Panel A: Scientist/engineer data						
	N	Mean	SD	P25	P50	P75
Hourly wage	132,581	26.56	65.67	16.82	23.52	31.71
Transparency	132,581	0.16	0.36	0.00	0.00	0.00
Minority	132,581	0.39	0.49	0.00	0.00	1.00
Employee age	132,581	38.83	10.87	30.00	38.00	47.00
Annual working hours	132,581	2112.10	492.89	2080.00	2080.00	2340.00
College education	132,581	0.63	0.48	0.00	1.00	1.00
Postgraduate	132,581	0.17	0.38	0.00	0.00	0.00
Panel B: Firm-level data						
	N	Mean	SD	P25	P50	P75
Pat/Inventor	67,685	0.16	0.21	0.00	0.10	0.21
Cit/Inventor	67,685	0.17	0.32	0.00	0.05	0.19
Val/Inventor	67,685	0.89	2.39	0.00	0.10	0.63
UCit/Inventor	67,685	3.90	9.45	0.00	0.48	3.11
Gen/Inventor	67,685	0.06	0.11	0.00	0.02	0.08
Ori/Inventor	67,685	0.06	0.10	0.00	0.02	0.08
R&D/Inventor	67,685	1.10	2.48	0.03	0.31	0.95
Claims	43,678	2.90	1.47	2.00	2.67	3.50
Average compensation (\$1000)	61,662	76.01	96.45	17.85	40.33	96.48
Process claims	43,678	0.31	0.28	0.04	0.29	0.49
Transparency	67,685	0.24	0.42	0.00	0.00	0.00
Existence of CNC	60,112	0.40	0.49	0.00	0.00	1.00
Enforcement of CNC	60,112	0.18	0.38	0.00	0.00	0.00
Larger pay secrecy (state-industry)	61,716	0.50	0.50	0.00	0.00	1.00
Higher minority ratio	65,531	0.47	0.50	0.00	0.00	1.00
Higher promotion raise	19,231	0.50	0.50	0.00	0.00	1.00
Assets (\$million)	67,685	2264.65	7036.25	49.81	190.83	1017.31
Cash	67,685	21.58%	24.21%	3.37%	11.42%	31.75%
R&D	67,685	7.91%	12.64%	0.32%	3.09%	9.77%
R&D Missing	67,685	0.21	0.41	0.00	0.00	0.00
ROA	67,685	-3.92%	24.85%	-4.43%	3.89%	8.12%
PPE	67,685	47.81%	32.15%	23.18%	41.38%	65.59%
Leverage	67,685	19.98%	18.84%	2.71%	16.98%	30.71%
Capital expenditure	67,685	5.44%	4.83%	2.12%	4.10%	7.19%
Tobin's Q	67,685	2.08	1.73	1.07	1.48	2.34
Age	67,685	20.17	14.18	9.00	17.00	29.00
State GDP (\$ million)	67,685	531,515.15	561,505.58	156,749.95	310,240.03	683,577.81
Per capita income (\$10,000)	67,685	2.88	1.33	1.81	2.74	3.86
State population (million)	67,685	14.43	10.92	5.80	11.31	19.74
Business combination	67,685	0.69	0.46	0.00	1.00	1.00
Good faith	67,685	0.32	0.47	0.00	0.00	1.00

(Continues)

TABLE 1 | (Continued)

Panel C: Pay gap analysis						
	N	Mean	SD	P25	P50	P75
Pay gap	2142	0.25	0.09	0.19	0.25	0.31
Larger pay secrecy (state)	2142	0.49	0.50	0.00	0.00	1.00
State GDP (\$ million)	2142	174,445.54	243,628.50	37,033.00	84,757.49	212,056.98
Per capita income (\$10,000)	2142	2.64	1.37	1.47	2.44	3.67
State population (million)	2142	5.27	5.73	1.33	3.61	6.23
Business combination	2142	0.42	0.49	0.00	0.00	1.00
Good faith	2142	0.17	0.37	0.00	0.00	0.00
Panel D: Inventor-level data						
D1. The sample for which we do not require inventors' gender and race to be identifiable.						
	N	Mean	SD	P25	P50	P75
InvPat	3,867,396	0.31	0.55	0.00	0.00	0.39
InvCit	3,867,396	0.31	0.78	0.00	0.00	0.22
Number patent	3,867,396	0.27	0.44	0.00	0.00	1.00
Number citation	3,867,396	686.23	1221.40	52.00	235.00	730.00
Transparency	3,867,396	651.72	1004.13	51.26	231.57	753.85
Assets (\$million)	3,867,396	52,641.11	101,654.86	2940.00	14,685.00	57,048.02
Cash	3,867,396	16.22%	16.92%	4.23%	10.05%	21.75%
R&D	3,867,396	6.29%	5.96%	2.43%	4.90%	8.49%
R&D missing	3,867,396	0.04	0.19	0.00	0.00	0.00
ROA	3,867,396	4.95%	10.61%	2.48%	6.30%	9.93%
PPE	3,867,396	51.10%	31.39%	25.49%	44.44%	71.61%
Leverage	3,867,396	21.86%	15.18%	10.95%	20.59%	29.78%
Capital expenditure	3,867,396	5.68%	4.04%	2.62%	4.52%	7.71%
Tobin's Q	3,867,396	2.09	1.31	1.23	1.69	2.46
Age	3,867,396	37.08	17.25	24.00	38.00	51.00
State GDP (\$ million)	3,867,396	676,681.73	638,102.50	220,581.98	408,941.19	964,185.88
Per capita income (\$10,000)	3,867,396	3.33	1.33	2.30	3.40	4.32
State population (million)	3,867,396	15.82	11.25	6.52	11.89	20.19
Business combination	3,867,396	0.82	0.39	1.00	1.00	1.00
Good faith	3,867,396	0.33	0.47	0.00	0.00	1.00
InvClaims	1,803,648	2.89	1.65	2.00	3.00	3.25
D2. The sample for which we require inventors' gender and race to be identifiable.						
	N	Mean	SD	P25	P50	P75
InvPat'	2,763,721	0.23	0.48	0.00	0.00	0.33
InvCit'	2,763,721	0.22	0.63	0.00	0.00	0.05
Number patent	2,763,721	0.24	0.43	0.00	0.00	0.00
Number citation	2,763,721	625.99	1110.42	47.00	213.00	664.00
Transparency	2,763,721	605.41	967.56	46.51	210.42	694.03
Minority	2,763,721	0.15	0.36	0.00	0.00	0.00
Assets (\$million)	2,763,721	50,305.52	100,468.87	2806.56	13,700.00	49,539.00
Cash	2,763,721	14.85%	16.04%	3.88%	9.29%	19.27%

(Continues)

TABLE 1 | (Continued)

D2. The sample for which we require inventors' gender and race to be identifiable.						
	N	Mean	SD	P25	P50	P75
R&D	2,763,721	5.94%	5.63%	2.31%	4.70%	8.02%
R&D Missing	2,763,721	0.04	0.19	0.00	0.00	0.00
ROA	2,763,721	4.92%	10.04%	2.48%	6.11%	9.63%
PPE	2,763,721	52.54%	31.23%	27.26%	46.52%	73.21%
Leverage	2,763,721	22.22%	15.09%	11.45%	20.88%	30.11%
Capital expenditure	2,763,721	5.81%	4.06%	2.75%	4.72%	7.85%
Tobin's Q	2,763,721	2.03	1.27	1.21	1.64	2.38
Age	2,763,721	37.50	17.02	25.00	39.00	51.00
State GDP (\$ million)	2,763,721	614,415.19	588,866.52	202,910.06	385,698.06	833,305.69
Per capita income (\$10,000)	2,763,721	3.21	1.32	2.19	3.24	4.17
State population (million)	2,763,721	14.99	10.72	6.42	11.69	19.31
Business combination	2,763,721	0.80	0.40	1.00	1.00	1.00
Good faith	2,763,721	0.31	0.46	0.00	0.00	1.00

Panel E: Patent-level data						
	N	Mean	SD	P25	P50	P75
For racial diversity analysis						
Inventor diversity (race)	1,430,670	0.16	0.28	0.00	0.00	0.00
Transparency	1,430,670	0.31	0.46	0.00	0.00	1.00
Patent citation	1,430,670	1.04	1.57	0.00	0.51	1.30
Patent value	1,430,670	13.81	23.14	2.43	6.03	14.28
For gender diversity analysis						
Inventor diversity (gender)	1,376,761	0.09	0.22	0.00	0.00	0.00
Transparency	1,376,761	0.30	0.46	0.00	0.00	1.00
Patent citation	1,376,761	1.04	1.56	0.00	0.52	1.31
Patent value	1,376,761	13.95	23.41	2.45	6.08	14.41

Note: This table reports summary statistics for the 1976–2017 period. Panel A reports the descriptive statistics for the scientist/engineer analysis. Panel B reports the descriptive statistics of the 67,685 firm-year observations for the firm-level analysis. Panel C reports the descriptive statistics for the pay gap analysis. Panel D reports the descriptive statistics for the inventor-level analysis. Panel E reports the descriptive statistics for the patent-level analysis. Variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles.

magnitude is also sizeable: considering that the coefficient on Minority is around -0.12 , pay secrecy laws reduce pay gaps by 25% ($= 0.03/0.12$). This finding, which is consistent with the findings of Kim (2015) and Baker et al. (2023), provides supporting evidence that pay secrecy laws are indeed effective in mitigating pay gaps of intellectual workers in the workplace.

3 | Inventor Productivity in the Firm Level

3.1 | Data

Following the literature, we use patent data to capture the performance and productivity of firms' and individuals' innovative activities (e.g., Kamien and Schwartz 1975; Griliches 1990). We collect information about all patents granted by the U.S. Patent

and Trademark Office (USPTO) from the PatentsView database. This database includes information about each inventor, assignee, technology group, filing date, grant date, and references (backward citations) for each utility patent. We then identify each patent granted to U.S. public firms in the Compustat database using the Kogan et al. (2017) and Stoffman et al. (2022).¹² We use the application year of a patent as the time of its invention to measure a firm's innovation output, which is common in the literature (Hall et al. 2005a, 2005b). Our sample starts in 1976; as it takes two to three years for the USPTO to approve a patent, we end our sample in 2017 to ensure that the majority of the patents applied for before 2019 have been granted by the USPTO and, thus, exist in our database. Following prior studies (e.g., Lerner et al. 2011; Aghion et al. 2013; Bloom et al. 2013), we drop firms that never applied for a single patent during our entire sample period. Our final panel data sample consists of 67,685 firm-year observations over the period 1976–2017.

TABLE 2 | Evidence on the effectiveness of pay secrecy laws.

	(1) ln(Hourly wage)	(2) ln(Hourly wage)
Transparency × Minority	0.032*** (0.009)	0.033*** (0.011)
Transparency	-0.009 (0.013)	-0.006 (0.014)
Minority	-0.125*** (0.005)	-0.116*** (0.004)
ln(Employee age)	0.539*** (0.008)	0.530*** (0.009)
ln(Annual working hours)	0.025*** (0.008)	0.050*** (0.007)
College education	0.270*** (0.005)	0.196*** (0.004)
Postgraduate	0.137*** (0.005)	0.143*** (0.006)
State fixed effects	Yes	Yes
Industry fixed effects	Yes	
Occupation fixed effects		Yes
Year fixed effects	Yes	Yes
Observations	132,581	132,581

Note: This table reports OLS regression results examining the effect of state-level pay secrecy laws on the salaries of scientists and engineers. Variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by location state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We focus on two primary measures for inventor productivity. Our first measure is patent count per inventor (Pat/Inventor), defined as the number of patents applied for by a firm in year t , scaled by the number of unique inventors in the most recent 10 years ($t - 9$ to t).¹³ This measure captures the quantity of innovation output of a firm in year t . Despite its simplicity, the number of patents has been widely used in the economics literature to capture firm-level innovation output since the seminal work of Griliches (1981). Another measure is the sum of forward citation counts received by these patents scaled by the number of unique inventors in the most recent 10 years (Cit/Inventor). The number of forward citations received by a patent (i.e., the number of references the patent receives by subsequent patents) reflects the importance of the patent (Trajtenberg et al. 1997; Hall et al. 2005b).¹⁴ We then add the forward citation counts of all patents applied for by a firm in year t to obtain the citation count of the firm in year t , as this citation count takes into account patent quality (Hall et al. 2005b; Aghion et al. 2013) and mitigates concerns about “weak patents” (Lemley and Sampat 2012; Picard and van Pottelsberghe de la Potterie 2013; Lei and Wright 2017).

3.2 | Main Results

As 12 states adopted pay secrecy laws at different time points during the sample period, we implement difference-in-differences tests following Bertrand and Mullainathan (2003). That is, we

compare changes in inventor productivity for firms headquartered in the states that adopt pay secrecy laws with changes in inventor productivity for firms headquartered in other states.¹⁵ We estimate the following ordinary least squares regression in a firm-year panel:

$$\ln(Y_{ijst} + 1) = \alpha_0 + \alpha_1 \text{Transparency}_{st} + \alpha_2 X_{ijst} + \gamma_i + \theta_{jt} + \varepsilon_{jst}, \quad (2)$$

The dependent variable Y_{ist} is the patent count (Pat/Inventor) and citation count (Cit/Inventor) per inventor of firm i that is in industry j (SIC 2-digit codes) and is headquartered in state, s in year, t .¹⁶ Similar to Equation (1), the indicator variable Transparency_{st} takes the value of one if pay secrecy laws are passed in state, s in year t , and zero otherwise. We also consider an extensive list of control variables X_{ijst} , and provide their detailed variable definitions in Appendix B.¹⁷ γ_i and θ_{jt} denote firm and industry × year fixed effects, respectively. Robust standard errors clustered by headquarters state are in parentheses. The summary statistics of all variables are provided in Table 1, panel B.

We present our results in Table 3. In column 1, the dependent variable is Pat/Inventor; we show that the coefficient estimate on Transparency is 0.013 and significant at the 1% level, suggesting that inventor productivity drops after the passage of pay secrecy laws. In terms of economic significance, a firm’s patent output per inventor increases by 1.5% after the passage of pay secrecy

TABLE 3 | Baseline results.

Variables	(1) lnPat/Inventor	(2) lnCit/Inventor	(3) lnPat/Inventor	(4) lnCit/Inventor
Transparency	0.013*** (0.003)	0.018*** (0.005)		
Year 7			0.007 (0.007)	0.011 (0.007)
Year 6			0.005 (0.004)	0.008 (0.006)
Year 5			-0.008 (0.007)	0.007 (0.009)
Year 4			-0.006 (0.006)	0.003 (0.008)
Year 3			-0.000 (0.007)	0.012 (0.009)
Year 2			-0.005 (0.006)	-0.002 (0.009)
Year 1			0.003 (0.006)	0.008 (0.008)
Year 0			0.002 (0.007)	0.016 (0.011)
Year 1			0.009 (0.008)	0.013 (0.009)
Year 2			0.012* (0.006)	0.020** (0.009)
Year 3			0.016** (0.007)	0.021** (0.009)
Year 4			0.008 (0.010)	0.021** (0.009)
Year 5			0.013** (0.006)	0.008 (0.006)
Year 6			0.005 (0.009)	0.020* (0.012)
Year 7 ⁺			0.019*** (0.006)	0.029*** (0.007)
ln(Assets)	0.023*** (0.003)	0.021*** (0.003)	0.023*** (0.003)	0.021*** (0.003)
Cash	0.025*** (0.009)	0.039*** (0.014)	0.025*** (0.009)	0.039*** (0.014)
R&D	0.072*** (0.008)	0.060*** (0.019)	0.072*** (0.008)	0.060*** (0.019)
R&D missing	0.003 (0.007)	0.004 (0.006)	0.003 (0.007)	0.004 (0.006)
ROA	0.032*** (0.004)	0.033*** (0.006)	0.032*** (0.004)	0.033*** (0.006)

(Continues)

TABLE 3 | (Continued)

Variables	(1)	(2)	(3)	(4)
	InPat/Inventor	InCit/Inventor	InPat/Inventor	InCit/Inventor
PPE	-0.012** (0.005)	-0.021*** (0.007)	-0.012** (0.005)	-0.021*** (0.007)
Leverage	-0.028*** (0.005)	-0.034*** (0.008)	-0.028*** (0.005)	-0.034*** (0.008)
Capex	0.161*** (0.016)	0.215*** (0.032)	0.162*** (0.016)	0.216*** (0.032)
Tobin's Q	0.007*** (0.001)	0.010*** (0.001)	0.006*** (0.001)	0.010*** (0.001)
ln(Age)	-0.113*** (0.005)	-0.117*** (0.012)	-0.113*** (0.005)	-0.117*** (0.012)
ln(State GDP)	-0.023 (0.022)	-0.030 (0.027)	-0.022 (0.021)	-0.028 (0.026)
Per capita income	-0.000 (0.007)	-0.003 (0.008)	0.000 (0.007)	-0.004 (0.009)
ln(State population)	0.020 (0.022)	0.025 (0.027)	0.017 (0.021)	0.020 (0.026)
Business combination	0.006 (0.007)	0.004 (0.009)	0.006 (0.007)	0.004 (0.009)
Good faith	-0.000 (0.005)	0.000 (0.005)	-0.001 (0.005)	-0.002 (0.006)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
Constant	0.527** (0.214)	0.638** (0.272)	0.514** (0.209)	0.621** (0.266)
Observations	67,222	67,222	67,222	67,222

Note: This table reports OLS regression results. In columns 1 and 2, we examine the effect of pay secrecy laws on inventor productivity using a difference-in-differences specification in Equation (2). In columns 3 and 4, we examine the effect of pay secrecy laws on inventor productivity using a difference-in-differences specification in Equation (3). We include firm and industry × year fixed effects. Our industry is defined by SIC 2-digit codes. Variable definitions are provided in Appendix B. Robust standard errors clustered by headquarters state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

laws, which corresponds to an increase of 10.07% of the sample mean. In column 2, the dependent variable is Cit/Inventor; we show that the coefficient on Transparency is 0.018 and significant at the 1% level. The magnitude of economic significance is also sizable: a firm's citation count per inventor increases by 2.1% after the passage of pay secrecy laws, which corresponds to an increase of 13.29% to the sample mean. This magnitude is economically significant, considering that one additional citation could increase a patent's value by one million U.S. dollars (Harhoff et al. 1999).

In terms of other control variables, we find that total assets, cash level, R&D intensity, ROA, profitability, and Tobin's Q are generally both positively and significantly related with inventor productivity, whereas age, asset tangibility, and leverage are negatively and significantly related with inventor productivity.

3.3 | The Pre-Treatment Trends Assumption

The validity of our difference-in-differences approach relies on the parallel trends assumption: absent pay secrecy laws, treated firms' innovation output would have evolved in the same way as that of control firms. To test the pre-treatment trends in innovation output for both the treated firms and control firms, we re-estimate Equation (2) after replacing Transparency with fifteen indicator variables (Year⁻⁷ to Year⁷⁺) as follows:

$$\ln(Y_{ijst} + 1) = \alpha_0 + \sum_{\tau=-7}^{7+} \alpha_{\tau} \times \text{Year}_{st}^{\tau} + \alpha_g X_{ijst} + \gamma_i + \theta_{jt} + \varepsilon_{jst}, \quad (3)$$

in which each Year variable indicates the time relative to the passage year. For example, Year⁻⁷ indicates that the sample year

is seven years before a state passes pay secrecy laws, Year⁰ indicates the year in which pay secrecy laws are passed, and Year⁷⁺ indicates that the sample year is seven or more years after the passage of pay secrecy laws. We focus on the coefficients on the indicators Year⁻⁷ to Year⁻¹ because their magnitude and significance indicate whether there are differences in innovation output between treated firms and their control firms prior to the adoption of pay secrecy laws. We present our results in columns 3 and 4 in Table 3 as well as Figure A1 in the Supporting Information. We find that the coefficients on Year⁻⁷ to Year⁻¹ are not significantly different from zero, suggesting that the parallel trends assumption of our difference-in-differences approach is not violated.

Further, we show that the coefficients on the indicators Year⁰ and Year¹ are small in magnitude and not statistically significant for both innovation measures. The effect of pay secrecy laws emerges 2 years after the laws' adoption: the coefficients on Year² to Year⁷⁺ are significantly positive in many cases, which is consistent with the intuition that it may take a longer time for pay secrecy laws to impose an effect on inventor productivity, if any.¹⁸ This finding further mitigates concerns of reverse causality and also supports a causal effect of pay secrecy laws.

Although Table 3 and Figure A1 in the Supporting Information do not reveal significant pre-trends, we follow Moser and Voena (2012) and re-estimate Equation (2) by additionally controlling for state-specific pre-trends. We acknowledge that the evidence of Table 3 and Figure A1 in the Supporting Information is only suggestive. Thus, our subsequent robustness checks as well as mechanism tests help strengthen a causal interpretation of our results. The results are presented in Table A1 in the Supporting Information. In columns 1 and 2 of Table A1 in the Supporting Information, we control for state-specific linear pre-trends; in columns 3 and 4, we further control for state-specific quadratic pre-trends.¹⁹ We find that the coefficient estimates on Transparency remain significantly positive. These results suggest that, even if we include pre-existing time trends (if any), our main findings nonetheless remain robust.

As a further check for the existence of any pre-trends, we consider another test: we keep only the observations of a treated state before the passage of pay secrecy laws and the observations in a never-treated state throughout the sample period. We then assign pseudo-event years as 3, 4, or 5 years before the true event years. As shown in Table A2 in the Supporting Information, we do not find any relation between pay secrecy laws and inventor productivity when we conduct this placebo test.

3.4 | The Timing of Adopting Pay Secrecy Laws

In conducting our difference-in-differences tests, we assume that a state's adoption of pay secrecy laws is not correlated with the pre-existing inventor productivity of firms headquartered in that state. To validate this assumption, we follow Acharya et al. (2014) and Png (2017b) and estimate a Weibull hazard model in which the "failure event" is the adoption of pay secrecy laws in a given state. The sample consists of all states over our sample period, with treated states being dropped from the

sample once they have adopted pay secrecy laws. The independent variables of interest are the levels, changes, and growth rates of $\ln(\text{Average Pat/Inventor})$ and $\ln(\text{Average Cit/Inventor})$, which are the average number of patent counts or citation counts per inventor of all public firms headquartered in a state in a given year. We also control for the levels, changes, and growth rates of the following state-level variables: state pay gaps, state GDP, population characteristics, unemployment rates, and political climate (i.e., whether or not a state is governed by a Republican), as well as state-level business combination laws and wrongful discharge laws.²⁰ We provide variable definitions in Appendix B.

In Table A3 in the Supporting Information, we present our results from this estimated hazard model. Panel A is based on the levels of explanatory variables, Panel B is based on the three-year average changes for each of the explanatory variables, and Panel C is based on the 3-year average of the growth rates of each of the explanatory variables.²¹ We show that the coefficients on the levels, changes, and growth rates of $\ln(\text{Average Pat/Inventor})$ and $\ln(\text{Average Cit/Inventor})$ are not statistically significant across all columns. These results indicate that a state's passage of pay secrecy laws is unrelated to the pre-existing inventor productivity of local firms, which supports the exogeneity of pay secrecy laws to local firms' inventor productivity and mitigates the concern that some omitted variables influence both the passage of pay secrecy laws and inventor productivity.

3.5 | Additional Tests for Staggered Difference-in-Differences Estimates

We are aware of potential bias with staggered difference-in-differences estimates and thus implement two robustness checks.

Our first check is to implement the stacked difference-in-differences estimates following Gormley and Matsa (2011), Deshpande and Li (2019), and Cengiz et al. (2019). This method allows us to mitigate the influence of heterogeneous treatment effects and avoids potential negative weights of specific treatments. For each treatment event (i.e., the event when a state adopted pay secrecy laws), we collect a cohort set that includes all firm-year observations in a window $[-10,10]$ that ranges from 10 years before the event to 10 years after the event. The control group includes all firm-year observations in the same window in never-treated states. Last, we stack all cohort sets together and estimate the following ordinary least squares regression using the stacked panel:

$$\ln(Y_{icj\tau} + 1) = \alpha_0 + \alpha_1 \text{Treatment}_{ic\tau} + \alpha_2 X_{icj\tau} + \gamma_i + \delta_c + \theta_{j\tau} + e_{icj\tau}. \quad (4)$$

The dependent variable $Y_{icj\tau}$ is the patent count (Pat/Inventor) or citation count (Cit/Inventor) per inventor for firm i that is in industry j and belongs to cohort c in event year τ (which is the calendar year minus the treatment year in cohort c). The indicator variable $\text{Treatment}_{ic\tau}$ takes the value of one if firm i is treated in an event year (i.e., $\tau \geq 0$) in cohort c , and zero otherwise. $X_{icj\tau}$ denotes the set of time-varying control variables. γ_i denotes the firm fixed effects, δ_c denotes the cohort fixed effects, and $\theta_{j\tau}$ denotes industry-event year joint fixed effects. The coefficient, α_1 , on

TABLE 4 | Additional tests for staggered difference-in-differences estimates.

Panel A: Stacked difference-in-differences estimates		
Variables	(1) lnPat/Inventor	(2) lnCit/Inventor
Transparency	0.016** (0.008)	0.016** (0.008)
Other controls	Same as those in Table 3	
Firm fixed effects	Yes	Yes
Cohort fixed effects	Yes	Yes
Industry × event year fixed effects	Yes	Yes
Observations	183,346	183,346
Panel B: Stacked difference-in-differences estimates with matched sample		
Variables	(1) lnPat/Inventor	(2) lnCit/Inventor
Transparency	0.025*** (0.008)	0.022* (0.011)
Other controls	Same as those in Table 3	
Firm fixed effects	Yes	Yes
Cohort fixed effects	Yes	Yes
Industry × event year fixed effects	Yes	Yes
Observations	12,779	12,779

Note: This table reports two additional tests on the staggered difference-in-differences estimates. In Panel A, we focus on a window that contains the 10 years before and after the adoption of pay secrecy laws. In Panel B, we use a matched sample. For each treatment event (i.e., the event when a state adopted pay secrecy laws), we collect a cohort set that includes all firm-year observations in a window $[-10,10]$ that ranges from 10 years before the event to 10 years after the event. In this cohort set, we have two groups of firms. The control group includes firm-year observations from the never-treated states. We then implement propensity score matching for treated and matched control firms based on all control variables in baseline regressions. Variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by headquarters state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Treatment_{ic τ} represents our difference-in-differences estimates. The standard errors are clustered by cohort-state.

We present the summary statistics of all variables in the stacked panel in Table A4 in the Supporting Information. We present the estimation of Equation (4) in Panel A of Table 4. The difference-in-differences estimates are 0.016, which are statistically significant. These results confirm that our difference-in-differences estimates are reasonably robust and are not driven by some early- or late-adopting states.

Our second check is to conduct a propensity score matching procedure to generate matched pairs of firms (one treated and one matched control) that are homogenous for all firm characteristics.²² We present the firm characteristics of treated and matched control firms before the treatment in Table A5 in the Supporting Information, which shows that our matching procedure indeed generates reasonably homogeneous firms before treatment. We then estimate Equation (4) using the matched sample and present the results in Panel B of Table 4. These results suggest that, even if we start with similar firms across treated and untreated states, we are still able to obtain consistent results.

3.6 | Robustness Check of Our Baseline Regression

In this section, we present a large number of robustness checks on our main findings. First, we consider the standard errors based on regular wild bootstrap and wild cluster bootstrap (Roodman et al. 2019) and cluster jackknife for standard errors (MacKinnon et al. 2023a, 2023b) to mitigate the estimation errors related to our cluster structures (i.e., only a few treated clusters that may make asymptotic inference unreliable).²³ As shown in Table A6 in the Supporting Information, we find that the coefficients on Transparency remain significantly positive.

Second, we estimate the following quasi-maximum likelihood Poisson estimation in a firm-year panel:

$$E[Y_{ijst} | \mathcal{X}] = \exp(\alpha_0 + \alpha_1 \text{Transparency}_{st} + \alpha_2 X_{ijst} + \gamma_i + \theta_{jt}). \quad (5)$$

We apply the quasi-maximum likelihood Poisson estimation of Correia et al. (2020) for patents and citations as dependent variables following Amore et al. (2013), Chava et al. (2013), and Bernstein (2015), because doing so can not only treat any non-

negative dependent variables, whether integer or continuous (Santos Silva and Tenreyro 2006), but its standard errors are also robust to arbitrary patterns of serial correlation (Wooldridge 1999). As shown in Table A7 in the Supporting Information, the coefficients on Transparency_{st} are significantly positive across all measures of inventor productivity.

Third, we exclude firms headquartered in California and Michigan—two states that adopted pay secrecy laws around the beginning of our sample period—and find a consistent result in Panel A of Table A8 in the Supporting Information. Fourth, in Panel B, we examine the relation between state-level pay secrecy laws and inventor productivity after we exclude companies headquartered in three states that adopted those laws around the end of our sample period: New Hampshire, Connecticut, and Oregon. We continue to find positive coefficients on Transparency. These results mitigate concerns that our results are driven by early or late treatment effects (Goodman-Bacon 2021). In Panel C, we consider only states that eventually pass pay secrecy laws and find consistent results.

Fifth, because there is a concern that the not-to-compete covenant may affect corporate innovation (Marx et al. 2009; Png 2017a, 2017b), we additionally control for the existence and enforcement of not-to-compete covenants.²⁴ Because our not-to-compete covenant data is available only up to 2011, the sample period is 1976–2011. We report these results in Table A9 in the Supporting Information. The coefficients on Transparency remain positive and significant at the 1% level.

Sixth, in Table A10 in the Supporting Information, we re-estimate Equation (2) by using several alternative measures of inventor productivity. In Panel A, we scale innovation output by the number of unique inventors who file patents with a firm in the same year, and find consistent results. In Panel B, we consider alternative measures of innovation output, including patent value, unadjusted citation counts (i.e., raw citation counts without any adjustment for the duration of patent citations), generality scores, and originality scores, all scaled by inventor number. As reported in columns 1–4 of Table A10, Panel B, in the Supporting Information the coefficients on Transparency are positive and significant at the 1% level. Taking column 1 as an example (in which the dependent variable represents patent value per inventor), the coefficient on Transparency is 0.047, which is higher than its counterparts in Table 3 (0.013 and 0.018 for patent count per inventor and forward citations per inventor, respectively), and is significant at the 1% level. Finally, in column (5), we re-estimate Equation (2) by using R&D expenditure scaled by the number of inventors as the dependent variable, and find an insignificant coefficient on Transparency. These results suggest that the relation between pay secrecy laws and inventor productivity is not driven by an increase in R&D investment.

Seventh, to further address the potential confounding effects of the creation of the Court of Appeals for the Federal Circuit (CAFC) and the enactment of the Bayh–Dole Act in the early 1980s (Henry and Turner 2006), we have conducted the following two tests. First, we start our sample in 1991 and find consistent results. Second, we drop patents that cite any university patents from our sample so that we can remove the effect of spillovers from universities' patents due to the Bayh–Dole Act. By dropping

patents that cite university patents, the number of patents covered in our sample drops by 12%. These results are presented in Table A11 in the Supporting Information and are consistent with our baseline results, suggesting that our results cannot be entirely attributed to these confounding events.

Finally, we acknowledge that inventors in the PatentsView database may not be officially affiliated with the assignee firms because some inventors may be independent inventors who can sell their patents to firms.²⁵ To mitigate this concern, we only consider an inventor as employed by a firm only after s/he have filed at least three patents that are assigned to the firm. Table A12 in the Supporting Information presents consistent results, suggesting that our baseline finding is not subject to the issue of independent inventors.

3.7 | Heterogeneous Effects

To further strengthen our argument that the effect of pay secrecy laws on inventor productivity is related to pay secrecy practices and rules in the workplace, we explore possible heterogeneous treatment effects. If improved inventor productivity after the passage of pay secrecy laws is due to reduced pay secrecy practices and rules in the workplace, then we expect this treatment effect to be stronger (i) in states with stronger ex ante pay secrecy practices and (ii) in firms with a higher ratio of minority inventors, who are more vulnerable to pay secrecy practices. Evidence from these tests helps alleviate concerns that our results are driven by omitted variables because it is quite unlikely that an omitted variable is correlated with the interaction terms (Claessens and Laeven 2003; Raddatz 2006).

For the first test, we measure the severity of pay secrecy practices and rules using ex ante unexplained pay differentials between white males and other groups. Ex ante unexplained pay differentials refer to the differences in hourly salaries that cannot be explained by observable characteristics (e.g., age, education, and working hours) in 1980. In particular, we estimate the following ordinary least squares regression for all individuals in each state-industry (2-digit SIC industry) combination in 1980:

$$\begin{aligned} \ln(\text{Hourly wage})_j = & \beta_0 + \beta_1 \text{White male}_j + \beta_2 \ln(\text{Employee age})_j \\ & + \beta_3 \text{College education}_j + \beta_4 \ln(\text{Annual working hour})_j \\ & + \varepsilon_j, \end{aligned} \quad (6)$$

in which $\ln(\text{Hourly wage})_j$ is the natural logarithm of hourly wage by employee j . White male_j is an indicator that represents white male employees.²⁶ All other variables have been defined in Appendix B. Also, we obtain data from the IPUMS-CPS-ASEC database. The coefficient estimate of β_1 is our measure of the severity of state-industry-level unexplained pay differentials in state s in industry l in 1980. A larger value of β_1 indicates a greater difference in salary between white males and other groups that cannot be explained by observable characteristics and thus supports greater pay secrecy.

We first examine if existing pay gaps are reduced upon the passage of pay secrecy laws, especially for states with higher ex

ante unexplained pay differentials. In particular, we estimate the following ordinary least squares regressions for a state-year panel:

$$\begin{aligned} \text{Pay gap}_{st} = & \beta_0 + \beta_1 \text{Transparency}_{st} \times \text{Larger pay secrecy}_s \\ & + \beta_2 \text{Transparency}_{st} + \beta_3 \text{Larger pay secrecy}_{st} \\ & + \beta_4 X_{st} + \delta_s + \lambda_t + e_{st}, \end{aligned} \quad (7)$$

in which Pay gap_{st} denotes the unexplained pay differentials in state s in year t .²⁷ $\text{Larger pay secrecy}_s$ is an indicator that equals one if a firm is located in a state where the state-level average unexplained pay differential in 1980 is larger than the median of all observations, and zero otherwise.²⁸ X_{st} includes state-level control variables, such as GDP, personal income per capita, population, business combination laws, and wrongful discharge laws; δ_s denotes state fixed effects; and λ_t denotes year fixed effects. We provide the summary statistics of related variables in Panel C of Table 1. As reported in Table A13 in the Supporting Information, the coefficients on $\text{Transparency}_{st} \times \text{Larger pay secrecy}_s$ are negative and significant in all columns, which is consistent with the expectation that pay secrecy laws close pay gaps.

We then further examine the heterogeneous treatment effects of pay secrecy laws on inventor productivity. In particular, we estimate the following regression that adds an interaction term to Equation (2):

$$\begin{aligned} \ln(Y_{ijst} + 1) = & \alpha_0 + \alpha_1 \text{Transparency}_{st} \times \text{Larger pay secrecy}_{js} \\ & + \alpha_2 \text{Transparency}_{st} + \alpha_3 \text{Larger pay secrecy}_{js} \\ & + \alpha_4 X_{ijst} + \gamma_i + \theta_{jt} + \varepsilon_{jst}, \end{aligned} \quad (8)$$

in which $\text{Larger pay secrecy}_{js}$ is an indicator that equals one if the state-industry level unexplained pay differentials in 1980 of a firm in industry j in state, s is larger than the median of all observations, and zero otherwise. We report our results in Table A14 in the Supporting Information. We find that across both columns, the coefficients on $\text{Transparency} \times \text{Larger pay secrecy}$ are positive and significant. This finding supports heterogeneous treatment effects of pay secrecy laws: when a state is subject to greater pay secrecy practices before the passage of pay secrecy laws, the inventor productivity of firms in that state increases more after the passage of pay secrecy laws.

For the second test, we estimate Equation (8) by replacing $\text{Larger pay secrecy}$ with $\text{Higher minority ratio}$, which equals one if a firm's ratio of minority inventors is above the sample median in the year, and zero otherwise. (We will define whether an inventor is a minority or not in Section 4.) We report our results in Table A15 in the Supporting Information. We find that the coefficients on $\text{Transparency} \times \text{Higher minority ratio}$ are positive and significant across all columns.

Overall, our interaction regression results suggest that the positive relation between pay secrecy laws and inventor productivity is indeed tied to pay secrecy practices and rules in the workplace; thus, such a relation is unlikely to be spuriously driven by unobserved heterogeneity and thus has a causal interpretation.

3.8 | Alternative Explanations

We also acknowledge the following alternative explanations that are not related to pay secrecy practices and/or minority inventors but may explain our baseline findings. First, under pay secrecy laws, firms may disclose employees' base salaries but not other forms of compensation that may be tied to employees' performance indicators, such as patents. Thus, inventors may be incentivized to produce more patents after the passage of pay secrecy laws. If this explains our main finding, then we would expect inventors to increase patent output by "piecemeal patenting" (i.e., splitting big patents into several smaller ones). However, we do not find a change in the average number of claims, which is a common measure for piecemeal patenting (Tong and Frame 1994; Dang and Motohashi 2015), related to pay secrecy laws, as shown in columns 1 and 2 in Table A16 in the Supporting Information.

Second, we acknowledge that the passage of pay secrecy laws may increase the overall bargaining power of employees as well as the level of average wages. Thus, inventors may be motivated to exert more effort and produce more patents. To address this possibility, we examine whether the average employee compensation level increases after the adoption of the laws. We use a firm's selling, general, and administrative (SG&A) expenses scaled by the number of employees to measure its average compensation level, following Eifeldt and Papanikolaou (2013). It is noteworthy that total wages and labor expenses are often missing in the Compustat database. On the other hand, a large part of SG&A consists of expenses related to human capital (e.g., white collar wages and training); it thus serves as a reasonable proxy for inventors' compensation level. As shown in column 3 in Table A16 in the Supporting Information, we do not find a significant increase in compensation after the passage of pay secrecy laws.

Third, as firms can no longer under-pay some inventors after the passage of pay secrecy laws, they face higher labor costs and may thus develop more labor-saving technologies, which will also result in more patent output. To address this issue, we use the new data of Ganglmair et al. (2022) in which each independent claim of a patent is classified as product-related or process-related. We calculate the average ratio of process claims of all patents filed by a firm in a year to measure firms' inclination toward labor-saving technologies that are more likely related to "process patents." As shown in column 4 in Table A16 in the Supporting Information, we do not find a significant increase in the ratio of process patents after the passage of pay secrecy laws.

4 | Mechanisms

4.1 | Motivating Inventors

The enactment of pay secrecy laws can motivate inventors to work harder and perform better from the perspectives of monetary incentives and morale. With respect to monetary incentives, pay transparency has been modelled as a way to reduce labor market frictions in Hsieh et al. (2019). In their framework, when pay is not transparent, employees may tend to believe that their salaries are subject to higher uncertainty, which discourages them from investing in human capital. In contrast, when pay secrecy laws

enhance pay transparency, employees' payoffs for their effort become less ambiguous, which increases their motivation to work harder. With respect to morale, Cullen and Perez-Truglia (2022) show that when pay is secretive, employees may assume that other factors are at play, such as unconscious bias, wage compression, playing favorites, or discrimination. As these negative factors usually lead to employee disengagement, enhanced pay transparency associated with pay secrecy laws could strengthen inventors' morale and, in turn, increase their productivity.

To examine this mechanism, we identify inventors using the unique inventor ID based on a disambiguation algorithm in the "inventor" file from the PatentsView database. In our sample, we have 655,653 unique inventors. This sample includes all inventors working for our sample firms. We identify inventors' gender and ethnicity based on their first and last names in the "inventor" file in the PatentsView database. Also, we use each inventor's state information, which could be different from firms' headquarters states, and which is also more related to labor laws (including labor union laws and anti-discrimination laws).²⁹ The detailed procedure is provided in Supporting Information A. We consider inventors working for firms that have "assignee_ID" in the database.

We implement a difference-in-differences analysis by estimating the following ordinary least squares regression for an inventor-year panel:³⁰

$$\ln(\text{Innovation}_{kist} + 1) = \alpha_0 + \alpha_1 \text{Transparency}_{st} + \alpha_2 X_{ist} + FEs + \varepsilon_{kist}, \quad (9)$$

in which Innovation_{kist} is one of our inventor-level productivity measures, InvPat and InvCit . These measures denote the patent count and adjusted citation count of inventor k located in state s and employed by firm i in year t , respectively. For each inventor, we measure her contribution to a patent as 1 divided by the number of inventors for the patent. We then calculate that inventor's patent count (InvPat) by adding up her contributions to the patents that list her as a (co-)inventor and are applied for in a given year. The inventor's citation count (InvCit) is calculated as her contribution to each patent times the number of forward citations received by each of these patents. In Table 1 Panel D, we provide summary statistics of these innovation measures of inventor-year observations over the period 1976–2017. We control for firm characteristics and state characteristics (X_{ist}) as in Equation (2) (if our sample only includes public firms), as well as control for different combinations of fixed effects (FEs): firm fixed effects, year fixed effects, and inventor fixed effects. In some regressions, we also additionally control for the number of patents filed by firm i in year t to capture firms' innovation capability that likely positively influences individual inventors' performance (e.g., clustering of capable inventors and spillovers, internal competition pressure). The coefficient of interest in Equation (9) is α_1 , which measures the effect of pay secrecy laws on inventor productivity.

We report our estimation results for Equation (9) in Table 5. We first consider public firms and include all firm characteristics and state characteristics, as well as firm and year fixed effects. We consider all inventors in columns 1 and 2; to avoid any possible confounding effects from inventor relocation, we only consider inventors who stay in the same state in all years (i.e., they have

never moved) in columns 3 and 4.³¹ We find that the coefficients on Transparency range between 0.0010 and 0.015, all of which are significant at least at the 1% level. In terms of economic significance, the coefficient estimates in columns 1 and 2 suggest that an inventor's patent count and citation count increase by 4.3% and 5.8%, respectively, after the passage of pay secrecy laws. These counts correspond to 0.013 more patents and 0.017 more citations for an average inventor in our sample who invents 0.300 patents per year that receive 0.292 forward citations before the passage of pay secrecy laws in her respective state.

This positive relation holds in many different regression specifications and samples, as shown in the Supporting Information. First, the positive relation remains even when we exclude firms' patent/citation counts, as we still obtain consistent results, which we provide in Table A17 in the Supporting Information. Second, we have also included inventor fixed effects and find consistent results in Table A18 in the Supporting Information. We do not include inventor fixed effects in our baseline results because: (i) 34% of inventors have only one patent in our sample and (ii) a large portion of (53%) of inventor-year observations do not have any patent records (and thus their output is set to zero).³² Thus, including inventor fixed effects may give us lower power. Finally, when we implement similar tests to include firms that are *not* publicly listed, we find consistent results, which we provide in Table A19 in the Supporting Information. Overall, our results support the mechanism that inventors are motivated to work harder after pay secrecy laws.

4.2 | Motivating Minority Inventors

Although pay transparency could improve all employees' motivation, it could have a particularly stronger effect on minority employees, as such employees are traditionally disadvantaged in the workplace and face a higher likelihood of being underpaid (Kim 2015). We thus implement a difference-in-differences analysis by estimating the following ordinary least squares regression for an inventor-year panel:

$$\ln(\text{Innovation}'_{kist} + 1) = \alpha_0 + \alpha_1 \text{Transparency}_{st} \times \text{Minority}_{kist} + \alpha_2 \text{Transparency}_{st} + \alpha_3 X_{ist} + FEs + \varepsilon_{ijst}, \quad (10)$$

in which all independent variables have been defined as in Equation (9) except Minority_{kist} , which takes the value of one if the inventor is not a white male, and zero otherwise. We require that sample inventors have identifiable gender and ethnicity information. Among unique inventors, 18.91% are minority inventors. For the dependent variables, $\text{Innovation}'_{kist}$, we only consider the values corresponding to patents that are coinvented by either all minority inventors or all non-minority inventors. This way, we can clearly separate the effect of pay secrecy laws on these two types of inventors and circumvent the issue that the post-event increase of inventor productivity results from either slightly more efforts from non-minority inventors or better collaboration within teams (e.g., Koning et al. 2021).

We present the results in Table 6 for all inventors and stayer inventors. Specifically, the coefficients on $\text{Transparency} \times \text{Minority}$ are significantly positive in all but one column. These results indicate

TABLE 5 | The Effect of Pay Secrecy Laws on Inventors' Innovation Output.

Variables	(1) lnInvPat	(2) lnInvCit	(3) lnInvPat	(4) lnInvCit
	All the inventors		Stayer inventors	
Transparency	0.010*** (0.003)	0.013*** (0.003)	0.010*** (0.003)	0.015*** (0.003)
ln(Number patent)	0.079*** (0.002)		0.077*** (0.002)	
ln(Number citation)		0.075*** (0.003)		0.073*** (0.003)
Other controls	Same as those in Table 3			
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	3,867,131	3,867,131	3,064,408	3,064,408

Note: This table examines the effect of state-level pay secrecy laws on inventors' innovation output using the difference-in-differences specification in Equation (9). The unit of analysis is an inventor-year observation. In columns 1 and 2, we include all the inventors. In columns 3 and 4, we focus on inventors who have never changed their states. We include firm and year fixed effects. Variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by location state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

that the positive relation between pay secrecy laws and inventor productivity is stronger for minority inventors than their counterparts. On the other hand, the coefficients on Transparency remain positive and largely significant, suggesting that even non-minority inventors' productivity increases after pay secrecy laws. Thus, our results in Table 6 support the mechanism that inventors, especially minority inventors, are motivated to exert more effort because of less discrimination and clearer expected payoffs. This finding is also consistent with our firm-level evidence of a stronger treatment effect in firms with a larger proportion of minority inventors (see Table A15 in the Supporting Information).

To further examine the motivation mechanism, we estimate Equation (10) in subsamples of high and low average employee compensation (measured by SG&A expenses scaled by the number of employees) and present the results in Table A20 in the Supporting Information. We find that the coefficients on Transparency \times Minority are significantly positive (insignificant) in the subsample of high (low) average employee compensation. These results suggest that minority inventors are motivated to exert more effort and produce more patents when they observe their peers' higher compensation. In addition, we notice that the coefficients on Transparency are significantly positive (insignificant) in the subsample of high (low) average employee compensation. This finding is intuitive because, for firms with lower compensation, the disclosure of peers' salary will not motivate any inventors to work harder.

4.3 | Diversity in Inventor Teamwork

Our second mechanism posits that pay secrecy laws contribute to more diversified inventor teams, which produce more high-quality innovation output. We expect that pay secrecy laws will increase the diversity of a firm's inventor teams and thus enhance

output quality. Employees with a variety of backgrounds may provide diverse perspectives, valuable ideas, and problem-solving abilities, which all facilitate optimal, creative solutions and innovation (Drach-Zahavy and Somech 2001; Berliant and Fujita 2011). Hong and Page (2001) construct a model of heterogeneous agents of bounded ability and analyze their individual and collective efforts to find solutions to difficult problems (e.g., searching for new cancer treatments, developing new software). Their model predicts that diverse perspectives and heuristics among these individuals help generate optimal solutions to address 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 (Watson et al. 1993; Amason 1996). As this literature stream predicts that firms with greater workforce diversity are more innovative, another channel for pay secrecy laws to enhance inventor productivity is to diversify inventor teams. After a state passes pay secrecy laws, we expect that inventor teams in that state become more diversified, as minority inventors are more willing/able to cooperate with others.

To test this mechanism, we measure diversity within the inventor team for each patent by using the Shannon index of diversity (Shannon 1948) based on the distribution of inventors' ethnicity and gender (all details are provided Section A in the Supporting Information). We provide the summary statistics of both diversity measures in Panel E of Table 1.

To examine how pay secrecy laws enhance inventor productivity through increasing inventor diversity, we estimate the following two ordinary least squares regressions at the patent level:

$$\text{Diversity}_{kst} = \alpha_0 + \alpha_1 \text{Transparency}_{st} + \gamma_i + \pi_h + \theta_t + \varepsilon_{kst}, \quad (11)$$

$$\ln(\text{PatentCitation or PatentValue} + 1)_{kst} = \beta_0 + \beta_1 \text{Diversity}_{kst} + \lambda_i + \Phi_h + \mu_t + e_{kst}, \quad (12)$$

TABLE 6 | Motivation of minority inventors.

Variables	(1)	(2)	(3)	(4)
	lnInvPat'	lnInvCit'	lnInvPat'	lnInvCit'
	All the inventors		Stayer inventors	
Transparency × Minority	0.010*	0.006	0.013**	0.008**
	(0.006)	(0.004)	(0.006)	(0.004)
Transparency	0.006*	0.008***	0.006	0.009***
	(0.003)	(0.002)	(0.004)	(0.003)
Minority	-0.081***	-0.069***	-0.083***	-0.071***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Number patent)	0.063***		0.061***	
	(0.001)		(0.001)	
ln(Number citation)		0.057***		0.055***
		(0.001)		(0.001)
Other controls	Same as those in Table 3			
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,763,437	2,763,437	2,150,901	2,150,901

Note: This table examines the effect of state-level pay secrecy laws on minority inventors' innovation output using the difference-in-differences specification in Equation (10). The unit of analysis is an inventor-year observation. In columns 1 and 2, we include all the inventors whose race and gender are identifiable. In columns 3 and 4, we focus on inventors who have never changed their states and whose race and gender are identifiable. Variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by location state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

in which $Diversity_{kst}$ is racial and gender diversity for the inventor team of patent k that is in technology group h and is filed by firm i located in state s in year t .³³ PatentCitation and PatentValue are the number of forward citations received by patent k and its patent value, respectively. γ_i , π_h , and θ_t denote firm, group, and year fixed effects, respectively, in Equation (11), and λ_i , Φ_h , and μ_t denote firm, group, and year fixed effects, respectively, in Equation (12).

Equation (11) estimates how a patent's inventor diversity changes after the passage of pay secrecy laws. Equation (12) examines how patent citations and values are associated with team diversity. Table 7 presents our results. In Panel A, we focus on racial diversity. As we show in column 1, the coefficient on Transparency is positive and significant at the 1% level, indicating that the racial diversity of inventor teams significantly increases after the passage of pay secrecy laws. Another interpretation to explain the increase in team member diversity could be that minority inventors now receive more credit for their work and are thus listed as co-inventors in documents. In column 2, we find that diversity has a positive and significant coefficient (at the 1% level), which supports the proposition that diversity in inventor teams helps to enhance patent quality. These findings are consistent with those of prior studies that suggest groups with more diversified members solve problems more creatively and efficiently (e.g., Wiersema and Bantel 1992; Watson et al. 1993; Hambrick et al. 1996; Hong and Page 2001). In Panel B, we focus on gender diversity and find a consistent result, which echoes Yang et al. (2022) that gender-diverse teams produce more novel and higher-impact publications. Our results from Table 7

support the view that one mechanism for pay secrecy laws to stimulate inventor productivity is to increase the diversity of inventor teams.

4.4 | Expected Promotion Raise

Our third mechanism suggests that, after the passage of pay secrecy laws, compensation for senior colleagues becomes more visible. Thus, for companies with a larger increase in promotion raises, all inventors should be encouraged to exert more effort to pursue promotions. To test this mechanism, we measure expected promotion raises associated with promotions in a firm by using the ratio of CEO compensation to average employee compensation. We then implement a difference-in-differences analysis by estimating the following ordinary least squares regression for firm-year observations:

$$\ln(Y_{ijst} + 1) = \alpha_0 + \alpha_1 \text{Transparency}_{st} \times \text{Higher promotion raises}_{it} + \alpha_2 \text{Transparency}_{st} + \alpha_3 \text{Higher promotion raise}_{it} + \alpha_4 X_{ijst} + \gamma_i + \theta_{jt} + \varepsilon_{ijst}, \quad (13)$$

in which all variables have been defined as in Equation (2) except Higher promotion raises_{it}, which equals one if a firm's ratio of CEO compensation to average employee compensation is above the median of all the firms in the year, and zero otherwise. The ratio of CEO compensation to average employee compensation is measured as the total compensation of the CEO divided by

TABLE 7 | Inventor diversity and patent quality.

Panel A: Racial diversity			
	(1)	(2)	
	Inventor diversity (race)	ln (PatentCitation + 1)	ln (PatentValue + 1)
Inventor diversity (race)		0.056*** (0.005)	0.014** (0.007)
Transparency	0.028*** (0.003)		
Firm fixed effects	Yes	Yes	Yes
Patent group fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	1,429,465	1,429,465	1,429,465
Panel B: Gender diversity			
	(1)	(2)	
	Inventor diversity (gender)	ln (Patent Citation + 1)	ln(Patent Value + 1)
Inventor diversity (gender)		0.036*** (0.004)	0.026*** (0.009)
Transparency	0.009*** (0.001)		
Firm fixed effects	Yes	Yes	Yes
Patent group fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	1,375,554	1,375,554	1,375,554

Note: This table reports OLS regression results for two separate regressions. The unit of analysis is a patent observation. Panel A focuses on the racial diversity of an inventor team. Panel B focuses on the gender diversity of an inventor team. In column 1, we examine the relation between inventor diversity and the passage of pay secrecy laws. In column 2, we examine the relation between inventor team diversity on patent citation and patent value. Variable definitions are provided in Appendix B. Robust standard errors clustered by technology group are in parentheses. All continuous variables are winsorized at the 1st and 99th percentiles. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8 | Heterogeneous treatment effects based on expected promotion raises.

Variables	(1)	(2)
	lnPat/Inventor	lnCit/Inventor
Transparency × Higher promotion raises	0.010*** (0.004)	0.013*** (0.004)
Transparency	0.003 (0.007)	0.002 (0.012)
Higher promotion raises	-0.003 (0.003)	-0.001 (0.004)
Other controls	Same as those in Table 3	
Firm fixed effects	Yes	Yes
Industry × year fixed effects	Yes	Yes
Observations	18,931	18,931

Note: This table examines the heterogeneous treatment effects of state-level pay secrecy laws on inventor productivity conditional on expected promotion raises in a firm. Variable definitions are provided in Appendix B. We include firm and industry × year fixed effects. Robust standard errors clustered by headquarters state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

average SG&A expenses per employee.³⁴ Our sample size is much smaller because we obtain CEO compensation data from the ExecuComp that only covers S&P 1500 firms since 1992.

As shown in Table 8, the coefficients on Transparency \times Higher promotion raises are significantly positive in all columns, confirming our third mechanism that inventors are encouraged to pursue promotions when they observe their senior colleagues' salaries. On the other hand, the coefficients on Transparency are insignificant. These results indicate that the positive relation between pay secrecy laws and inventor productivity is only concentrated in firms with high expected promotion raises. This finding is intuitive because pay transparency should not matter for firms with a fairly flat compensation structure.

5 | Conclusion

Does pay transparency affect productivity? In this article, we propose and empirically test the effect of pay transparency on corporate innovation and inventor productivity by exploiting the staggered adoption of pay secrecy laws in different U.S. states. We find a significant increase in firms' inventor productivity following the passage of pay secrecy laws, relative to firms in states without such laws. These results are robust to various alternative specifications. We also show that the adoption of pay secrecy laws mitigates the pay differentials between minority employees and their counterparts, supporting the relevance of these laws. We find that the adoption of pay secrecy laws is unrelated to the pre-existing innovation of local firms, mitigating the concern of reverse causality. Various tests indicate that there is no time trend difference in inventor productivity between the treated group and the control group prior to the passage of pay secrecy laws, and that the improvement in inventor productivity occurs several years after the passage of such laws. Further, our tests for heterogeneous treatment effects suggest that these treatment effects are indeed related to pay secrecy practices and rules in the workplace. All these results collectively support a positive effect of pay transparency on productivity in terms of innovation activities.

Moreover, we provide some suggestive evidence to support the three underlying mechanisms for pay secrecy laws to promote inventor productivity: (i) motivating inventors (especially minority inventors) to exert more effort; (ii) increasing the diversity of inventor teams; and (iii) encouraging inventors to pursue promotions. Overall, our findings suggest that a transparent pay system helps spur corporate innovation and individual productivity.

We acknowledge that a causal interpretation of our analysis presumes that these laws are exogenous to firms' innovation activities. Although we can neither claim that such legislation is entirely exogenous nor rule out all endogeneity concerns, we believe that the political factors that underpin these laws and our explanation of firms' and managers' opposition to such laws, as well as all of our empirical analyses (including additional checks for staggered difference-in-differences, state-specific pre-trends, the dynamic effect analysis, hazard model estimation, analysis

of heterogeneous treatment effects, and all mechanism tests), collectively mitigate endogeneity concerns to a certain extent.

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Endnotes

- ¹In the U.S., several states have adopted pay transparency laws that require employers to disclose pay ranges for job candidates (California in 2016, Washington in 2019, and Colorado, Connecticut, Maryland, Nevada, and Rhode Island in 2021).
- ²According to the Institute for Women's Policy Research/Rockefeller Survey of Economic Security conducted in 2010, about half of all workers report that discussions of salary information are either discouraged or prohibited and could even lead to punishment (Hayes and Hartmann 2011; U.S. Department of Labor 2016).
- ³For instance, the U.S. Department of Labor filed a lawsuit against Google on Wednesday, January 4, 2017. In another case, a former female teacher working in Google's childcare center, Heidi Lamar, filed a complaint in San Francisco Superior Court.
- ⁴Pay gaps exist among knowledge workers in high-tech firms and research institutes (Goyette and Xie 1999; Prokos and Padavic 2005; Sauer mann 2018; Lyons and Zhang 2023). Such a gap may have implications for productivity (Ding et al. 2006; Azoulay et al. 2007; Koffi and Marx 2023).
- ⁵Kim (2015) finds that the adoption of pay secrecy laws helps to reduce gender pay gaps, especially among women with college or graduate degrees. Also, Baker et al. (2023) and Bennedsen et al. (2022) examine the impact of pay disclosure laws in Canada and Denmark, respectively.
- ⁶Prior studies find that groups consisting of more diverse individuals produce higher quality and more innovative decisions (Watson et al. 1993; Amason 1996). Niebuhr (2010), Singh and Fleming (2010), Qian et al. (2012), Parrotta et al. (2014), Nathan (2015), and Yang et al. (2022) show that team diversity positively influences innovation quality.
- ⁷For example, a 2017 survey conducted by the Institute for Women's Policy Research shows that 25 percent of private sector employees work in environments that formally prohibit them from discussing salaries, and another 41 percent work in environments that discourage them from discussing salaries (Hayes and Hartmann 2011).
- ⁸Ledbetter vs. Goodyear & Rubber Co. is a classic legal case in which pay information facilitates efforts to combat pay discrepancy. In this

case, Lilly Ledbetter consistently received wages lower than her male colleagues, but she was not aware of this fact (Ramachandran 2012).

- ⁹The full list of occupations can be found at https://cps.ipums.org/cps-action/variables/OCC90LY#codes_section
- ¹⁰We include each person's age, annual working hours, whether s/he has completed a college degree, and whether s/he has a postgraduate degree.
- ¹¹We also test the sum of the coefficients on Transparency \times Minority and Transparency, and find that their sum is insignificantly different from zero. One interpretation for this finding is that although minorities' wages increase, the majority experience no significant changes in their wages.
- ¹²The data are available from the website of Noah Stoffman: <https://kelley.iu.edu/nstoffma/>. We only include companies that are headquartered in the U.S. We exclude firms in financial industries and utility industries. Finally, we exclude all firm-year observations with book values of assets below \$5 million.
- ¹³Because not every inventor files a patent each year, we focus on the number of unique inventors in the most recent 10 years to provide a more stable estimation of the size of a firm's inventor team. Nevertheless, we find consistent results in a robustness check using the number of unique inventors in year t as the denominator.
- ¹⁴We only consider a patent's forward citations that happen in a five-year window since the patent's grant year (Lerner et al. 2011; Bernstein 2015; Hsu et al. 2024). In addition, we scale a patent's forward citation count by the average forward citation count of all patents in the same technology group and the same grant year (Seru 2014).
- ¹⁵We use a firm's headquarters location for law changes because top executives and R&D facilities tend to be geographically close to a firm's headquarters (Coval and Moskowitz 1999, 2001; Pirinsky and Wang 2006; Acharya et al. 2014).
- ¹⁶We obtain historical headquarters data from Bai et al. (2020). The data is publicly available at <https://sites.google.com/site/johnbaijianqiu/data>
- ¹⁷Following Bebchuk et al. (2011), we set missing R&D as zero and include a dummy variable R&D missing. To minimize the effect of outliers, we winsorize all continuous variables at the 1st and 99th percentiles. We find consistent results if we do not include any control variable or if we do not include R&D intensity and the R&D missing dummy.
- ¹⁸Prior empirical studies have posited that it takes less than one year for increases in R&D input to generate increases in patent applications (Hausman et al. 1984; Hall et al. 1986; Lerner and Wulf 2007; de Rassenfosse 2012; de Rassenfosse and Jaffe 2018).
- ¹⁹In columns 1 and 2, we additionally include $\sum_2^{51} \beta_s \times \text{Pre} - \text{trend}_s$, in which Pre-trend is equal to the number of years from the current year to the law passage year before a state passes a pay secrecy law, and is equal to 0 in the years after or in states that never pass a pay secrecy law.
- ²⁰We obtain the data on GDP, per capita income, and population from the Bureau of Economic Analysis, and we obtain the data on state governors' party affiliation from the National Governors Association. The data on state-level unemployment and demographics are from the IPUMS-CPS-ASEC database.
- ²¹When we consider growth rates, we do not include explanatory variables that are dummies.
- ²²For each firm in the stacked sample, we use the value of all the firm-level characteristics in the year -1 (i.e., $\tau = -1$). We then run a Probit model with all these variables. For each treatment firm-cohort, we identify a control firm-cohort with the closest propensity score, without replacement.
- ²³It is challenging for us to implement random inferences, such as Heß (2017), in our two-way fixed effect setting.

- ²⁴The dummy for the existence of not-to-compete covenants is one if a state enacted such covenants, and zero otherwise. The dummy for the enforcement of such covenants is one if a state indeed enforced them, and zero otherwise.
- ²⁵All granted patents must be issued to human inventors first (and then transferred to the companies they work for) based on U.S. patent laws before September 16, 2012 (Zhang 2024).
- ²⁶According to the instructions from the U.S. Census Bureau, white, black, and Asian are race categories, whereas Hispanic is an ethnicity category. In this article, we do not distinguish between the concepts of race and ethnicity.
- ²⁷We estimate Equation (6) in each state-industry for every year. We then use the average β_1 in each state-year as our measure of state-specific pay gap.
- ²⁸We use the state-level average unexplained pay differential in 1980 to mitigate two endogeneity concerns. First, contemporaneous pay differentials may be related to local job market competitiveness that affects employees' work incentives and productivity. Second, contemporaneous pay differentials may reflect technological opportunities.
- ²⁹Because 48% of inventor-year observations are in the same state as a firm's headquarters, we are unable to fully separate the effects from inventors' residential state and headquarters state in the same regression. Prior studies that connect labor laws to residential states include Gao and Zhang (2017) and Bloom et al. (2019).
- ³⁰The use of inventor ID based on disambiguation algorithms can be traced back to Li et al. (2014) and has been widely used in the literature (e.g., Bernstein 2015; Gao and Zhang 2017; Galasso and Schankerman 2018). However, we acknowledge that it is subject to errors in disambiguation algorithms (Bernstein 2015, page 1388).
- ³¹Hoisl (2007) provides empirical evidence that inventor productivity and relocation simultaneously affect each other. More productive inventors tend to be more mobile (Stark and Bloom 1985; Autor and Dorn 2013; Gao and Zhang 2017), and inventors tend to relocate to places with more favorable compensation schemes (Akcigit et al. 2016).

³²The coefficient estimates on Transparency in Table A18 in the Supporting Information, including inventor fixed effects, are of similar magnitudes as those in Table 5, suggesting that the results we report in the inventor level are more attributable to the treatment effect rather than the composition effect.

³³We use the majority of co-inventors to define the location of an inventor team.

³⁴As a large portion of firms do not report that accounting item, we use SG&A expenses following the literature (Eisfeldt and Papanikolaou 2013) as it includes most human capital expenses (e.g., white collar wage and training costs).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting information A: Identification of Each Inventor's Ethnicity/Gender

Appendix A: List of States Legislating Pay Secrecy Laws

Information is provided by the U.S. Department of Labor (Permanent Link: <https://hdl.handle.net/1813/78735>)

State	Pass year	Details
Michigan	1982	<p>Mich. Comp. Laws Section 408.483a Prohibited conduct. Sec. 13a. (1) An employer shall not do any of the following:</p> <ul style="list-style-type: none"> (a) Require as a condition of employment nondisclosure by an employee of his or her wages. (b) Require an employee to sign a waiver or other document which purports to deny an employee the right to disclose his or her wages. (c) Discharge, formally discipline, or otherwise discriminate against for job advancement an employee who discloses his or her wages. <p>This provision was added to Act 390 of 1978, Payment of Wages and Fringe Benefits, by Act 524 of 1982, effective March 30, 1983.</p>
California	1984	<p>Labor Code, Section 232 “No employer may do any of the following:</p> <ul style="list-style-type: none"> (a) Require, as a condition of employment, that an employee refrain from disclosing the amount of his or her wages. (b) Require an employee to sign a waiver or other document that purports to deny the employee the right to disclose the amount of his or her wages. (c) Discharge, formally discipline, or otherwise discriminate against an employee who discloses the amount of his or her wages.”
Illinois	2003	<p>ST CH 820 § 112/10 Sec. 10. Prohibited Acts.</p> <ul style="list-style-type: none"> (b) It is unlawful for any employer to interfere with, restrain, or deny the exercise of or the attempt to exercise any right provided under this Act (Equal Pay Act of 2003). It is unlawful for any employer to discharge or in any other manner discriminate against any individual for inquiring about, disclosing, comparing, or otherwise discussing the employee’s wages or the wages of any other employee, or aiding or encouraging any person to exercise his or her rights under this Act.
Vermont	2005	<p>Title 21 (Labor), Chapter 5 (Employment Practices), Sec. 495 (Unlawful Employment Practices). Sec. 495(a) It shall be unlawful employment practice, except where a bona fide occupational qualification requires persons of a particular race, color, religion, national origin, sex, sexual orientation, gender identity, ancestry, place of birth, age, or physical or mental condition:</p> <p>(7)(B)(i) No employer may do any of the following:</p> <ul style="list-style-type: none"> (I) Require, as a condition of employment, that an employee refrain from disclosing the amount of his or her wages or from inquiring about or discussing the wages of other employees. (II) Require an employee to sign a waiver or other document that purports to deny the employee the right to disclose the amount of his or her wages or to inquire about or discuss the wages of other employees. (ii) Unless otherwise required by law, an employer may prohibit a human resources manager from disclosing the wages of other employees. (8) Retaliation prohibited. An employer, employment agency, or labor organization shall not discharge or in any other manner discriminate against any employee because the employee: <ul style="list-style-type: none"> (D) has disclosed his or her wages or has inquired about or discussed the wages of other employees.
Maine	2009	<p>Chapter 29, S.P. 33 – L.D. 84, An Act to Ensure Fair Pay, effective 9/12/09 Sec.1. 26 MRSA Sec. 628, first paragraph, as amended by PL 2001, c. 304, Sec. 2, is further amended to read: “An employer may not discriminate between employees in the same establishment on the basis of sex by paying wages to any employee in any occupation in this State at a rate less than the rate at which the employer pays any employee of the opposite sex for comparable work on jobs that have comparable requirements relating to skill, effort and responsibility. Differentials that are paid pursuant to established seniority systems or merit increase systems or difference in the shift or time of the day worked that do not discriminate on the basis of sex are not within this prohibition. An employer may not discharge or discriminate against any employee by reason of any action taken by such employee to invoke or assist in any manner the enforcement of this section. An employer may not prohibit an employee from disclosing the employee’s own wages or from inquiring about another employee’s wages if the purpose of the disclosure or inquiry is to enforce the rights granted by this section. Nothing in this section creates an obligation to disclose wages.”</p>

(Continues)

State	Pass year	Details
Colorado	2009	<p style="text-align: center;">Senate Bill 08–122, approved 4/17/08</p> <p>Sec. 1. 24-34-402(1), Colorado Revised Statutes, is amended BY THE ADDITION OF A NEW PARAGRAPH to read:</p> <p style="text-align: center;">24-34-402.Discriminatory or unfair employment practices.</p> <p style="text-align: center;">(1) It shall be a discriminatory or unfair employment practice:</p> <p>(i) unless otherwise permitted by federal law, for an employer to discharge, discipline, discriminate against, coerce, intimidate, threaten, or interfere with any employee or other person because the employee inquired about, disclosed, compared, or otherwise discussed the employee’s wages; to require as a condition of employment nondisclosure by an employee of his or her wages; or to require an employee to sign a waiver or other document that purports to deny an employee the right to disclose his or her wage information. this paragraph (i) shall not apply to employers who are exempt from the provisions of the ‘National Labor Relations Act,’ 29 U.S.C., sec. 151 et seq.</p>
Louisiana	2013	<p style="text-align: center;">Chapter 6-A (Louisiana Equal Pay for Women Act) of Title 23 of the Louisiana Revised Statutes of 1950 §664. Prohibited acts</p> <p>D. It shall be unlawful for an employer to interfere with, restrain, or deny the exercise of, or attempt to exercise, any right provided under this Chapter. It shall be unlawful for any employer to discriminate, retaliate, or take any adverse employment action, including but not limited to termination or in any other manner discriminate against any employee for inquiring about, disclosing, comparing, or otherwise discussing the employee’s wages or the wages of any other employee, or aiding or encouraging any other employee to exercise his or her rights under this Chapter.</p> <p>Note: This Act applies only to any department, office, division, agency, commission, board, committee or other organizational unit of the state.</p>
New Jersey	2013	<p style="text-align: center;">Title 10. Civil Rights</p> <p style="text-align: center;">Sec. 10:5-12. Unlawful employment practices, discrimination.</p> <p>11. It shall be an unlawful employment practice, or, as the case may be, an unlawful discrimination:</p> <p>r. For any employer to take reprisals against any employee for requesting from any other employee or former employee of the employer information regarding the job title, occupational category, and rate of compensation, including benefits, of any employee or former employee of the employer, or the gender, race, ethnicity, military status, or national origin of any employee or former employee of the employer, regardless of whether the request was responded to, if the purpose of the request for the information was to assist in investigating the possibility of the occurrence of, or in taking of legal action regarding, potential discriminatory treatment concerning pay, compensation, bonuses, other compensation, or benefits.</p> <p>Nothing in this subsection shall be construed to require an employee to disclose such information about the employee herself to any other employee or former employee of the employer or to any authorized representative of the other employee or former employee.</p>

(Continues)

State	Pass year	Details
Minnesota	2014	<p>Ch. 239—H.F. No. 2536 Article 3. Labor Standards and Wages Sec. 2. [181.172] WAGE DISCLOSURE PROTECTION.</p> <p>(a) An employer shall not:</p> <ol style="list-style-type: none"> (1) Require nondisclosure by an employee of his or her wages as a condition of employment; (2) Require an employee to sign a waiver or other document which purports to deny an employee the right to disclose the employee's wages; or (3) Take any adverse employment action against an employee for disclosing the employee's own wages or discussing another employee's wages which have been disclosed voluntarily. <p>(b) Nothing in this section shall be construed to:</p> <ol style="list-style-type: none"> (1) Create an obligation on any employer or employee to disclose wages; (2) Permit an employee, without the written consent of the employer, to disclose proprietary information, trade secret information, or information that is otherwise subject to a legal privilege or protected by law; (3) Diminish any existing rights under the National Labor Relations Act under United States Code, title 29; (4) Permit the employee to disclose wage information of other employees to a competitor of their employer. <p>(c) An employer that provides an employee handbook to its employees must include in the handbook notice of employee rights and remedies under this section.</p> <p>(d) An employer may not retaliate against an employee for asserting rights or remedies under this section.</p> <p>(e) An employee may bring a civil action against an employer for a violation of paragraph (a) or (d). If a court finds that an employer has violated paragraph (a) or (d), the court may order reinstatement, back pay, restoration of lost service credit, if appropriate, and the expungement of any related adverse records of an employee who was the subject of the violation.</p>
Connecticut	2015	<p>Conn. Gen. Stat. § 31–40z(b)-(c)</p> <p>(b) No employer shall:</p> <ol style="list-style-type: none"> (1) Prohibit an employee from disclosing or discussing the amount of his or her wages or the wages of another employee of such employer that have been disclosed voluntarily by such other employee; (2) Prohibit an employee from inquiring about the wages of another employee of such employer; (3) Require an employee to sign a waiver or other document that denies the employee his or her right to disclose or discuss the amount of his or her wages or the wages of another employee of such employer that have been disclosed voluntarily by such other employee; (4) Require an employee to sign a waiver or other document that denies the employee his or her right to inquire about the wages of another employee of such employer; (5) Discharge, discipline, discriminate against, retaliate against or otherwise penalize any employee who discloses or discusses the amount of his or her wages or the wages of another employee of such employer that have been disclosed voluntarily by such other employee; or (6) Discharge, discipline, discriminate against, retaliate against or otherwise penalize any employee who inquires about the wages of another employee of such employer. <p>(c) Nothing in this section shall be construed to require any employer or employee to disclose the amount of wages paid to any employee.</p>

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State	Pass year	Details
New Hampshire	2015	<p>N.H. Rev. Stat. § 275:38-a(I)(b)-(II)</p> <p>I. No employer shall discharge or in any other manner discriminate against any employee because he or she:</p> <p>(b) Inquired about, discussed, or disclosed his or her wages or those of another employee.</p> <p>II. This section shall not apply to any employee who has access to the wage information of other employees as a part of such employee's essential job functions who discloses the wages of such other employees to individuals who do not otherwise have access to such information, unless such disclosure is in response to a complaint or charge or in furtherance of an investigation, proceeding, hearing, or action under RSA 275:41-a, including an investigation conducted by the employer.</p> <p>Nothing in this section shall be construed to limit the rights of an employee provided under any other provision of law.</p> <p>N.H. Rev. Stat. § 275:41-b(I)-(II)</p> <p>I. No employer shall require the following as a condition of employment:</p> <p>(a) That an employee refrain from disclosing the amount of his or her wages.</p> <p>(b) That an employee sign a waiver or other document that purports to deny the employee the right to disclose the amount of his or her wages, salary, or paid benefits.</p> <p>II. No employer shall discharge, formally discipline, or otherwise discriminate against an employee who discloses the amount of his or her wages, salary, or paid benefits.</p>
Oregon	2016	<p>Or. Rev. Stat. § 659A.355(1)-(2)</p> <p>(1) It is an unlawful employment practice for an employer to discharge, demote or suspend, or to discriminate or retaliate against, an employee with regard to promotion, compensation or other terms, conditions or privileges of employment because the employee has:</p> <p>(a) Inquired about, discussed or disclosed in any manner the wages of the employee or of another employee; or</p> <p>(b) Made a charge, filed a complaint or instituted, or caused to be instituted, an investigation, proceeding, hearing or action based on the disclosure of wage information by the employee.</p> <p>(2) This section does not apply to an employee who has access to wage information of employees as part of the job functions of the employee's position and discloses the wages of those employees to individuals not authorized access to the information, unless the disclosure is in response to a charge or complaint or is in furtherance of an investigation, proceeding, hearing or action, including but not limited to an investigation conducted by the employer.</p>

Appendix B: Variable Definitions

Variable	Definition
<i>Measures of innovation output</i>	
Pat/Inventor	Number of patents filed (and subsequently awarded) by a firm in a year, scaled by the number of unique inventors working for the firm in a ten-year rolling window. We only have comprehensive coverage of patents awarded since 1976 due to the truncation issue in available patent data. Thus, for each firm-year observation in the 1976–1983 period, we proportionately adjust its denominator, which is the number of unique inventors by year t multiplied by $10/(t - 1974)$.
Cit/Inventor	Number of adjusted forward citations received by all the patents that are applied for (and subsequently awarded) by a firm in a given year, scaled by the number of unique inventors working for the firm in a ten-year rolling window. The number of adjusted forward citations of each patent is defined as the number of forward citations received by the patent (within a 5-year window from its grant year) scaled by the average forward citations received by all patents in the same CPC 4-digit group.
Pat/Inventor1	Number of patents filed (and subsequently awarded) by a firm in a year, scaled by the number of unique inventors who file patents with the firm in the same year.
Cit/Inventor1	Number of adjusted forward citations received by all the patents that are applied for (and subsequently awarded) by a firm in a given year, scaled by the number of unique inventors who file patents with the firm in the same year.
Val/Inventor	Sum of values of all patents applied for by a firm in year t scaled by the number of inventors; each patent's value is the stock market reaction to its grant news (Kogan et al. 2017).
Ucit/Inventor	Number of all forward citations received by all the patents that are applied for (and subsequently awarded) by a firm in a given year scaled by the number of unique inventors working for the firm in a ten-year rolling window.
Gen/Inventor	A firm's generality score in a given year is scaled by the number of unique inventors working for the firm in a 10-year rolling window. The generality score of a patent is defined as one minus the Herfindahl index of the technology group distribution of all subsequent patents citing the patent (Hall et al. 2005a). A firm's generality score in a year is defined as the sum of the generality scores of all patents filed by a firm in a given year (Hsu et al. 2014).
Ori/Inventor	A firm's originality score in a given year is scaled by the number of unique inventors working for the firm in a 10-year rolling window. The originality score of a patent is defined as one minus the Herfindahl index of the technology group distribution of all prior patents being cited by the patent (Hall et al. 2005a). A firm's originality score in a year is defined as the sum of the originality scores of all patents filed by a firm in a given year (Hsu et al. 2014).
R&D/Inventor	R&D expenditures by a firm in a given year are scaled by the number of unique inventors working for the firm in a 10-year rolling window.
Claims	The average number of claims of all the patents that are filed (and subsequently awarded) by a firm in a year.
lnPat/Inventor	Natural logarithm of one plus Pat/Inventor.
lnCit/Inventor	Natural logarithm of one plus Cit/Inventor.
lnPat/Inventor1	Natural logarithm of one plus Pat/Inventor1.
lnCit/Inventor1	Natural logarithm of one plus Cit/Inventor1.
lnClaims	Natural logarithm of claims.
Process claims	The average ratio of process claims of all the patents that are filed (and subsequently awarded) by a firm in a year.
lnVal/Inventor	Natural logarithm of one plus Val/Inventor.
lnUcit/Inventor	Natural logarithm of one plus UCit/Inventor.
lnGen/Inventor	Natural logarithm of one plus Gen/Inventor.
lnOri/Inventor	Natural logarithm of one plus Ori/Inventor.
lnR&D/Inventor	Natural logarithm of one plus R&D/Inventor.
<i>Firm characteristics</i>	
Assets	Total assets.
Cash	Cash and short-term investments normalized by total assets.

(Continues)

Variable	Definition
R&D	R&D expenditures normalized by total assets. If the R&D expenditures variable is missing, we set the missing value to zero.
R&D missing	An indicator variable that equals one if the R&D expenditures variable is missing, and zero otherwise.
ROA	Net income normalized by total assets.
PPE	Gross property, plant, and equipment normalized by total assets.
Leverage	Total debt normalized by total assets.
Capex	Capital expenditures normalized by total assets. If the capital expenditures variable is missing, we set the missing value to zero.
Tobin's Q	Market value of equity plus the book value of total assets minus the book value of equity minus balance sheet deferred taxes, normalized by the book value of total assets.
Age	Number of years since a firm's first appearance in the Compustat database. In Table A19 in the Online Appendix for which the sample includes both public firms and private firms. Age is defined as the number of years since a firm's first appearance in the innovation database.
Higher minority ratio	An indicator variable that equals one if the percentage of minority inventors in a firm is larger than the median of all the firms in the year, and zero otherwise. The percentage of minority inventors is calculated as the number of minority inventors / (number of minority inventors + number of majority inventors), all measured in a 10-year rolling window.
Higher promotion raises	An indicator variable that equals one if a firm's promotion raise is larger than the median of all the firms in the year, and zero otherwise. CEO-employee pay disparity is measured as the total compensation of a CEO divided by the average selling, general, and administrative expenses per employee.
Average compensation	Selling, general, and administrative expenses are divided by the number of employees.
Larger pay secrecy (state-industry)	An indicator variable that equals one if the state-industry group level unexplained pay differentials in 1980 of a firm is larger than the median of all observations, and zero otherwise.
<i>State characteristics</i>	
Transparency	An indicator variable that equals one if the state has adopted pay secrecy laws in a given year, and zero otherwise.
Pay gap	We first estimate β_1 from the following regression of all individuals within each state-industry-year combination: $\ln(\text{Hourly wage})_{jt} = \beta_0 + \beta_1 \text{White male}_j + \beta_2 \ln(\text{Employee age})_{jt} + \beta_3 \text{College education}_{jt} + \beta_4 \ln(\text{Annual working hour})_{jt} + \varepsilon_{jt}$. We then use the average β_1 in each state-year as our measure of state-year level pay gap.
State GDP	Annual GDP of a given state.
Per capita income	Annual personal income per capita in a given state.
State population	Population of a given state.
State unemployment rate	The unemployment rate of a state.
Republican governor	An indicator variable that equals one if the state is governed by a republican in a given year, and zero otherwise. The value is always zero for companies located in D.C.
State education	Percentage of the labor force who finish 4-years' college education in a given state.
Percentage of males	Percentage of males in the labor force in a given state.
Percentage of whites	Percentage of whites in the labor force in a given state.
Business combination	An indicator variable that equals one if the state adopts business combination laws, following Bertrand and Mullainathan (2003).
Good faith	An indicator variable that equals one if the state adopts the good-faith exception, following Autor et al. (2006).
$\ln(\text{Average Pat/Inventor})$	Natural logarithm of one plus the average Pat/Inventor across all public firms headquartered in a state.
$\ln(\text{Average Cit/Inventor})$	Natural logarithm of one plus the average Cit/Inventor across all public firms headquartered in a state.

(Continues)

Variable	Definition
Larger pay secrecy (state)	An indicator variable that equals one if the state-level unexplained pay differentials in 1980 of a firm is larger than the median of all observations, and zero otherwise.
Existence of CNC	An indicator variable for the existence of not-to-compete covenants that equals one if a state enacted such covenants, and zero otherwise.
Enforcement of CNC	An indicator variable for the enforcement of not-to-compete covenants that equals one if a state indeed enforced them, and zero otherwise.
<i>Inventor characteristics</i>	
lnInvPat	Natural logarithm of one plus the number of patents filed by an inventor in a year. If X inventors file a patent together, we deem each inventor filed $1/X$ patents.
lnInvCIt	Natural logarithm of one plus the number of forward citations of the patents filed by an inventor in a year. If X inventors file a patent together, we normalize the total forward citations by inventor number.
lnInvPat'	Natural logarithm of one plus the number of patents filed by an inventor in a year. If X inventors file a patent together, we deem each inventor filed $1/X$ patents. We only include patents for which all the inventors are majority or minority. However, the inventor team may include inventors whose gender or race are not identifiable.
lnInvCIt'	Natural logarithm of one plus the number of forward citations of the patents filed by an inventor in a year. If X inventors file a patent together, we normalize the total forward citations by inventor number. We only include patents for which all the inventors are majority or minority. However, the inventor team may include inventors whose gender or race are not identifiable.
lnInvClaims	Natural logarithm of one plus the average number of claims per patent filed by an inventor in a year.
Minority	An indicator variable that equals one if an inventor is not a white male, and zero otherwise.
ln(Number patent)	Natural logarithm of one plus the number of patents that are applied for (and subsequently awarded) by a firm in a given year.
ln(Number citation)	Natural logarithm of one plus the number of adjusted forward citations received by all patents that are applied for (and subsequently awarded) by a firm in a given year. The number of adjusted forward citations of each patent is defined as the number of forward citations received by the patent (within a 5-year window from its grant year) scaled by the average forward citations received by all patents in the same CPC 4-digit group.
<i>Patent/team characteristics</i>	
Inventor diversity (race)	$\sum_{i=1}^5 \text{Proportion of the race}_i * \ln\left(\frac{1}{\text{Proportion of the race}_i}\right)$ <p>in which proportion of the race is the number of inventors from a given ethnic group divided by the total number of inventors in the team. The detailed procedure for ethnicity identification is provided in Section A in the Online Appendix.</p>
Inventor diversity (gender)	$\sum_{i=1}^2 \text{Proportion of the gender}_i * \ln\left(\frac{1}{\text{Proportion of the gender}_i}\right)$ <p>in which <i>Proportion of the gender</i> is the number of people from a given gender group divided by the total number of inventors in the team. The detailed procedure for gender identification is provided in Section A in the Online Appendix.</p>
PatentCitation	The number of adjusted forward citations received by a patent. The number of adjusted forward citations of each patent is defined as the number of forward citations received by the patent (within a 5-year window from its grant year) scaled by the average forward citations received by all patents in the same CPC 4-digit group.
PatentValue	A patent's value is the stock market reaction to its grant news as defined in Kogan et al. (2017).
<i>Scientist/engineer characteristics</i>	
Minority	An indicator variable that equals one if an inventor is not a white male, and zero otherwise.
Employee age	Age of the person.
Annual working hours	Number of working weeks in a calendar year times usual working hours per week.
Hourly wage	Annual wage divided by annual working hours, adjusted to 1999 dollars.
College education	An indicator variable that equals one if the person has completed a college education, and zero otherwise.
Postgraduate	An indicator variable that equals one if the person has a postgraduate degree, and zero otherwise.