Does Trade Secret Protection Spur Human Capital Investment?

Evidence from the Inevitable Disclosure Doctrine

Abstract

This study investigates the effect of trade secret protection on corporate investment in human capital. By leveraging the staggered adoption of the Inevitable Disclosure Doctrine (IDD) by U.S. states as an exogenous shock that significantly reduces talent mobility, we find that IDD adoption results in firms overinvesting in human capital, suggesting that firms strategically engage in precautionary human capital hoarding in response to the reduced talent supply in the labor market and increased labor adjustment costs. Our cross-sectional analyses show that the effect of IDD adoption on human capital investment is more pronounced for (1) firms in high-skill industries and (2) firms facing higher levels of product market competition. Finally, further analyses reveal that, in the context of a limited talent supply under IDD restrictions, high-skill firms with human capital reserves enjoy superior performance to those without such reserves. Overall, our study reveals an unintended consequence of growing trade secret protection in shifting the focus of firms' human capital investment from "head-hunting" talent from rivals to "internal cultivation" of existing human capital within firms and has implications for both managers and policymakers amid the increasingly knowledge-intensive economic environment.

Keywords: Human Capital Investment; Labor Investment; Talent Mobility; Trade Secret Protection; Inevitable Disclosure Doctrine

JEL Classification: D22; G30; J62; K3

"Stiff competition for professionals with in-demand skills isn't likely to ease. So, it's likely you'll need to invest more in growing at least some talent in-house."

- Forbes, June 9th, 2021

1. INTRODUCTION

As technology continues to reshape today's business environment and the overall knowledge economy, a firm's ability to innovate and protect its trade secrets to retain its competitive advantage has become vital. Given that competitive advantage often rests on the skills and expertise of employees, a firm's human capital can be its primary source of competitive advantage (Barney, 1991; Campbell et al., 2012b; Castanias and Helfat, 1991; Hall, 1993; Kor and Leblebici, 2005; Raffiee, 2017). However, unlike tangible assets, employees may leave their employers and join rivals (Castanias and Helfat, 2001; Coff, 1997; Ganco et al., 2015; Kacperczyk, 2012; Singh and Agrawal, 2011). The departing employees with knowledge of a firm's trade secrets pose a high risk of leaking the firm's proprietary information, and the divulgence of trade secrets may cause a substantial economic loss (Agarwal et al., 2009; Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Starr et al., 2019). According to a survey sponsored by the U.S. Chamber of Commerce (ASIS International, 2002), firms experience proprietary information and intellectual property losses of $53 to $59 billion owing to the leakage of their trade secrets. In fact, prior studies suggest that a primary channel through which firms' proprietary information and trade secrets are leaked to competitors is the departing employees (Almeida and Kogut, 1999; Breschi and Lissoni, 2001; Jaffe et al., 1993; Matusik, 2018).[1] Against this backdrop, extant studies investigate the importance of trade secret protection (Almeling, 2012; Almeling et al., 2010) and the role of mobility barriers in the labor market (Aobdia, 2018; Campbell et al., 2012a; Cici et al., 2022, 2021; Garmaise, 2011; Leung et al., 2018; Marx, 2011; Marx et al., 2015, 2009; Younge et al., 2015; Younge and Marx, 2016). In the absence of trade secret protection, firms may be reluctant to invest in the training and development of employees and generate firm-specific knowledge if

[1] According to a large survey study by Ponemon Institute (2009), 59% of departing employees took proprietary information from their original employers, and 60% of all respondents indicated that a newly hired employee had offered to use the information they had obtained while working for a competitor.

they anticipate that their trade secrets and proprietary information will be easily leaked to rivals through employee movement (Qiu and Wang, 2018).

Despite the importance of trade secret protection, it is unclear how the growing protection of trade secrets affects corporate decisions regarding human capital investment. On the one hand, the adoption of the Inevitable Disclosure Doctrine (IDD) may create incentives for firms to engage in human capital hoarding by adjusting both hiring and firing strategies. First, IDD adoption considerably restricts talent mobility by enabling firms to prevent employees from joining competitors, thus reducing the external supply of qualified talent in the labor market. Consequently, knowing that hiring suitable talent can become increasingly difficult and costly in the future, firms are expected to proactively hire qualified but less experienced candidates (e.g., university graduates) as they become available in the job market to gain competitive advantages over their rivals. Second, stronger knowledge protection after IDD adoption also provides firms with more incentives to invest in training and development and internally cultivate their existing human capital with a long-term orientation, as firms are less concerned about the potential leakage of proprietary knowledge due to employee departures and competitors' poaching practices. Therefore, we predict that firms located in IDD-adopting states are likely to hire more employees than necessary for the long-term strategic planning of human capital in response to the decrease in talent supply caused by IDD adoption, thus resulting in larger human capital reserves. Furthermore, IDD adoption may affect firms' firing decisions. In response to the reduced talent supply in the context of IDD adoption, firms may also be more reluctant to fire existing employees with proprietary knowledge, even when they have more employees than needed, thus leading to under-firing. This is because if a firm fires an employee with proprietary knowledge today, it would be extremely difficult for the firm to rehire the employee in the future if the departing employee joins a new employer.

On the other hand, despite the above arguments for human capital hoarding behaviors, it is also plausible that the reduction in the external talent pool caused by IDD adoption could lead to an overall under-investment in human capital, as firms may face difficulties sourcing and recruiting sufficient talent to meet their operational and strategic needs. Hence, although knowledge protection is expected to fundamentally reshape firms' hiring and firing strategies, whether and how legal protection of trade secrets would affect human capital investment is ultimately an empirical question worth investigating.

To answer this important research question and as our identification strategy, in this study, we exploit the staggered adoption of the IDD by the U.S. state courts as a natural experiment and empirically investigate whether exogenous changes in the level of legal protection of trade secrets influence a firm's human capital investment strategy. Previous literature suggests that a primary knowledge spillover channel through which a firm's proprietary information is leaked to competitors is the departing employees with valuable proprietary information (Almeida and Kogut, 1999; Breschi and Lissoni, 2001; Jaffe et al., 1993; Matusik, 2018). The IDD is specifically designed and implemented to prevent employees with proprietary information from working for rival firms in the future on the legal grounds that they would inevitably disclose their current employers' proprietary knowledge or trade secrets to the new employers. Therefore, the IDD reduces the threat of knowledge spillover by restraining interfirm mobility of employees who have access to a firm's proprietary information and thus prevents firm-specific trade secrets from being leaked to the rivals. By investigating IDD adoption by state courts as our research design, we are able to draw a strong causal inference for the impact of the stronger legal protection of trade secrets on firms' human capital investment strategy.

Using a sample consisting of an unbalanced panel of 79,571 firm-year observations from more than 8,000 U.S. firms and a difference-in-differences (DiD) method, we find that IDD adoption by state courts, on average, results in a greater deviation from the employment levels predicted by fundamental economics for firms headquartered in adopting states. In contrast, the rejection of the previously adopted IDD brings firms' employment level closer to the employment level predicted by their fundamental economics. Specifically, we find that the influence of IDD adoption on human capital investment is primarily driven by over-investment in human capital,[2] indicating that firms strategically build precautionary human capital reserves in response to the reduced talent supply due to the enhanced trade secret protection law.

Building on our main findings, we further examine the cross-sectional variation in the effect of IDD adoption on human capital investment by considering firms' reliance on high-skilled labor and the intensity of product market competition. As high-skill firms typically face higher labor adjustment costs and therefore

[2] Over-investment in labor occurs when a firm hires more employees than it should according to underlying economic fundamentals (over-hiring) and/or a firm fires fewer employees than it should according to its underlying economic fundamentals (under-firing). In contrast, under-investment in labor occurs when a firm hires fewer employees than it should according to underlying economic fundamentals (under-hiring) and/or a firm fires more employees than it should according to its underlying economic fundamentals (over-firing).

have stronger ex-ante incentives to establish precautionary human capital reserves when employee mobility declines due to enhanced trade secret protection, we predict that the influence of IDD adoption on human capital investment will be more pronounced in industries with a greater dependence on high-skilled employees. Similarly, as human capital is a crucial source of competitive advantage and hence highly valuable for firms facing intense product market competition, we expect the effect of IDD to be stronger for firms operating in more competitive industries, where human capital is more valuable and competition for talent is more intense. Consistent with these predictions, our empirical results show that the positive effect of IDD adoption on human capital investment is significantly more pronounced for firms in high-skill industries and for firms facing higher product market competition. These findings reinforce the view that human capital is a key strategic asset, particularly for firms operating in skill-intensive sectors and competitive environments, leading them to respond strongly to trade secret protection by adjusting their human capital investment strategies. Finally, we also test whether building human capital reserves in response to IDD adoption can translate into tangible benefits for firms and document robust evidence suggesting that high-skill firms with substantial human capital reserves outperform those without human capital reserves located in the same state during the same year with similar firm characteristics.

Our study contributes to the literature on multiple fronts. First, our study contributes to the burgeoning literature on corporate labor investment decisions by providing evidence that trade secret protection has an "unintended" consequence on corporate investment in human capital as a key factor of production. Unlike traditional studies that primarily focus on firm characteristics or capital market conditions, our research provides evidence of how external legal frameworks can reshape firms' labor investment strategies. Specifically, our findings suggest that enhancing trade secret protection motivates firms to build up precautionary human capital reserves and focus on internal cultivation through training and development.

Second, our study also contributes to the emerging body of literature on the impact of enhanced legal protection of trade secrets and intellectual property on corporate outcomes and decisions (Ali et al., 2019; Callen et al., 2020; Chen et al., 2021; Çolak and Korkeamäki, 2021; Flammer and Kacperczyk, 2019; Gao et al., 2018; Glaeser, 2018; Klasa et al., 2018; Li et al., 2018; Li et al., 2021). Complementing Chen et al. (2021) and Qiu and Wang (2018), who show an increase in corporate acquisitions to acquire external talent and greater investment in knowledge assets after IDD adoption, we present novel evidence that firms strategically establish precautionary human capital reserves and shift their focus to the internal cultivation of human capital through training and development in response to increased trade secret protection and, consequently, reduced talent mobility following IDD adoption.

Finally, our study also offers important implications for both managers and policymakers. Given the increasingly vital role of human capital in today's economy (Zingales, 2000), in the context of stiff talent competition, managers should consider shifting their emphasis from constantly involving themselves in "talent wars" to the upskilling and cultivation of their existing human capital internally. Meanwhile, given the concern of curbing the effect of stringent trade secret protection legislation on talent mobility and innovation (Contigiani et al., 2018), our study offers timely evidence and assurance to policymakers by showing an unintended benefit of such legislation in promoting the internal cultivation of the existing labor force and young talent. To facilitate the internal cultivation of human capital in light of the growing protection of intellectual property, policymakers should also introduce more financial incentives and fiscal support dedicated to helping businesses retrain and upskill their labor force to maintain competitiveness in today's knowledge-intensive economy.

The remainder of this paper is organized as follows. Section 2 describes the IDD legal setting and reviews the related literature, followed by the development of our hypothesis. Section 3 describes our data and empirical strategies. Section 4 presents our main empirical results. Section 5 summarizes the findings and discusses the contributions of our study.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Knowledge protection and impact of the IDD

The IDD is a concept of common law adopted by state courts to strengthen the legal protection of trade secrets for firms located in the state. The legal doctrine adopted by state courts effectively prevents a firm's departing employees from working for its rival firms where the departing employees will inevitably use or disclose knowledge of such trade secrets under the new employment relations framework. With IDD adoption by a state court, firms located in the IDD-adopting state can obtain an injunction to prohibit employees from working for competitors if the current firm believes its trade secrets are at risk of divulgence. In contrast, the rejection of the previously adopted IDD effectively removes the constraint originally imposed on the mobility of employees with proprietary information, allowing employees to join rival firms and thus making a firm's proprietary knowledge and trade secrets more vulnerable.

A growing body of research has investigated the implications of IDD adoption for corporate policies, and several recent studies show that firms make strategic decisions in response to the enhanced protection of trade secrets (Ali et al., 2019; Callen et al., 2020; Chen et al., 2021; Çolak and Korkeamäki, 2021; Flammer and Kacperczyk, 2019; Gao et al., 2018; Glaeser, 2018; Klasa et al., 2018; Li et al., 2018). For instance, Flammer and Kacperczyk (2019) show that firms strategically increase their engagement in corporate social responsibility (CSR) to counter the risk of trade secret leakage following IDD rejection. Klasa et al. (2018) suggest that the risk of leaking trade secrets to competitors is a serious competitive threat and that the stronger legal protection of trade secrets afforded by IDD adoption in a firm's home state can reduce this risk. Specifically, their study documents that firms strategically choose a more conservative capital structure when they face greater trade secret spillover threats and increase their financial leverage after IDD adoption relative to unaffected rivals. Moreover, Li et al. (2018) suggest that IDD adoption represents an exogenous shock that increases the marginal costs of proprietary information disclosure and the marginal benefits of nondisclosure. They show that IDD adoption makes a firm's competitors less likely to access the firm's trade secrets through employee movements, and the rival firms therefore rely more on the firm's public disclosures to discover its proprietary information. Consequently, IDD adoption increases the marginal cost of disclosure for the firm because its public disclosure becomes more valuable to its competitors, and therefore, firms located in IDD-adopting states reduce the level of proprietary information disclosure. Furthermore, Glaeser (2018) suggests that the total effect of trade secrecy leads to a decrease in corporate disclosure. The findings of Glaeser (2018) and Li, Lin, and Zhang (2018) are consistent with those of Aobdia (2018), who finds a negative association between a state's enforcement of non-compete agreements and the disclosure activities of firms headquartered in that state because stricter enforcement of non-compete agreements makes firms less informed about competition due to reduced knowledge spillover from employee job shifting. Apart from the literature above, Chen et al. (2018) find that firms in IDD-adopting states are more likely to be acquired because acquiring firms strategically use acquisition as an alternative approach to gain human capital. Gao et al. (2018) find a significant decrease in income-increasing earnings management for firms headquartered in IDD-adopting states that adopt the IDD relative to firms headquartered elsewhere, suggesting that IDD adoption also has important implications for firms' financial reporting behavior. In terms of the impact of IDD adoption on the capital market, Qiu and Wang (2018) find positive abnormal stock returns around the IDD adoption day for firms headquartered in the state and identify a positive causal effect of IDD adoption on these firms' investment in knowledge assets.

2.2 Human capital investment decisions

Investment in human capital remains one of the most crucial and substantial investment decisions for firms, as it represents a significant allocation of resources toward an organization's future growth, productivity, and innovation. Although research has extensively addressed capital investment, the focus on labor investment, a critical factor of production, has been relatively limited (Falato & Liang, 2016; Pinnuck & Lillis, 2007). Efficient labor investment, which optimally balances workforce levels without overextending or underutilizing resources, is increasingly recognized as essential for firm productivity and competitive advantage (Ben-Nasr & Alshwer, 2016; Ha & Feng, 2018). Suboptimal labor investment can be costly: over-investment strains resources and incurs unnecessary costs, whereas under-investment limits growth potential and curtails productivity (Ghaly et al., 2020; Jung et al., 2014). In today's knowledge-based economy with increased reliance on human capital, achieving labor investment efficiency has become a strategic priority for businesses (Zingales, 2000).

Recognizing the economic significance of labor investment efficiency, a growing line of literature explores the factors influencing the efficiency of investment in this crucial factor of production and intangible assets of firms. High adjustment costs related to recruitment, training, and retention, combined with the constraints of labor market frictions, affect how efficiently firms can align labor investments with changing operational needs (Danthine & Donaldson, 2002; Diamond, 1982; Farmer, 1985; Hamermesh & Pfann, 1996; Mortensen & Pissarides, 1994; Pissarides, 2011; Yashiv, 2007). Capital market imperfections, arising from information asymmetries, can affect labor investment decisions, as firms may require external financing to support investments in human capital. Studies show that financing constraints and high capital costs can disrupt labor investment, ultimately leading to suboptimal employment decisions (Benmelech et al., 2019; Michaels et al., 2019).

High-quality financial reporting and stock price informativeness are shown to mitigate inefficiencies, as they allow firms to better signal their financial health, thus improving access to capital and supporting labor investment (Ben-Nasr & Alshwer, 2016; Jung et al., 2014). Additionally, internal governance and external monitoring influence labor investment efficiency (Ee et al., 2020; Ghaly et al., 2020; Khedmati et al., 2020). For example, institutional investors with longer investment horizons and stock liquidity are associated with more efficient labor investment decisions due to stronger monitoring and the threat of shareholder exit (Ee et al., 2020; Ghaly et al., 2020). Sualihu et al. (2021) show that executive equity compensation, such as restricted stock, can incentivize managers to improve the efficiency of investment in human capital. However, strong CEO–board ties may diminish labor investment efficiency due to reduced oversight, leading to empire-building behaviors that deviate from optimal labor investment decisions (Khedmati et al., 2020). Moreover, Cao and Rees (2020) show that firms with better employee treatment exhibit significantly higher labor investment efficiency due to lower exposure to labor market friction and lower labor adjustment costs.

Despite the above evidence, it remains unclear how trade secret protection legislation, an increasingly relevant factor in today's knowledge-driven economy, might reshape firms' labor investment decisions. Existing studies have yet to explore how firms adapt labor investment strategies in response to such legal changes, which is likely to have substantial implications for human capital investments, especially for innovation-driven and human capital-intensive firms. Addressing this gap could provide timely insights into human capital investment strategies in the context of heightened protection of intellectual properties and trade secrets in today's knowledge-intensive economy.

2.3 Precautionary human capital reserves hypothesis

The exogenous increase in trade secret protection caused by IDD adoption can affect firms' decisions regarding human capital investment. Prior studies show that one primary knowledge spillover channel through which a firm's trade secrets are leaked to its rivals is the departing employees who will inevitably use or disclose knowledge of the trade secrets to their new employers (Almeida and Kogut, 1999; Breschi and Lissoni, 2001; Jaffe et al., 1993; Matusik and Hill, 1998). Recent research also shows that IDD adoption can significantly decrease employee mobility. For instance, Png and Samila (2015) investigate the job-hopping behaviors of engineers and scientists and find that IDD adoption makes it difficult for competitors to poach these employees. Furthermore, Chen et al. (2018) show that firms headquartered in states with IDD adoption are more likely to be acquired in comparison with firms headquartered in states where the IDD is rejected. Their study suggests that gaining human capital is an important motivation for corporate acquisition, which can be an alternative to normal recruiting practices, indicating that firms strategically adjust their human capital investment in response to trade secret protection legislation. In a similar vein, we argue that an important channel through which IDD adoption can affect human capital investment decisions is that firms subject to IDD restrictions have a greater ex-ante incentive to establish a precautionary human capital reserve in response to decreased talent mobility following the passage of trade secret protection legislation.

While research in economics and finance has emphasized the inefficiency and costliness of holding resource slack (e.g., Biddle et al., 2009; Jensen and Meckling, 1976; Richardson, 2006), the potential benefits and costs of slack have been theorized and empirically examined by previous studies (Bourgeois III, 1981; Cyert and March, 1963, 1956; Love and Nohria, 2005; Singh, 1986; Tan and Peng, 2003; Wiseman and Bromiley, 1996). Specifically, studies (Lecuona and Reitzig, 2014; Mishina et al., 2004; Voss et al., 2008) show that human capital differs from other corporate resources in that employees hold proprietary knowledge that is intangible and context-dependent. We argue that IDD adoption can influence firms' hiring and firing practices in two ways. First, IDD adoption makes it difficult for firms to poach desirable talent from their competitors due to the significant reduction in talent supply in the labor market. A firm located in an IDD-adopting state can obtain an injunction to prohibit its employees from working for its rivals, which reduces the number of qualified candidates in the external labor market who could otherwise have been hired by the competing firms in the absence of IDD adoption. Therefore, by restricting job switches and labor mobility, IDD adoption effectively reduces the supply of qualified talent. As a result, knowing that hiring suitable talent can become increasingly difficult and costly in the future, firms are expected to proactively hire qualified but less experienced candidates (e.g., university graduates) as they become available in the job market to gain competitive advantages over their rivals for the long-term strategic management of human capital. More importantly, enhanced trade secret protection affects not only recruitment practices but also firms' engagement in cultivating existing human capital. On the one hand, hiring less experienced talent (e.g., university graduates) requires firms to invest more in these nascent recruits to help them adapt their knowledge and skills to meet their job requirements and create value. On the other hand, better knowledge protection provides firms with more incentives to invest in training and development and to internally cultivate their existing human capital assets instead of poaching competitors' employees.[3] As IDD ensures that proprietary knowledge will not be easily leaked to competitors through employees' job switching, firms headquartered in IDD-adopting states are more willing to invest in employee training and development. Hence, IDD adoption increases the marginal benefit of human capital investment through training and development. As a result, firms strategically over-hire qualified but less experienced employees (e.g., university graduates) who are competent but not subject to IDD restrictions, so as to internally cultivate their human capital for the future (e.g., through graduate management trainee programs and future leader graduate programs).[4] Therefore, we predict that firms located in IDD-adopting states are likely to hire more employees than needed for the long-term strategic planning of human capital in response to the decrease in talent supply generated by IDD adoption, thus resulting in larger human capital reserves.

In addition, firms may be reluctant to fire current employees with proprietary knowledge even if it results in having more employees than necessary for routine operations (i.e., under-firing). There are two potential reasons why a firm may under-fire in the context of IDD adoption. First, from a practical standpoint, if a firm fires an employee with proprietary knowledge today, it would be extremely difficult for the firm to rehire that employee in the future if the departing employee joins a new employer. Second, given that the IDD considerably limits proprietary information spillover, the proprietary costs of losing talent are expected to be significantly higher when a firm fires an employee with valuable trade secrets (Li et al., 2018). Thus, we predict that firms are likely to under-fire existing employees following IDD adoption for fear of losing valuable proprietary information to their competitors. Despite the overwhelming arguments for human capital hoarding in response to IDD adoption, it is also possible that IDD implementation could result in under-investment in human capital due to the reduced talent supply in the labor market.

[3] According to a report by the Association for Talent Development (ATD), U.S. firms spent $164.2 billion on employee learning and development in 2012, with 61% of those expenditures allocated to internal expenses ($100.2 billion).
[4] Almost all multinational companies in the US have "graduation schemes" or "future leadership programs" dedicated to attracting and investing in highly skilled young talent as an important source of their human capital reserves.

Taken together, we argue that firms strategically invest in human capital through over-hiring and under-firing labor to build precautionary human capital reserves in response to the decreased employee mobility exogenously caused by IDD adoption. Hence, we propose our main hypothesis:

Hypothesis: IDD adoption leads to higher human capital reserves for firms headquartered in IDD-adopting states.

3. DATA AND METHODOLOGY

3.1 Measure of human capital investment

To capture a firm's investment in human capital, we follow previous studies to measure human capital reserves based on a predicted value approach and use the firm's net hiring, as measured by the change in the number of employees (Ben-Nasr and Alshwer, 2016; Jung et al., 2014; Khedmati et al., 2020; Pinnuck and Lillis, 2007; Shen et al., 2014; Wang et al., 2016). We estimate abnormal net hiring as the absolute value of the difference between the actual level of labor investment and the expected level justified by economic fundamentals. We define positive abnormal net hiring as the proxy for over-investment in human capital and negative abnormal net hiring as the proxy for under-investment in human capital. Our primary estimate of expected net hiring is based on the model employed by previous studies (Ben-Nasr and Alshwer, 2016; Jung et al., 2014; Khedmati et al., 2020; Pinnuck and Lillis, 2007), which is a regression of the percentage change in the number of employees on several explanatory variables capturing underlying economic fundamentals[5]: The descriptive statistics and results generated from Model 1 are reported in Appendix 2.

$$NET\_HIRE_{it} = \beta_0 + \beta_1 SALEGROWTH_{it-1} + \beta_2 SALEGROWTH_{it} + \beta_3 \Delta ROA_{it} + \beta_4 \Delta ROA_{it-1} + \beta_5 ROA_{it} + \beta_6 4RETURN_{it} + \beta_7 SIZE\_P_{it-1} + \beta_8 LIQ_{it-1} + \beta_9 \Delta LIQ_{it-1} + \beta_{10} \Delta LIQ_{it} + \beta_{11} LEV_{it-1} + \beta_{12} LOSSBIN1_{it-1} + \beta_{13} LOSSBIN2_{it-1} + \beta_{14} LOSSBIN3_{it-1} + \beta_{15} LOSSBIN4_{it-1} + \beta_{16} LOSSBIN5_{it-1} + \text{Industry Fixed Effects} + \varepsilon_{it} \quad (1)$$

[5] In the robustness section, we also report our empirical results using five alternative measures of abnormal net hiring used in the previous literature (Table 14).

3.2 Baseline models

To examine the influence of the IDD on firms' human capital strategies, we follow Klasa et al. (2018) to identify IDD adoption. Their IDD adoption identification strategy is based on a number of IDD cases collected from previous legal studies (Kahnke et al., 2008; Waldref, 2012) and lists all of the precedent-setting cases from 1919 to 2011. Appendix 3 summarizes the IDD adoption cases. In line with prior IDD studies (Callen et al., 2020; Chen et al., 2021; Çolak and Korkeamäki, 2021; Gao et al., 2018; Glaeser, 2018; Klasa et al., 2018; Li et al., 2018), the underlying assumption of the identification strategy is that firms notice the precedent-setting cases in the state where they are headquartered. Our primary analyses of the impact of IDD adoption on human capital investment are based on the following model:

$$AB\_NETHIRE_{it} = \beta_0 + \beta_1 IDD_{s,t} + \beta_2 MTB_{it-1} + \beta_3 SIZE_{it-1} + \beta_4 LIQ_{it-1} + \beta_5 LEV_{it-1} + \beta_6 DIVD_{it-1} + \beta_7 TANGIBLES_{it-1} + \beta_8 LOSS_{it-1} + \beta_9 LABINT_{it-1} + \beta_{10} ABINVEST_{it} + \beta_{11} SD\_CFO_{it-1} + \beta_{12} SD\_SALES_{it-1} + \beta_{13} SD\_NETHIRE_{it-1} + \beta_{14} GDP_{st-1} + \beta_{15} EMPLOYMENT_{st-1} + \beta_{16} POPULATION_{st-1} + \beta_{17} INCOME\_CAPITA_{st-1} + \text{Firm Fixed Effect} + \text{Industry-by-Year Fixed Effect} + \varepsilon_{ist} \quad (2)$$

Following previous literature (Ben-Nasr and Alshwer, 2016; Biddle et al., 2009; Jung et al., 2014), we control for the following variables that are likely to be associated with hiring: growth options (MTB_{it-1}), firm size ($SIZE_{it-1}$), liquidity (LIQ_{it-1}), leverage (LEV_{it-1}), dividend payout ($DIDV_{it-1}$), tangibility ($TANGIBLE_{it-1}$), loss occurrence ($LOSS_{it}$), and labor intensity ($LABINT_{it-1}$). We further control for the volatility of firms' cash flow (SD_CFO_{it-1}), sales (SD_SALES_{it-1}), and net hiring ($SD\_NETHIRE_{it-1}$) over the period from $t-5$ to $t-1$.

Finally, to control for the potential effect stemming from other non-labor investment decisions on abnormal net hiring, we include AB_INVEST_{it}, which measures the magnitude of non-labor investments deviating from their expected level. As in Biddle et al. (2009), we use the absolute value of the residual from the regression of non-labor investment ($INVEST_{it}$) on sales growth ($SALESGROWTH_{it-1}$), where $INVEST_{it}$ is the sum of capital expenditures, acquisition expenditures, and research and development (R&D) expenditures, minus the cash receipts from the sale of property, plant, and equipment, scaled by lagged total assets. We also control for several state-level factors, including state-level GDP (GDP_{st-1}), state-level employment number ($EMPLOYMENT_{st-1}$), state-level population number ($POPULATION_{st-1}$), and state-level income per capita ($INCOME\_CAPITA_{st-1}$). In addition, we include firm fixed effects and industry-by-year fixed effects to control for time-invariant unobservable firm characteristics and time-specific and industry-specific changes in economic conditions. Given that the IDD treatment is defined at the state level, we cluster standard errors at the state level (Imbens and Wooldridge, 2009; Petersen, 2009). For robustness, we also cluster standard errors at both the state and year levels to address potential serial correlations within state and year groups, as suggested by Petersen (2009).

The coefficient β_1 captures the average changes in human capital investment of firms headquartered in IDD-adopting states relative to the contemporaneous changes in human capital investment of firms headquartered in states that are not affected by IDD adoption. Given that the time of the treatment (i.e., IDD adoption) is different across states, a given adopting state can be both a treatment state and a control state at different times. Prior studies investigating the influence of IDD adoption also use the same approach to draw causal inferences (Callen et al., 2020; Chen et al., 2021; Çolak and Korkeamäki, 2021; Flammer and Kacperczyk, 2019; Gao et al., 2018; Klasa et al., 2018; Li et al., 2018; Qiu and Wang, 2018).

3.3 Sample

We start with all of the U.S. public firms in the COMPUSTAT database. We exclude firms with negative sales and assets and missing historical SIC codes. We merge our data with CRSP to obtain total annual stock returns and exclude firm-year observations associated with firms in financial services (primary two-digit SIC codes between 60 and 69). To identify IDD adoption, we follow Klasa et al. (2018) who present 21 precedent-setting cases in which state courts adopt the IDD and 3 cases in which state courts initially adopt the IDD but later reject it. Our final sample for the estimation of our baseline regression includes all firms that meet the following criteria: the firm is publicly traded and has non-missing financial data available from COMPUSTAT and security price and return information from CRSP to estimate human capital investment using Model 1 and the baseline regression. After imposing all of the above data requirements, we obtain a final sample consisting of 79,571 firm-year observations from approximately 8,500 U.S. firms. Table 1 reports the descriptive statistics for the main variables in our final sample. Specifically, the mean value of IDD adoption is 0.496, meaning that 49.6% of our sample observations are in IDD-adopting states, which is highly comparable to the values reported in prior studies on the IDD (Chen et al., 2021; Gao et al., 2018; Glaeser, 2018; Li et al., 2018). We provide a table of variable definitions in Appendix 1.

[Insert Table 1 about here]

4. EMPIRICAL RESULTS

4.1 The impact of IDD on human capital investment

4.1.1 IDD adoption

Table 2 presents our main results. To ensure that our results are not driven by particular specifications, we repeat our analyses using various specifications in the prior IDD literature (e.g., Chen et al., 2021; Glaeser, 2018; Klasa et al., 2018; Li et al., 2018; Qiu and Wang, 2018). In column 1, following Li et al. (2018), we include firm and year fixed effects, as well as state fixed effects to capture time-invariant differences across states such as different economic conditions and legal environments. In column 2, to control for time-varying industry heterogeneity, we follow Klasa et al. (2018) and include industry-by-year fixed effects along with firm fixed effects. By applying various specifications in the prior IDD literature (Chen et al., 2021; Flammer and Kacperczyk, 2019; Gao et al., 2018; Klasa et al., 2018; Li et al., 2018; Qiu and Wang, 2018), we find the coefficient on IDD is consistently positive and statistically significant across all models, suggesting that IDD adoption leads to a higher deviation from the optimal employment level predicted by the underlying economic fundamentals.[6]

[Insert Table 2 about here]

4.1.2 IDD rejection

So far, our results show that IDD adoption increases abnormal net hiring. To ensure that our results are not spurious, as a robustness test, we also exploit the exogenous increase in talent mobility due to IDD rejection in three states that previously adopted the IDD, namely Florida, Michigan, and Texas, as shown

[6] To address the serial correlation within the state, we cluster standard errors at the state level, as our key variable of interest—the IDD—is at the state level in all specifications (Bertrand et al., 2004; Gao et al., 2018; Klasa et al., 2018; Li et al., 2018). In our untabulated robustness test, we cluster standard errors at both the state and year levels to address potential serial correlations within state and year groups, as suggested by Petersen (2009), and our results remain unchanged.

in Appendix 3. These three IDD rejection cases are essentially court overrulings whereby IDD legislation that had been previously adopted in Florida, Michigan, and Texas was overturned. In other words, these IDD rejection cases are highly unexpected and arguably most exogenous, thus offering an ideal and alternative setting to study the impact of trade secret protection on human capital investment decisions. If IDD adoption indeed leads to higher abnormal net hiring, as our main results in Table 2 suggest, then we expect IDD rejection to have an opposite effect, i.e., a decrease in abnormal net hiring.

To test the effect of IDD rejection, we focus on the post-adoption observations. We then construct a dummy variable *IDD_REJECT*, which equals one if a firm-year observation is after the firm's headquarter state rejects the previously-adopted IDD and zero otherwise. Essentially, to gauge the treatment effect of IDD rejection, we compare the firms headquartered in IDD-rejecting states (i.e., the treated group) and those headquartered in other IDD-adopting states (i.e., the control group). Thus, the indicator *IDD_REJECT* captures the DiD treatment effect of IDD rejection on human capital investment decisions.

We report the results for IDD rejection in Table 3. In line with our prediction, the *IDD_REJECT* coefficients indicate that IDD rejection in a state that had previously adopted the IDD leads to a statistically significant reduction in abnormal net hiring. More importantly, the opposite effect of IDD rejection lends additional support to our main results in Table 2 and suggests a plausibly causal effect of the IDD on firms' human capital investment.

By examining the causal effects of both IDD adoption and IDD rejection using a DiD approach, we find consistent evidence that IDD adoption increases abnormal net hiring, whereas IDD rejection reduces abnormal net hiring, which supports our conjecture that trade secret protection affects human capital investment decisions.

[Insert Table 3 about here]

4.2 Potential channels: Under-investment vs over-investment

The deviation from the optimal employment level predicted by economic fundamentals can stem from either under-investment or over-investment in human capital. Intuitively, under-investment in the labor force occurs when the employment level of a firm is lower than the optimal level or the level required to fulfill its business demand, as predicted by its underlying economic fundamentals. Conversely, if the employment level of a firm is higher than the optimal level predicted by its economic fundamentals, the firm is considered to hold human capital reserves. We thus further investigate the channel through which IDD adoption drives abnormal net hiring in labor investment decisions by creating two subsamples based on the sign of *AB_NETHIRE*, the under-investment group (negative *AB_NETHIRE*) and the over-investment group (positive *AB_NETHIRE*), which represents human capital reserves.

We report the results in Panel A of Table 4 with the under-investment group in columns 1–2 and the over-investment group in columns 3–4. In contrast to the insignificant results for the under-investment group, we find that IDD adoption leads to a significant increase in human capital reserves as shown in the over-investment group, suggesting that firms strategically hoard human capital in response to reduced employee mobility following IDD adoption, supporting our precautionary human capital reserves hypothesis. Economically, the magnitude of our coefficient suggests that IDD adoption is associated with a 10.3% increase in firms' precautionary human capital reserves, which is economically meaningful.

Following Panel A of Table 4, we further study the timing of changes in human capital investment relative to the timing of IDD adoption to ensure that firms' strategic human capital hoarding does not happen prior to IDD adoption. Given that we do not find significant results for the under-investment group, we expect that the dynamic timing tests for the under-investment group will also not produce significant results. In contrast, we expect to find significant results for the over-investment group only after IDD adoption in affected states to ensure no pretreatment trend of strategic human capital accumulation before IDD adoption. In Panel B of Table 4, we present the estimation results of the dynamic timing tests. In line with our expectations, we find no significant results for the under-investment group. For the over-investment group, the coefficients on IDD_{-2} and IDD_{-1} are insignificant, indicating that there is no pretreatment trend of firms engaging in strategic human capital accumulation before IDD adoption. In contrast, the coefficients on IDD_{2+} are positive and statistically significant, suggesting that IDD adoption has a profound impact on human capital hoarding from two years after IDD enactment. Hence, the results in Panel B of Table 4 show that human capital reserves appear only after IDD adoption and not before, indicating that the observed relationship is not driven by reverse causality and that the parallel trend assumption is not violated.

[Insert Table 4 about here]

In Table 5, we further conduct tests to decompose firms' over-investment in human capital. Specifically, firms can build human capital reserves in two ways: (1) over-hiring, where firms hire more employees than they need when they are expected to expand, given their economic fundamentals; (2) under-firing, where firms fire fewer employees than they should when they are expected to downsize, given their economic fundamentals. To distinguish the two channels, in Table 5, we further decompose the over-investment group into the over-hiring (columns 1–2) and under-firing (columns 3–4) subgroups based on the sign of the expected value of net hiring.

The results of subsample analysis show that IDD adoption leads to both over-hiring and under-firing. On the one hand, our results suggest that firms subject to IDD legislation strategically retain their surplus human capital even if this results in a deviation from the optimal employment level predicted by their economic fundamentals. On the other hand, it is worth noting that the positive effect on over-hiring following IDD adoption implies that firms proactively hire and invest in candidates who lack knowledge of trade secrets, such as university graduates, who are qualified but not subject to IDD restrictions. The underlying rationale for such a recruitment strategy is twofold. First, following IDD adoption, highly qualified candidates working for competitors are typically not accessible due to their knowledge of the proprietary information of their current employers. Second and perhaps more importantly, knowing that their employees will not be able to join their competitors and potentially leak trade secrets, firms in IDD-adopting states have more incentives to cultivate human capital internally by investing in young talent through training and development programs (Qiu and Wang, 2018).

[Insert Table 5 about here]

To substantiate this conjecture, we conduct further analysis to test the change in training and development following IDD adoption. Specifically, to proxy for the level of investment in training and development, we use the "Training & Development" scores from Refinitiv ESG (formerly the Thomson

Reuters ASSET4 ESG database).[7] To capture the change in the level of investment in training and development following IDD adoption, we calculate the change in "Training & Development" within the small window of (0,1) as our outcome variable. To allow for additional time for firms to react to IDD and adjust their investment in training and development, we also use alternative windows (including 2 and 3 years) to capture the post-IDD change in training and development. Table 6 reports our results. In columns 1–2, the IDD dummy is consistently positive and statistically significant after controlling for various fixed effects and cluster standard errors at both the state and year levels, suggesting that the change within one year following IDD adoption is higher among firms in IDD-adopting states than among those in non-IDD-adopting states. Our results hold when we relax the window to 2 and 3 years in columns 3–6.

[Insert Table 6 about here]

Taken together, we find that the increase in abnormal net hiring following IDD adoption is mainly driven by firms' strategic human capital accumulation through both over-hiring and under-firing. We interpret such results as firms proactively engaging in strategic precautionary human capital reserves in response to IDD adoption, which severely restricts the mobility of employees and makes it harder for firms to hire talent from competitors. By hoarding human capital, firms can gain a competitive advantage in the competition for talent, securing sustainable human capital reserves to succeed in the long run.

4.3 Cross-sectional analysis

4.3.1 High-skilled labor

In this section, we explore potential cross-sectional variations in the impact of IDD adoption on human capital investment decisions. Given that the IDD is introduced to protect trade secrets by restricting

[7] Refinitiv ESG (formerly ASSET4 ESG), a widely used database of CSR data, provides scores for the "training and development" dimension (SOTD) based on percentile ranks for each fiscal year. Admittedly, it would be ideal to use actual costs or expenditures in dollars to measure the level of investment in training and development programs for each firm. However, no database reports this type of information as firms are not mandated to disclose training and development expenses. As a result, we rely on the scores in the ASSET4 database as a proxy for the level of investment in training and development. Given that the score is a percentile rank from 1 to 100, it is reasonable to assume that a firm would need to invest more resources than its competitors in order to improve its ranking and, consequently, its score for "training and development" (SOTD).

employee mobility, the effect of IDD adoption should be stronger for firms in high-skill industries for two reasons. First, firms in high-skill industries employ and rely more on high-skilled employees who are more likely to possess or access trade secrets or proprietary information. Therefore, firms operating in high-skill industries are expected to be more affected by IDD legislation. Second, as a consequence of trade secret protection, the mobility of high-skilled employees within the industry is significantly restricted. Thus, firms that are more dependent on high-skilled labor are also more likely to face the issue of shortage of talent supply in the external labor market as the most qualified and suitable talent is barred from joining rival firms. If firms strategically invest in human capital reserves following IDD adoption to establish precautionary human capital reserves, we predict that the effect of IDD adoption will be more pronounced for firms that are more reliant on high-skilled labor.

To proxy for the labor skill level, we construct an industry-specific labor skill index following previous studies (Belo et al., 2017; Ghaly et al., 2017) and use the industry average number of employees working in occupations with a JobZones index of 4 or 5 as a proxy for the degree of reliance on skilled labor. Essentially, the labor skill index captures the weighted average of the occupations within an industry based on data from the Occupational Employment Statistics and O*NET program compiled by the U.S. Department of Labor. For each fiscal year, we construct a dummy variable *High_LaborSkill*, which equals one if the labor skill level in that industry is above the top tercile and zero if the level is below the bottom tercile (Ali et al., 2019; Kim et al., 2021; Li et al.,2021). In addition, for robustness, we use two alternative proxies for skilled labor based on R&D expenditure at the firm level following prior studies (Cao and Rees, 2020; Ghaly et al., 2015).[8]

Table 7 reports our cross-sectional results conditional on the labor skill level. The variable of interest is the interaction term *IDD×High_LaborSkill*, which captures the differential effect of IDD adoption on human capital investment between firms in high-skill industries and those in low-skill industries. In column 1, we include *High_LaborSkill* and *IDD×High_LaborSkill* in the regressions in addition to the same control variables and fixed effect specifications included in our main results. In line with our prediction, the interaction term *IDD×High_LaborSkill* is consistently positive and statistically significant across all specifications, suggesting that the effect of IDD adoption on human capital investment is stronger for firms

[8] We thank the anonymous reviewer for suggesting alternative proxies for labor skills at the firm level.

in high-skill industries where skilled labor is more important. As the labor skill industry is measured at the industry level, to capture intra-industry variation in labor skills at the firm level and ensure that our results are not sensitive to the labor skill measure, we use two alternative measures: 1) RD_SALE, defined as R&D expense scaled by total sales, and *2) RD_AT*, defined as R&D expense scaled by total assets, to proxy for labor skills at the firm level. As presented in columns 2 and 3, we find consistent results when using these two alternative proxies for labor skills.

These cross-sectional results not only provide additional support for our precautionary human capital reserves hypothesis but also imply that our main results are causal, that is, if our main results presented in Table 2 are spurious, we should not find supporting evidence in our cross-sectional analysis.

[Insert Table 7 about here]

4.3.2 Product market competition

As IDD adoption limits the leakage of proprietary information to competitors, this trade secret protection law is arguably more important for firms facing a higher degree of competition and entry threats. Consequently, the restriction effect on talent mobility should be stronger for firms subject to higher market competition than firms in less competitive industries. Thus, we predict that the effect of IDD adoption on human capital investment is likely to be more pronounced for firms facing higher product market threats.

To proxy for market competition, we use a firm-specific measure of product similarity developed by Hoberg and Phillips (2016),[9] which suggests that intuitively higher product similarity reflects higher market competition. Unlike the industry-level proxies based on static industry classifications such as SIC or NAICS codes, the product similarity data are measured at the firm level, providing a more accurate reflection of the market competition faced by each firm based on its product portfolio. Another appealing feature is that the data are dynamic as they are recalculated and updated annually to reflect the change in product market conditions (Aobdia and Cheng, 2018; Hoberg and Phillips, 2016; Mattei and Platikanova, 2017). To condition our results on product market competition, we construct a *High_SIMILARITY* indicator, which equals one if the level of product similarity is above the top tercile and zero if it is below the bottom tercile.

[9] The data are publicly available on the authors' website at http://hobergphillips.usc.edu/industryconcen.htm. Detailed information regarding the construction of the data is also provided on the website.

All of the specifications are the same as in Table 7 and consistent with prior studies (Klasa et al., 2018; Li et al., 2018).

In Table 8, we provide empirical evidence to support our cross-sectional prediction. The interaction term *IDD×High_SIMILARITY*, which is the variable of interest, is positive and statistically significant, suggesting that the impact of IDD adoption on human capital reserves is stronger for firms facing higher levels of product market competition.

For robustness, we also use an alternative proxy, product fluidity,[10] to measure the level of market entry threats and partition our sample (Giroud and Mueller, 2011; Hoberg et al., 2014). Our results show that our results remain significant and qualitatively similar when using this alternative proxy for product market competition.

[Insert Table 8 about here]

4.4 Benefits of human capital reserves in a trade secret protection environment

So far, we have demonstrated that firms engage in human capital hoarding in response to IDD adoption, which significantly curbs talent mobility and undermines firms' ability to attract valuable talent. While building a strong talent pool offers a competitive advantage and a sustainable source of innovation to employers, it is also true that maintaining precautionary human capital reserves creates an additional financial burden for employers and may decrease financial performance. Assuming that firms behave rationally, one would expect firms to invest in human capital reserves only if the benefits of having such a reserve outweigh the costs of employing additional talent. However, it is neither obvious nor guaranteed that firms will eventually benefit from holding precautionary human capital reserves. Therefore, in this section, we directly test whether firms indeed benefit from holding such precautionary human capital reserves in the context of limited talent supply and intensified competition for human capital due to IDD restrictions.

To empirically test the performance implications of human capital reserves in the context of limited talent mobility, we focus exclusively on observations subject to IDD legislation (*IDD* = 1), thus providing

[10] This measure is also developed by Hoberg et al. (2014). The data are accessible on the authors' website http://hobergphillips.usc.edu/idata/Readme_FluidityData.txt, where detailed procedures for constructing this measure are also provided.

a "laboratory" for us to observe and compare performance between firms with precautionary human capital reserves (i.e., over-investment in human capital, *Strategic_Hoarding* = 1) and those without such reserves (*Strategic_Hoarding* = 0) when facing the same IDD restrictions. Given that human capital reserves are valuable and strategically crucial to the long-term success of firms competing in high-skill industries, we also include a dummy variable for high-skill industries (*High_Skill* = 1) and interact it with the indicator for human capital hoarding (*Strategic_Hoarding*). Essentially, the interaction term (*Strategic_Hoarding*×*High_Skill*) enables us to examine whether high-skill firms with precautionary human capital reserves can indeed benefit when talent mobility is limited following IDD adoption. Furthermore, we control for a number of firm characteristics, in addition to firm, year, and state fixed effects, in the regressions. In terms of the dependent variable, in addition to accounting performance measured as return on assets (*ROA*), we use Tobin's Q (*TOBINQ*), which is a forward-looking and market-based performance measure, as the dependent variable (Bharadwaj et al., 1999; Wernerfelt and Montgomery, 1988). Panel A of Table 9 presents the results for both market performance (*TOBINQ*) and accounting performance (*ROA*). As shown in columns 1–2, in line with our expectation, the interaction term of interest, *Strategic_Hoarding*×*High_Skill*, is positively and significantly associated with Tobin's Q, suggesting that, under IDD restrictions, high-skill firms with additional human capital reserves exhibit superior market performance to those without such reserves. Moreover, in columns 3–4, we find that hoarding human capital does not harm the accounting performance of firms that heavily rely on high-skilled employees, despite the additional costs of maintaining excessive human capital.

While in the above analysis we ensure that all firms are subject to the same restrictions imposed by IDD legislation and control for several firm characteristics in addition to firms, year, and state fixed effects, one might still be concerned that there are significant differences in local economic and labor market conditions, which might confound our analysis. For example, firms engaging in human capital hoarding may happen to be concentrated in states with more favorable economic environments, which are likely to be positively correlated with the financial performance of firms located in those states. In other words, the superior performance of firms with excessive human capital (*Strategic_Hoarding = 1*) in Panel A could simply be driven by favorable economic and market conditions in the local states, where firms are more likely to make more profit and afford to hire additional talent to expand human capital reserves than those firms located in states with unfavorable economic and market conditions. Therefore, to address endogeneity concerns and further enhance the causal inference, we resort to the propensity score matching (PSM) technique to ensure that the hoarding firms (i.e., treated group) and non-hoarding firms (i.e., control group) are highly comparable in terms of firm and industry characteristics.[11] Specifically, after removing observations without IDD legislation (*IDD* = 0), we match firms with human capital reserves (Strategic_Hoarding = 1) to firms without human capital reserves (*Strategic_Hoarding* = 0) based on state, year, and the control variables included in the ordinary least squares (OLS) model using the one-to-one nearest neighbor algorithm with a caliper of 0.01 without replacement.[12] Importantly, by imposing such stringent and rigorous matching criteria, we ensure that each pair of firms is subject to the identical economic and legal environment in the same state during the same year with similar firm characteristics and comparable levels of dependence on high-skilled employees. Therefore, any differences in the performance measures (*TOBINQ* and *ROA*) between the two groups can be plausibly attributed to over-investment (i.e., human capital hoarding). After performing the PSM matching, we obtain a PSM sample of 14,206 matched observations, with 7,103 observations for the over-investment group (*Strategic_Hoarding* = 1) and 7,103 observations for the control group (*Strategic_Hoarding* = 0).

Panel B of Table 9 presents the results based on PSM samples. Similar to the OLS results, we find that although there is no significant difference in accounting performance between the two groups, the treated firms (i.e., firms with human capital reserves) outperform the control firms in market-based performance, suggesting that investors and market participants recognize and appreciate the value of maintaining precautionary human capital for firms' future economic prospects and long-term success. Finally, in Panel C, we conduct multivariate regression analyses by repeating our OLS model in Panel A using our PSM sample, and we obtain similar results that maintaining human capital reserves is particularly beneficial for high-skill firms in terms of improving market performance but does not significantly affect their accounting performance, despite the potentially increase in payroll expenses associated with maintaining human capital reserves.

[11] The variables we use in the first-stage logit regression for the generation of propensity scores include all of the control variables in the OLS model in Panel A and an important industry characteristic, i.e., the labor skill at the industry level (*LSI*). All of the variables, except for the industry-level labor skill index, are lagged.

[12] For robustness, we also perform PSM with replacement and obtain qualitatively similar results.

Taken together, the results in Table 9 from OLS regressions (Panel A) and the PSM sample (Panel B and Panel C) present consistent evidence that, when facing reduced talent supply in the context of trade secret protection, high-skill firms with precautionary human capital reserves are rewarded by market participants and exhibit superior market performance and future growth prospects without compromising their accounting performance, despite the additional costs of maintaining such precautionary human capital reserves.

[Insert Table 9 about here]

4.5 Placebo tests

4.5.1 Neighboring non-IDD-adopting states as the fictitious treatment group

Following Qiu and Wang (2018), we use neighboring non-IDD-adopting states as the fictitious treatment group to address concerns about potentially omitted time-varying state characteristics affecting IDD court rulings. Specifically, we conduct a placebo test by examining the reactions of firms located in untreated states that are neighboring the states experiencing changes in IDD enforcement levels. The merit of our test lies in the geographical proximity of neighboring states, which subjects them to similar time-varying local market dynamics, including trends in economic development and local economic shocks (e.g., resource discovery and natural hazards). In particular, this test exploits the fact that neighboring states face similar economic conditions and market dynamics but differ in IDD adoption status. If unobserved local factors are driving our results, we should observe similar patterns in neighboring states. Conversely, if state-specific changes in IDD enforcement are truly driving firm labor investment in the law-change state, we should observe no significant reaction from firms located in neighboring states (i.e., non-IDD-adopting states) where knowledge protection and talent mobility regulations remain unchanged. Our results in Table 10 suggest that there are no significant effects in these neighboring states, supporting our identification strategy and further enhancing the causal inference of our main findings.

[Insert Table 10 about here]

4.5.2 The influence on human capital investment of neighboring non-IDD-adopting states around actual IDD adoption

To further confirm the validity of our identification strategy and enhance the causal inference of our main findings, we conduct further placebo tests following Qiu and Wang (2018) by examining whether there is any impact on the outcome variable for the placebo group (untreated neighboring states) around the events of actual IDD adoption. The rationale of such a placebo test is that if our identification is clean and valid, then we should only observe the IDD result for the real treated group but not for the placebo group, which is not subject to the treatment of IDD adoption in reality. Thus, we follow Qiu and Wang (2018) and empirically test whether there is any change in our outcome variable up to 5 years before and after the actual year of IDD adoption. Consistent with the placebo test earlier and in line with our expectations, the insignificant results in our dynamic placebo test across all columns in Table 11 confirm that there is no effect on or adjustment in labor investments in the placebo group up to 5 years before and after IDD adoption in neighboring states.

Therefore, the fact that we do not observe any IDD effect on human capital investment in the placebo group further supports our use of IDD adoption as our main identification strategy and enhances the reliability of our main results.

[Insert Table 11 about here]

4.5.3 Pseudo-IDD adoption based on randomized treatment assignment

We further conduct a third placebo test using *pseudo_IDD* adoption. In this test, we randomly assign values to IDD and generate a new indicator variable, *pseudo_IDD*. Particularly, if a firm is not in an IDD-adopting state, we assign a pseudo value of one to the *pseudo_IDD* variable. We then estimate our baseline regression and repeat this procedure 500 times to generate a distribution of coefficients.

Our actual IDD coefficient from our baseline results (as denoted by the red dashed line) is to the right of the entire distribution of coefficients from the placebo test and is substantially larger than the mean of the estimated coefficients around zero from the placebo test. These results provide robust support for our findings that, on average, firms located in IDD-adopting states strategically hoard their human capital compared with firms without IDD adoption, and our findings are not spurious. The results of this analysis are presented in Figure 1, which graphically illustrates the distribution of placebo coefficients, which are centered and concentrated around zero.

[Insert Figure 1 about here]

4.6 Alternative control group: Non-IDD-adopting neighboring states

To make sure that our treated group and control group are highly comparable and further mitigate the impact of unobservable local economic factors, we conduct further tests by using firms located in untreated neighboring states as an alternative and high-quality control group (Qiu and Wang, 2018). Specifically, we restrict the control group to only the (untreated) neighboring states next to each treated state with IDD adoption. By ensuring that we are comparing the treated states with the untreated neighboring states as the control group, we are able to use a control group with highly comparable local conditions and characteristics (e.g., economic, employment, cultural, demographic, and climate conditions), thus allowing us to further alleviate the concern that our results may be driven or confounded by differences in local conditions, in addition to the state-level control variables and state fixed effects that we include in the baseline results.

Notably, the rationale and main strength of this test is that instead of comparing a treated state with IDD adoption with another state that is far and different from the treated state, we require a high-quality control group comprising only neighboring states, which are likely to be highly comparable in terms of local characteristics and factors such as local economic and labor market conditions. To illustrate our approach, we use IDD adoption in the state of Washington in 1997 as an example. Instead of using all of the non-IDD-adopting states in the U.S. as the control group, we require the control group to comprise non-IDD-adopting states that are adjacent to Washington. Essentially, in this instance, only Oregon and Idaho are considered as the control group for the treatment state of Washington, and we should ignore other non-IDD-adopting states, such as Kentucky, which, despite being a non-IDD-adopting state, is graphically located far from Washington and is likely to be very different in terms of various state-level conditions and characteristics. In terms of implementation, for each IDD-adopting state, we search and identify whether any of the neighboring states have remained in the control group and have never adopted IDD. In our above example, for Washington, which adopted the IDD in 1997, we search for control states among its neighboring states and identify only Oregon and Idaho as the control group as neither of them ever adopted

IDD law. Subsequently, we record the identified control states and label Washington, Oregon, and Idaho as a unique cohort. We then repeat the same process for all of the other states that have adopted the IDD, and we are able to identify the respective untreated neighboring states for each IDD-adopting state.

Using the neighboring and untreated states as the control group, we repeat our baseline DiD regression using all of the control variables, including state-level controls as well as *Cohort×Firm Fixed Effect*, *Cohort×Year Fixed Effect*, *Cohort×State Fixed Effect*, or *Cohort×Industry-by-Year Fixed Effect*, following Gormley and Matsa (2011) for rigorousness and consistency. In line with our expectations and consistent with our baseline results, we find that IDD adoption is positively associated with abnormal net hiring, thus confirming the robustness of our main results.

[Insert Table 12 about here]

4.7 Addressing potential biases in staggered DiD designs

4.7.1 Parallel trends using various methods

To address important concerns regarding potential biases in staggered DiD designs, as outlined by Baker, Larcker, and Wang (2022), we use a combination of econometric techniques suggested by recent studies to ameliorate concerns for bias and ensure the robustness of our empirical findings.

We first employ methods suggested by Borusyak et al. (2022) and Sun and Abraham (2021), which are designed to correct for the biases identified in traditional staggered DiD designs. These approaches allow for a more accurate estimation of treatment effects by properly accounting for the variation in timing and potential violation of parallel trends. To visually demonstrate the robustness of our findings, we construct a series of plots and use a comprehensive event window spanning four years before and after IDD adoption, which help us to confirm the stability of trends prior to IDD adoption and reinforce the validity of the causal effects we report. Furthermore, we complement the above methods with the cohort-based approach advocated by Cengiz et al. (2019), which involves the construction of a stacked dataset that aligns treatment events in a relative time framework, mitigating the risk of confounding effects from staggered adoption. In addition, for completeness and to facilitate a more direct comparison, we plot the trends using the staggered DiD design (TWFE OLS). To provide a comprehensive and cohesive visual representation of our results, we combine the aforementioned plots into a single figure. Thus, this consolidated plot integrates the insights from the methodologies suggested by Borusyak et al. (2022) and Sun and Abraham (2021) with the trend shown by Cengiz et al. (2019), presenting consistent visual evidence of the treatment effect after we account for the potential biases in staggered DiD estimations. Overall, the combined plot further corroborates our findings, showing a consistent and significant increasing trend of our labor investment measure after IDD adoption across all of the econometric techniques we use. We present the consolidated plot in Figure 2.

[Insert Figure 2 about here]

4.7.2 Stacked regression approach

To further address the potential biases and concerns in staggered DiD estimations, we also follow the suggestions in Baker et al. (2022) to ameliorate concerns for bias by crafting a stacked DiD sample.[13] To construct our stacked sample, we create event-cohort datasets for each year a state adopted the IDD. Each dataset includes firms headquartered in IDD-adopting states (i.e., treatment firms) and firms headquartered in non-IDD-adopting states (i.e., control firms). We retain observations for three years pre- and post-adoption (t−3 to t+3). This stacked sampling process is performed for each adoption year, which results in some control firms appearing in multiple cohorts due to their respective states' adoption timelines. Finally, by repeating this sampling process across all adoption years and subsequently combining all event-cohort datasets into one comprehensive dataset, we are able to re-estimate our baseline model. Table 13 shows that our results using the stacked sample are qualitatively similar to our main findings.

[Insert Table 13 about here]

4.8 Robustness tests

4.8.1 Alternative measures of the outcome variable

In our main analyses, we use various specifications applied in previous IDD literature (Chen et al., 2021; Klasa et al., 2018; Li et al., 2018) to alleviate endogeneity concerns and ensure that our main results are not sensitive to specification choices. In this section, to further test the robustness of our results, we follow previous studies (Biddle et al., 2009; Cella, 2020; Jung et al., 2014; Pinnuck and Lillis, 2007) and

[13] We thank the anonymous reviewer for suggesting this test.

construct five alternative proxies for expected net hiring to address the concern that our results might be driven by a particular measure of abnormal net hiring.

To check the robustness of our main finding, we use five different alternative measures for abnormal net hiring. First, we report the results by following Cella (2020) and use a firm's industry median level of net hiring as a proxy for the optimal employment level. Second, we report the results by following Biddle et al. (2009) and estimate a firm-specific model of human capital investment as a function of sales growth and use the absolute value of the residual as a proxy for the deviation from the expected investment in human capital. Third, we report the results by using the augmented version of Pinnuck and Lillis (2007) and re-estimate Model 1 with additional variables, including capital expenditure, R&D expenses, acquisition expenses, lagged value of observed labor investment, and the logarithm of GDP per capita. Fourth, we report the results using the expected employment level predicted by the model of Pinnuck and Lillis (2007) with both industry and year fixed effects. Lastly, we report the results using the expected employment level predicted by the model of Pinnuck and Lillis (2007) with both firm and year fixed effects.

In Table 14, our main findings are robust to all five alternative proxies and remain qualitatively similar, thus further confirming that our main results are not sensitive to a particular measure of abnormal net hiring and are robust.

[Insert Table 14 about here]

4.8.2 Adjustment for using residuals as dependent variables and additional control variables

In this section, we examine the robustness of our results by incorporating a range of additional control variables based on previous literature (e.g., Biddle et al., 2009; Jung et al., 2014; Klasa et al., 2018). First, Garmaise (2011) shows that the non-compete covenant is also effective in protecting firms' trade secrets when employees wish to join competing firms. We therefore include the non-compete covenant enforcement index (*NON-COMPETE*) following Garmaise (2011) as an additional control variable. Furthermore, based on the previous investment literature, we include institutional investor ownership (*INSOWN*), earnings quality (*EQUALITY*) measured following Kothari et al. (2005), operating cycle (*OPERCYC*), financial constraint (*KZINDEX*), slack (*SLACK*), cash to sales ratio (*CFOSALE*), and distress (*ZSCORE*) computed following Altman (1968). In column 1 of Table 15, we find that our results are robust to the inclusion of these additional control variables.

Chen et al. (2018) find that the implementation of the two-stage approach in previous empirical research (i.e., adopting OLS to decompose a dependent variable into its fitted and residual parts and using the residuals as the outcome variables in the second stage) can produce biased coefficients and standard errors that lead to incorrect inferences. As our outcome variable is the residual from Pinnuck and Lillis (2007), we alleviate this concern by following a solution suggested in Chen et al. (2018) and regressing the residual from the first-stage regression on all first-stage and second-stage regressors. In column 2 of Table 15, we find that our results still hold.

In column 3 of Table 15, we include all of the additional control variables together with all first-stage and second-stage regressors to re-estimate the influence of IDD adoption on the firm's abnormal net hiring. Overall, we find that our results remain robust after incorporating additional control variables and adjusting for the use of the residual as the dependent variable.

[Insert Table 15 about here]

5. CONCLUSION AND DISCUSSION

In this paper, we empirically investigate the impact of trade secret protection on firms' human capital investment strategies. By exploiting the exogenous state-level variation in talent mobility generated by the staggered adoption of the IDD in the U.S., we find strong and consistent causal evidence that IDD adoption results in increased precautionary human capital reserves in response to decreased talent supply. Specifically, we show that IDD adoption leads to under-firing as firms are more reluctant to fire existing employees with trade secrets. Meanwhile, we also document evidence suggesting that firms engage in over-hiring in their recruitment following IDD adoption. Given that IDD adoption restricts the mobility of employees with proprietary knowledge, we interpret this evidence as firms shifting their emphasis toward attracting young talents who are not subject to IDD restrictions. Our results also show that, due to the enhanced protection of trade secrets and decreased risk of losing employees with proprietary information to competitors, firms are more willing to nurture young talent in-house by investing in training and development. Subsequent cross-sectional analyses show that the influence of IDD adoption on human capital investment is more pronounced for firms relying on high-skill labor and for firms facing higher product market competition. Finally, we find that human capital reserves are particularly beneficial for improving market performance in firms in high-skill industries where the value and reliance on human capital are substantially greater. Our results are robust to a battery of sensitivity tests, including placebo tests, alternative control group, stacked regression, alternative measures, and additional control variables, as well as additional tests to address the biases in staggered DiD analysis and using residual-based outcome variables as suggested by Baker et al. (2022) and Chen et al. (2018), respectively.

Our study contributes to the growing literature on the effect of the IDD on corporate policies. Extant literature shows that IDD adoption can be an influential factor for corporate decision-making and strategic planning (Chen et al., 2021; Gao et al., 2018; Glaeser, 2018; Klasa et al., 2018; Li et al., 2018; Png and Samila, 2015). Our study contributes to this body of literature by providing evidence that firms strategically adjust their human capital strategy in response to trade secret protection. In light of the unprecedentedly crucial role played by human capital in the economy (Zingales, 2000) and the growing protection of intellectual property, our study also speaks to managers and practitioners by echoing the importance of human capital investment (Becker, 1962) to nurture a high-quality and sustainable human capital reserve, which is essential for succeeding in the increasingly competitive business environment. Policymakers should also offer financial incentives and fiscal support to facilitate the retraining and upskilling of the labor force, thus making the workforce more skilled and competitive overall which will play a crucial role in the economic recovery following the COVID-19 pandemic.

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Table 1 The summary statistics for the variables in our main sample.

Descriptive statistics of variables in the baseline regression. AB_NETHIRE is the absolute value of the difference between actual net hiring and the expected level measured on Pinnuck and Lillis (2007). MTB is the ratio of market to book value of common equity at the beginning of the year. SIZE is the log of the market value of equity at the beginning of the year. LIQ is the ratio of cash and short-term investments plus receivables to current liabilities. LEV is the ratio of long-term debt to total assets at the beginning of the year. DIVD is an indicator variable equal to 1 if the firm pays dividends in the previous year, 0 otherwise. TANGIBLES is the ratio of property, plant, and equipment to total assets at the beginning of the year. LOSS is an indicator variable equal to 1 if the firm reported a loss in the previous year, 0 otherwise. LABINT is the ratio of employees to total assets at the beginning of the year. AB_INVEST it the absolute value of the residual from the model of Biddle et al (2009). SD_CFO is the standard deviation of cash flow from operation over year t-5 to t-1. SD_SALES is the standard deviation of sales revenue over year t-5 to t-1. SD_NETHIRE is the standard deviation of the percentage change in employee over year t-5 to t-1. GDP is the natural logarithm of the GDP of the state for the year where the firm's headquarters is located. EMPLOYMENT is the natural logarithm of the employment number of the state where the firm's headquarters is located. POPULATION is the natural logarithm of the total population of the state where the firm's headquarters is located. INCOME_CAPITA is the natural logarithm of income per capita of the state where the firm's headquarters is located. Variable definitions are provided in Appendix-1.

	N	Mean	Std.Dev.	P25	Median	P75
AB_NETHIRE	79,571	0.151	0.199	0.039	0.086	0.176
IDD	79,571	0.496	0.500	0.000	0.000	1.000
MTB	79,571	2.637	4.039	1.035	1.785	3.165
SIZEPCR	79,571	0.514	0.283	0.272	0.524	0.759
LIQ	79,571	1.856	2.244	0.703	1.175	2.067
LEV	79,571	0.275	0.321	0.036	0.210	0.386
DIVD	79,571	0.331	0.470	0.000	0.000	1.000
TANGIBLES	79,571	0.287	0.238	0.096	0.215	0.421
LOSS	79,571	0.344	0.475	0.000	0.000	1.000
LABINT	79,571	0.010	0.032	0.002	0.005	0.011
AB_INVEST	79,571	11.126	13.014	4.578	8.305	11.956
SD_CFO	79,571	0.090	0.133	0.029	0.052	0.095
SD_SALES	79,571	0.205	0.218	0.075	0.138	0.252
SD_NETHIRE	79,571	0.242	0.352	0.075	0.142	0.264
GDP	79,571	12.895	0.963	12.288	12.899	13.596
EMPLOYMENT	79,571	15.589	0.827	15.061	15.579	16.221
POPULATION	79,571	16.142	0.858	15.561	16.137	16.782
INCOME_CAPITA	79,571	10.402	0.306	10.161	10.43	10.637

Table 2 The influence of IDD adoptions on firms' abnormal net hiring.
This table reports the results of the test that examines the impacts of IDD adoptions on the firm's human capital investment decisions. The dependent variable is the absolute value of abnormal net hiring. The variable of interest is IDD, which takes the value of one if the IDD is recognized in a state, and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	(1) *AB_NETHIRE*	(2) *AB_NETHIRE*
IDD	**0.0063*** **	**0.0078*** **
	(3.27)	**(3.67)**
MTB	0.0014***	0.0014***
	(5.69)	(5.44)
SIZEPCR	-0.0054***	-0.0059***
	(-3.19)	(-3.23)
LIQ	0.0074***	0.0075***
	(11.64)	(11.55)
LEV	0.0133***	0.0133***
	(3.54)	(3.08)
DIVD	0.0031	0.0042
	(0.93)	(1.27)
TANGIBLES	-0.0415***	-0.0395***
	(-3.62)	(-3.56)
LOSS	0.0070***	0.0054**
	(3.08)	(2.57)
LABINT	-0.0714	-0.0722
	(-1.01)	(-0.98)
INVEST	0.0042***	0.0042***
	(17.93)	(18.23)
SD_CFO	0.0317*	0.0318*
	(1.97)	(2.01)
SD_SALES	0.0152***	0.0115***
	(3.53)	(2.77)
SD_NETHIRE	-0.0373***	-0.0389***
	(-6.68)	(-7.29)
GDP	-0.0704*	-0.0571
	(-1.85)	(-1.35)
EMPLOYMENT	0.0222	0.0187
	(0.51)	(0.38)
POPULATION	0.0215	0.0217
	(0.61)	(0.55)
INCOME_CAPITA	0.0636	0.0489
	(1.49)	(1.13)
Firm Fixed Effect	Y	Y
Year Fixed Effect	Y	N
State Fixed Effect	Y	N
Industry-by-Year Fixed Effect	N	Y
R2	0.326	0.342
N	79,571	79,571

Table 3 The influence of IDD rejections on firms' abnormal net hiring.
This table reports the results of the test that examines the impacts of IDD rejections on the firm's human capital investment decisions. The dependent variable is the absolute value of abnormal net hiring. The variable of interest is IDD_REJECT, which takes the value of one if equal to one if the firm-year observation is after the firm's headquarters state rejects the previously-adopted IDD and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	(1) *AB_NETHIRE*	(2) *AB_NETHIRE*
IDD_REJECT	**-0.0086*****	**-0.0109****
	(-2.85)	**(-2.58)**
MTB	0.0012***	0.0012***
	(4.04)	(3.92)
SIZEPCR	-0.0044*	-0.0049*
	(-1.96)	(-2.05)
LIQ	0.0058***	0.0060***
	(6.55)	(6.44)
LEV	0.0163***	0.0166***
	(4.19)	(3.58)
DIVD	-0.0014	-0.0010
	(-0.42)	(-0.32)
TANGIBLES	-0.0416***	-0.0362***
	(-3.19)	(-3.55)
LOSS	0.0083**	0.0068*
	(2.44)	(2.08)
LABINT	-0.0223	-0.0250
	(-0.35)	(-0.35)
INVEST	0.0035***	0.0035***
	(14.12)	(14.43)
SD_CFO	0.0272	0.0242
	(1.31)	(1.16)
SD_SALES	0.0091	0.0045
	(1.52)	(0.88)
SD_NETHIRE	-0.0420***	-0.0453***
	(-5.19)	(-5.98)
GDP	-0.0406*	-0.0174
	(-1.82)	(-0.73)
EMPLOYMENT	-0.0261	-0.0246
	(-0.42)	(-0.43)
POPULATION	0.0588	0.0270
	(1.11)	(0.49)
INCOME_CAPITA	0.0259	0.0187
	(0.77)	(0.51)
Firm Fixed Effect	Y	Y
Year Fixed Effect	Y	N
State Fixed Effect	Y	N
Industry-by-Year Fixed Effect	N	Y
R2	0.328	0.352
N	46,811	46,811

Table 4 Potential channels: Human capital under-investment vs Human capital over-investment.
Panel A of Table 4 reports results of the test that examines the impacts of IDD adoptions on the firm's human capital investment decisions, namely human capital under-investment (*UNDER_LABOR*) in columns 1 to 2 and human capital over-investment (*OVER_LABOR*) in columns 3 to 4. The dependent variable is the absolute value of abnormal net hiring. The indicator variable IDD takes the value of one if the IDD is recognized in a state, and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

Panel A	*UNDER_LABOR*		*OVER_LABOR*	
	(1)	(2)	(3)	(4)
IDD	-0.0008	0.0002	**0.0191*** **	**0.0201** **
	(-0.35)	(0.07)	**(3.43)**	**(2.46)**
MTB	0.0003	0.0003	0.0029***	0.0027***
	(1.57)	(1.56)	(4.19)	(3.82)
SIZEPCR	-0.0653***	-0.0647***	-0.0602*	-0.0730**
	(-5.75)	(-5.50)	(-1.85)	(-2.19)
LIQ	0.0043***	0.0042***	0.0141***	0.0143***
	(5.87)	(5.76)	(7.11)	(6.42)
LEV	0.0290***	0.0293***	0.0215**	0.0211**
	(4.06)	(3.77)	(2.67)	(2.27)
DIVD	0.0041	0.0055*	0.0114	0.0123*
	(1.52)	(1.99)	(1.62)	(1.87)
TANGIBLES	-0.0231**	-0.0186*	-0.0562**	-0.0469
	(-2.11)	(-1.70)	(-2.04)	(-1.62)
LOSS	0.0219***	0.0210***	-0.0077	-0.0120**
	(9.36)	(9.55)	(-1.54)	(-2.22)
LABINT	0.1609	0.1562	-1.4611**	-1.3946**
	(1.56)	(1.50)	(-2.46)	(-2.38)
INVEST	0.0016***	0.0016***	0.0059***	0.0059***
	(5.62)	(5.55)	(22.35)	(22.19)
SD_CFO	0.0192	0.0185	0.0627***	0.0652***
	(0.78)	(0.76)	(2.69)	(2.94)
SD_SALES	0.0011	-0.0005	0.0473***	0.0401***
	(0.15)	(-0.07)	(3.95)	(3.13)
SD_NETHIRE	0.0177***	0.0171***	-0.1327***	-0.1324***
	(3.27)	(3.25)	(-10.89)	(-11.05)
GDP	0.0081	0.0358	-0.2411***	-0.2886***
	(0.21)	(0.91)	(-3.23)	(-3.38)
EMPLOYMENT	-0.0640*	-0.0856*	0.2020*	0.2214**
	(-1.75)	(-1.79)	(1.94)	(2.04)
POPULATION	0.0408	0.0329	-0.0171	0.0497
	(1.09)	(0.76)	(-0.16)	(0.42)
INCOME_CAPITA	0.0269	0.0103	0.0896	0.1505
	(0.69)	(0.24)	(0.85)	(1.35)
Firm Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	N	Y	N

State Fixed Effect	Y	N	Y	N
Industry-by-Year Fixed Effect	N	Y	N	Y
R2	0.392	0.413	0.406	0.450
N	49,851	49,851	29,720	29,720

Table 4 The timing of changes in firms' human capital investment around the adoption of the IDD.

Panel B of Table 4 reports the dynamic effect of IDD adoptions on human capital investment decisions, namely human capital under-investment (*UNDER_LABOR*) in columns 1 to 2 and human capital over-investment (*OVER_LABOR*) in columns 3 to 4. The dependent variable is the absolute value of abnormal net hiring. IDD_{-1} is an indicator variable equals one if the IDD is recognized in a state in one year and zero otherwise. IDD_0 is an indicator variable equals one if the IDD is recognized in a state in the current year and zero otherwise. IDD_{+1} is an indicator variable equals one if the IDD is recognized in a state one year ago and zero otherwise. IDD_{2+} is an indicator variable equals one if the IDD is recognized in a state two or more years ago and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

Panel B	*UNDER_LABOR*		*OVER_LABOR*	
	(1)	(2)	(3)	(4)
IDD-2	-0.0027	-0.0028	-0.0014	-0.0061
	(-0.51)	(-0.57)	(-0.11)	(-0.55)
IDD-1	-0.0046	-0.0055	0.0100	0.0002
	(-1.23)	(-1.52)	(0.50)	(0.01)
IDD0	-0.0065	-0.0082	-0.0067	-0.0104
	(-1.48)	(-1.05)	(-0.47)	(-0.82)
IDD+1	-0.0037	-0.0041	0.0162	0.0090
	(-0.38)	(-0.49)	(0.87)	(0.55)
IDD2+	0.0015	-0.0011	**0.0223*** **	**0.0139** **
	(0.24)	(-0.20)	**(2.88)**	**(2.20)**
Control Variables	N	Y	N	Y
Firm Fixed Effect	Y	Y	Y	Y
Industry-by-Year Fixed Effect	Y	Y	Y	Y
R2	0.398	0.413	0.373	0.459
N	49,851	49,851	29,720	29,720

Table 5 Human capital reserve channels: Over-hiring vs Under-firing.

Table 5 reports the results of the test that examines the impacts of IDD adoptions on the firm's human capital over-investment, namely over-hiring (*OVER_HIRING*) in columns 1-2 and under-firing (*UNDER_FIRING)* in columns 3-4. The indicator variable IDD takes the value of one if the IDD is recognized in a state, and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	OVER_HIRING		*UNDER_FIRING*	
	(1)	(2)	(3)	(4)
IDD	**0.0158****	**0.0165****	**0.0367*****	**0.0454****
	(2.60)	**(2.31)**	**(3.00)**	**(2.38)**
MTB	0.0026***	0.0026***	0.0015	0.0012
	(4.94)	(4.45)	(1.66)	(1.18)
SIZEPCR	-0.0612**	-0.0781**	0.0075	-0.0061
	(-2.02)	(-2.40)	(0.23)	(-0.14)
LIQ	0.0090***	0.0091***	0.0030	0.0013
	(6.39)	(5.90)	(1.18)	(0.37)
LEV	0.0063	0.0077	0.0252	0.0300
	(0.78)	(0.93)	(1.47)	(1.64)
DIVD	0.0075	0.0092	-0.0061	-0.0016
	(1.35)	(1.64)	(-0.39)	(-0.08)
TANGIBLES	-0.0928***	-0.0915***	0.0944	0.1563**
	(-4.46)	(-4.25)	(1.52)	(2.31)
LOSS	-0.0029	-0.0079	0.0084	0.0024
	(-0.58)	(-1.49)	(0.67)	(0.22)
LABINT	-0.9285*	-0.9078*	-1.1535**	-1.0124*
	(-1.91)	(-1.84)	(-2.09)	(-1.82)
INVEST	0.0047***	0.0046***	0.0032***	0.0031***
	(25.09)	(24.70)	(4.88)	(4.37)
SD_CFO	0.0884**	0.0831**	0.0987*	0.0596
	(2.67)	(2.35)	(1.74)	(1.42)
SD_SALES	0.0294*	0.0260*	0.0446	0.0556
	(1.99)	(1.69)	(1.56)	(1.62)
SD_NETHIRE	-0.0662***	-0.0666***	-0.1082***	-0.1076***
	(-7.89)	(-7.83)	(-4.13)	(-3.88)
GDP	-0.1384**	-0.1684**	-0.5559***	-0.5798**
	(-2.15)	(-2.25)	(-2.89)	(-2.51)
EMPLOYMENT	0.0565	0.0357	0.4612	0.4387
	(0.70)	(0.36)	(1.61)	(1.63)
POPULATION	0.0365	0.1045	0.1600	0.3384
	(0.43)	(1.05)	(0.50)	(0.93)
INCOME_CAPITA	0.1268	0.1748	0.3178	0.2969
	(1.41)	(1.61)	(1.40)	(1.12)
Firm Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	N	Y	N
State Fixed Effect	Y	N	Y	N
Industry-by-Year Fixed Effect	N	Y	N	Y
R2	0.455	0.502	0.483	0.576
N	22,286	22,286	7,434	7,434

Table 6 Recognition of the IDD and change in training & development.

Table 6 reports the results of the test that examines the firm's change in training and development following the recognition of the IDD. The dependent variable is the change in training and development scores from ASSET4 ESG database within the respective windows. The indicator variable IDD takes the value of one if the IDD is recognized in a state, and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	Post-IDD Change in Employee Training & Development					
	[0,1]		[0,2]		[0,3]	
	(1)	(2)	(3)	(4)	(5)	(6)
IDD	**9.8102*** **	**10.5849*** **	**9.6075*** **	**10.4626*** **	**5.7124** **	**6.1318** **
	(6.65)	**(6.10)**	**(10.34)**	**(7.59)**	**(2.97)**	**(2.26)**
Control Variables	N	Y	N	Y	N	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y
Industry-by-Year Fixed Effect	Y	Y	Y	Y	Y	Y
R2	0.208	0.210	0.267	0.269	0.326	0.329
N	5,021	5,021	4,286	4,286	3,801	3,801

Table 7 Cross-sectional analysis: High-skilled labor.

Table 7 reports the results of the test that examines the role of high-skilled labor on the relationship between IDD and firms' human capital investment decisions. The High_LaborSkill dummy is equal to one if the level of labor skills measure is above the top tercile, and zero if it is below the bottom tercile. High_RD_SALE is equal to one if the level of R&D expense scaled by total sales is above the top tercile, and zero if it is below the bottom tercile. High_RD_AT is equal to one if the level of R&D expense scaled by total assets is above the top tercile, and zero if it is below the bottom tercile. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	(1) *AB_NETHIRE*	(2) *AB_NETHIRE*	(3) *AB_NETHIRE*
IDD×High_LABOR_SKILL	**0.0219*** **		
	(3.41)		
IDD×High_RD_SALE		**0.0202** **	
		(2.67)	
IDD×High_RD_AT			**0.0121** **
			(2.33)
High_LABOR_SKILL	-0.0001		
	(-0.02)		
High_RD_SALE		-0.0651**	
		(-2.36)	
High_RD_AT			-0.0437**
			(-2.71)
IDD	0.0044	0.0093	0.0094*
	(0.53)	(1.52)	(2.07)
Control Variables	Y	Y	Y
Firm Fixed Effect	Y	Y	Y
Industry-by-Year Fixed Effect	Y	Y	Y
R2	0.371	0.342	0.341
N	32,339	18,892	18,892

Table 8 Cross-sectional analysis: Product market competition.

Table 8 reports the results of the test that examines the role of product market competition on the relationship between IDD and human capital investment decisions. The High_FLUIDITY dummy is equal to one if the level of product fluidity is above the top tercile, and zero if it is below the bottom tercile. High_SIMILARITY dummy is equal to one if the level of product similarity is above the top tercile, and zero if it is below the bottom tercile. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	(1) *AB_NETHIRE*	*(2)* *AB_NETHIRE*
IDD×High_SIMILARITY	**0.0215****	
	(2.07)	
IDD×High_FLUIDITY		**0.0154****
		(2.26)
High_SIMILARITY	-0.0282**	
	(-2.02)	
High_FLUIDITY		0.0161**
		(2.77)
IDD	-0.0047	0.0083
	(-0.75)	(0.82)
Control Variables	Y	Y
Firm Fixed Effect	Y	Y
Industry-by-Year Fixed Effect	Y	Y
R2	0.383	0.352
N	35,117	35,117

Table 9 The benefits of human capital reserves under the trade secret protection environment.

Table 9 reports the results of the test that examines the performance effect of human capital reserves for high-skilled firms in IDD adopted states. The dependent variable is Tobin's Q (*TOBINQ*) in columns 1 and 2 and Returns on Assets (*ROA*) in columns 3 and 4. High_Skill is a dummy variable equal to one if the labor skill index is above the sample median, and zero otherwise. Panel A reports the results based on an IDD-adopted sample. In Panel B and Panel C, we repeat the analyses using the propensity score matching (PSM) approach where we match each firm with human capital reserves (Strategic_Hoarding =1) to a firm without human capital reserves (Strategic_Hoarding=0) in the same state and same year with highly comparable firm characteristics using the one-to-one nearest-neighbor algorithm with a caliper of 0.01 without replacement. In untabulated results, the PSM results remain qualitatively similar when matching with replacement. Standard errors are clustered at the firm level. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

Panel A	*(1)* *TOBINSQ*	*(2)* *TOBINSQ*	*(3)* *ROA*	*(4)* *ROA*
Strategic_Hoarding × High_Skill	0.0987***	0.0813**	-0.0033	-0.0006
	(2.72)	(2.19)	(-0.46)	(-0.09)
Strategic_Hoarding	-0.0379*	-0.0308	-0.0022	-0.0053
	(-1.73)	(-1.35)	(-0.50)	(-1.15)
High_Skill	0.0125	0.0030	0.0056	0.0075
	(0.32)	(0.07)	(0.89)	(0.98)
MTB	0.0410***	0.0404***	0.0018*	0.0020**
	(7.00)	(6.73)	(1.87)	(1.99)
SIZEPCR	1.5573***	1.6409***	-0.0648*	-0.0767**
	(8.91)	(9.01)	(-1.84)	(-2.05)
LEV	-0.6149***	-0.6015***	-0.0412*	-0.0435*
	(-5.61)	(-5.35)	(-1.80)	(-1.87)
DIVD	-0.0521*	-0.0324	-0.0103**	-0.0097**
	(-1.75)	(-1.01)	(-2.43)	(-2.09)
SALESGROWTH	0.2445***	0.2360***	0.0223**	0.0221**
	(6.49)	(6.19)	(2.32)	(2.27)
SALESGROWTH_LAG	0.0834***	0.0813**	0.0103	0.0098
	(2.61)	(2.48)	(1.43)	(1.34)
ZSCORE	-0.0211**	-0.0244***	0.0251***	0.0254***
	(-2.53)	(-2.92)	(9.67)	(9.73)
KSTRUCTURE	-0.8673***	-0.8094***	0.0032	-0.0025
	(-8.47)	(-7.69)	(0.14)	(-0.11)
SD_CFO	1.1329***	1.1943***	-0.2428***	-0.2323***
	(3.21)	(3.25)	(-2.78)	(-2.69)
FIRMAGE	-0.3542***	-0.3318***	0.0267	0.0239
	(-3.60)	(-3.01)	(1.40)	(1.18)
Firm Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	N	Y	N
State Fixed Effect	Y	N	Y	N
Industry-by-Year Fixed Effect	N	Y	N	Y
R2	0.652	0.667	0.691	0.702
N	24,029	24,029	24,029	24,029

Univariate analysis using PSM sample

Panel B	Post-Match Results: Over-Invest Firms (Treated, n = 7,103) vs Non-Over-Invest Firms (Control, n = 7,103)				
	SAMPLE	*TREATED*	*CONTROL*	*DIFFERENCE*	*T-stat*
TOBINSQ	ATT	2.932	2.857	0.075	2.46**
ROA	ATT	-0.053	-0.049	-0.004	-0.89

Panel C	(1) *TOBINSQ*	(2) *TOBINSQ*	(3) *ROA*	(4) *ROA*
Treat * High_LaborSkill	0.0893**	0.0916**	0.0028	0.0060
	(2.06)	(2.03)	(0.33)	(0.68)
Treat	-0.0475*	-0.0492*	-0.0032	-0.0060
	(-1.78)	(-1.73)	(-0.62)	(-1.08)
Hign_LaborSkill	-0.0200	-0.0136	0.0048	-0.0018
	(-0.38)	(-0.23)	(0.58)	(-0.17)
MTB	0.0424***	0.0412***	0.0027*	0.0027*
	(5.20)	(4.80)	(1.74)	(1.70)
SIZEPCR	1.7573***	1.8248***	-0.0351	-0.0460
	(8.09)	(7.78)	(-0.81)	(-1.00)
LEV	-0.6096***	-0.5754***	-0.0307	-0.0295
	(-4.54)	(-4.09)	(-1.19)	(-1.10)
DIVD	-0.0650	-0.0394	-0.0053	-0.0055
	(-1.54)	(-0.85)	(-0.96)	(-0.88)
SALESGROWTH	0.2949***	0.2838***	0.0432***	0.0419***
	(6.23)	(5.90)	(3.57)	(3.37)
SALESGROWTH_LAG	0.0650*	0.0681*	0.0180**	0.0176**
	(1.76)	(1.77)	(2.14)	(2.03)
ZSCORE	-0.0331***	-0.0353***	0.0248***	0.0256***
	(-3.18)	(-3.34)	(8.00)	(8.18)
KSTRUCTURE	-0.9180***	-0.9003***	-0.0024	-0.0079
	(-6.91)	(-6.35)	(-0.09)	(-0.28)
SD_CFO	0.8836**	0.9653**	-0.2183**	-0.2248**
	(2.09)	(2.17)	(-2.24)	(-2.27)
FIRMAGE	-0.2910**	-0.2792**	0.0377*	0.0348
	(-2.43)	(-1.99)	(1.92)	(1.55)
Firm Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	N	Y	N
State Fixed Effect	Y	N	Y	N
Industry-by-Year Fixed Effect	N	Y	N	Y
R2	0.665	0.684	0.677	0.691
N	14,206	14,206	14,206	14,206

Table 10 Neighboring non-IDD-adopting states as the fictitious treatment group.

Table 10 reports the results of the test that examines the impact of IDD adoptions on firms' human capital investment decisions using neighboring non-IDD states as the fictitious treatment group. The dependent variable is the absolute value of abnormal net hiring. The variable of interest is IDD_NEIGHB_PLACEBO, which takes the value of one if the firm is located in a non-IDD state but also is neighboring to an IDD-adoption state (i.e., fictitious treatment group), and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	(1) *AB_NETHIRE*	(2) *AB_NETHIRE*
IDD_NEIGHB_PLACEBO	-0.0075	-0.0077
	(-1.02)	(-1.02)
MTB	0.0015***	0.0015***
	(5.61)	(5.44)
SIZEPCR	-0.0555***	-0.0609***
	(-3.64)	(-3.80)
LIQ	0.0083***	0.0084***
	(10.46)	(10.43)
LEV	0.0133***	0.0133***
	(3.30)	(2.82)
DIVD	0.0047	0.0058
	(1.31)	(1.64)
TANGIBLES	-0.0498***	-0.0490***
	(-3.78)	(-3.75)
LOSS	0.0065***	0.0048**
	(2.78)	(2.31)
LABINT	-0.1385*	-0.1354
	(-1.75)	(-1.64)
INVEST	0.0048***	0.0048***
	(17.79)	(18.03)
SD_CFO	0.0354*	0.0357*
	(1.93)	(1.95)
SD_SALES	0.0213***	0.0174***
	(3.95)	(3.35)
SD_NETHIRE	-0.0579***	-0.0597***
	(-8.72)	(-9.26)
GDP	-0.0836*	-0.0740
	(-1.96)	(-1.55)
EMPLOYMENT	0.0092	0.0134
	(0.19)	(0.24)
POPULATION	0.0269	0.0273
	(0.66)	(0.59)
INCOME_CAPITA	0.0766	0.0610
	(1.50)	(1.11)
Firm Fixed Effect	Y	Y
Year Fixed Effect	Y	N
State Fixed Effect	Y	N
Industry-by-Year Fixed Effect	N	Y
R2	0.314	0.331
N	79,571	79,571

Table 11 The influence on human capital investment of neighboring non-IDD-adopting states around actual IDD adoption.

Table 11 reports the results of the test that examines the impact of IDD adoptions on firms' human capital investment decisions using neighboring non-IDD states as the fictitious treatment group. The dependent variable is the absolute value of abnormal net hiring 1, 2 and 5 years before and after the actual IDD adoptions. The variable of interest is IDD_NEIGHB_PLACEBO, which takes the value of one if the firm is located in a non-IDD state but also is neighboring to an IDD-adoption state (i.e., fictitious treatment group), and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	Dependent Variable: *AB_NETHIRE*						
	5 Years Before the Actual IDD Adoption	2 Years Before the Actual IDD Adoption	1 Years Before the Actual IDD Adoption	Actual IDD Adoption	1 Years After the Actual IDD Adoption	2 Years After the Actual IDD Adoption	5 Years After the Actual IDD Adoption
IDD_NEIGHB_PLACEBO	0.0031	0.0040	0.0001	-0.0077	-0.0039	-0.0089	-0.0096
	(0.72)	(1.02)	(0.02)	(-1.02)	(-0.54)	(-1.04)	(-0.95)
MTB	-0.0001	-0.0002	0.0007***	0.0015***	0.0007	0.0005	0.0017***
	(-0.67)	(-0.91)	(3.35)	(5.44)	(1.57)	(1.52)	(5.14)
SIZEPCR	-0.0184	0.0339***	0.0540***	-0.0609***	-0.0466***	-0.1052***	-0.1072***
	(-1.37)	(3.30)	(4.96)	(-3.80)	(-4.45)	(-6.86)	(-6.08)
LIQ	-0.0007	0.0004	0.0020***	0.0084***	-0.0008	0.0035***	0.0057***
	(-1.18)	(0.94)	(2.83)	(10.43)	(-0.99)	(5.18)	(6.13)
LEV	-0.0164***	-0.0134***	0.0905***	0.0133***	-0.0132**	-0.0079	-0.0170**
	(-4.13)	(-4.76)	(10.67)	(2.82)	(-2.32)	(-0.97)	(-2.47)
DIVD	-0.0053	-0.0042	-0.0005	0.0058	0.0026	0.0051	0.0094*
	(-1.50)	(-1.29)	(-0.15)	(1.64)	(0.62)	(0.94)	(1.74)
TANGIBLES	-0.0221*	-0.0239**	-0.0789***	-0.0490***	0.0224	0.0058	-0.0221
	(-1.73)	(-2.35)	(-7.39)	(-3.75)	(1.63)	(0.43)	(-1.60)
LOSS	-0.0038*	0.0061***	0.0153***	0.0048**	-0.0038	0.0021	0.0068**
	(-1.77)	(3.39)	(8.24)	(2.31)	(-1.40)	(1.08)	(2.44)
LABINT	-0.0650	-0.1737***	-0.2091***	-0.1354	0.1947*	0.0679	-0.0124
	(-1.12)	(-3.43)	(-4.11)	(-1.64)	(1.69)	(0.68)	(-0.17)
INVEST	0.0000	-0.0004***	0.0005***	0.0048***	-0.0002	-0.0002*	0.0002

	(0.01)	(-6.37)	(5.57)	(18.03)	(-1.54)	(-1.73)	(1.42)
SD_CFO	0.0437	0.0913***	0.0628***	0.0357*	-0.0578*	0.0543**	0.0835***
	(1.67)	(8.57)	(4.93)	(1.95)	(-1.80)	(2.32)	(5.30)
SD_SALES	-0.0267**	0.0793***	0.0441***	0.0174***	-0.0016	0.0010	0.0217***
	(-2.62)	(11.37)	(6.96)	(3.35)	(-0.14)	(0.14)	(2.89)
SD_NETHIRE	0.1456***	0.1225***	0.1189***	-0.0597***	-0.0305***	-0.0497***	-0.0642***
	(18.38)	(26.48)	(23.25)	(-9.26)	(-4.73)	(-9.29)	(-10.50)
GDP	0.0529	-0.0247	-0.0148	-0.0740	-0.0881*	-0.0629	-0.0779
	(1.61)	(-1.00)	(-0.45)	(-1.55)	(-1.74)	(-1.43)	(-1.61)
EMPLOYMENT	-0.1263***	-0.0171	0.0156	0.0134	0.0152	0.0020	-0.0116
	(-2.86)	(-0.35)	(0.33)	(0.24)	(0.21)	(0.03)	(-0.22)
POPULATION	-0.0202	0.0014	-0.0184	0.0273	0.0344	0.0140	0.0392
	(-0.59)	(0.03)	(-0.48)	(0.59)	(0.37)	(0.19)	(0.74)
INCOME_CAPITA	0.0230	0.0026	-0.0016	0.0610	-0.0652	0.0109	0.0656
	(0.55)	(0.08)	(-0.04)	(1.11)	(-0.90)	(0.16)	(1.02)
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y
Industry-by-Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y
R2	0.338	0.342	0.360	0.331	0.275	0.276	0.276
N	43,595	61,685	69,506	79,571	69,506	61,685	43,595

Table 12 Alternative control group: Non-IDD-adopting neighboring states

Table 12 reports the results of the test that examines the impact of IDD adoptions on firms' human capital investment decisions using neighboring non-IDD (untreated) states adjacent to the treated states with IDD adoptions as an alternative and high-quality control group that is more comparable to the treated states in terms of local conditions due to geographic proximity. The dependent variable is the absolute value of abnormal net hiring. . The variable of interest is IDD, which takes the value of one if the IDD is recognized in a state, and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	(1) *AB_NETHIRE*	(2) *AB_NETHIRE*
IDD	0.0114**	0.0142**
	(2.69)	(2.06)
MTB	0.0012***	0.0011***
	(2.70)	(3.00)
SIZEPCR	-0.0062***	-0.0065***
	(-3.27)	(-2.75)
LIQ	0.0081***	0.0076***
	(7.75)	(6.39)
LEV	0.0139**	0.0152**
	(2.31)	(2.08)
DIVD	0.0013	-0.0000
	(0.43)	(-0.01)
TANGIBLES	-0.0368**	-0.0373**
	(-2.62)	(-2.16)
LOSS	0.0075**	0.0046
	(2.68)	(1.54)
LABINT	-0.0869	-0.0950
	(-1.05)	(-0.87)
INVEST	0.0046***	0.0044***
	(20.28)	(17.01)
SD_CFO	0.0330	0.0272
	(1.56)	(1.12)
SD_SALES	0.0163***	0.0068
	(2.81)	(1.12)
SD_NETHIRE	-0.0367***	-0.0439***
	(-5.37)	(-5.56)
GDP	-0.0432	-0.0713
	(-0.64)	(-0.99)
EMPLOYMENT	0.1310	0.0315
	(1.61)	(0.31)
POPULATION	-0.1038	0.0049
	(-1.07)	(0.04)
INCOME_CAPITA	0.1150	0.1595
	(1.00)	(1.39)
Cohort×Firm Fixed Effect	Y	Y
Cohort×Year Fixed Effect	Y	N
Cohort×State Fixed Effect	Y	N
Cohort×Industry-by-Year Fixed Effect	N	Y
R2	0.335	0.443
N	77,982	77,982

Table 13 The stacked regression approach.

Table 13 reports the results from the stacked regression analyses exploring the impact of IDD adoptions on firms' human capital investment decisions. The dependent variable is the absolute value of abnormal net hiring. The variable of interest is IDD, which takes the value of one if the IDD is recognized in a state, and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	(1) *AB_NETHIRE*	(2) *AB_NETHIRE*	(3) *AB_NETHIRE*
IDD	0.0081**	0.0096**	0.0073**
	(2.33)	(2.33)	(2.21)
Control Variables	Y	Y	Y
Firm Fixed Effect	Y	Y	N
Year Fixed Effect	Y	N	N
State Fixed Effect	Y	N	N
Industry-by-Year Fixed Effect	N	Y	N
Cohort×Firm Fixed Effect	N	N	Y
Cohort×Industry-by-Year Fixed Effect	N	N	Y
R2	0.368	0.389	0.448
N	110,973	110,973	110,973

Table 14 Alternative proxy for human capital investment.

Table 14 This table reports the results of the test that examines the impacts of IDD adoptions on the firm's human capital investment decisions using alternative measures. In columns 1 to 2, we report the results by following Cella (2020) and use a firm's industry median level of net hiring as the proxy for the optimal employment level. In columns 3 to 4, we report the results by following Biddle et al (2009) and estimate a firm-specific model of labor investment as a function of sales growth and use the absolute value of the residuals as the proxy for the deviation s from the expected investment in labor. In columns 5 to 6, we report the results by using the augmented version of Pinnuck and Lillis (2007) and re-estimate Model 1 with additional variables, including capital expenditure, research and development expenses, acquisition expenses, lagged value of observed labor investment and the logarithm of GDP per capita. In columns 7 to 8, we report the results by using the model of Pinnuck and Lillis (2007) with both industry and year fixed effects. In columns 9 to 10, we report the results by using the model of Pinnuck and Lillis (2007) with both firm and year fixed effects. The variable of interest is IDD, which takes the value of one if the IDD is recognized in a state, and zero otherwise. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	ALT_ABHIRING1		*ALT_ABHIRING2*		*ALT_ABHIRING3*		*ALT_ABHIRING4*		*ALT_ABHIRING5*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IDD	0.0076***	0.0102***	0.0059***	0.0079***	0.0043**	0.0067**	0.0065***	0.0082***	0.0054**	0.0063**
	(2.94)	(3.37)	(2.91)	(3.42)	(2.37)	(2.42)	(2.93)	(3.17)	(2.02)	(2.65)
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	N	Y	N	Y	N	Y	N	Y	N
State Fixed Effect	Y	N	Y	N	Y	N	Y	N	Y	N
Industry-by-Year Fixed Effect	N	Y	N	Y	N	Y	N	Y	N	Y
R2	0.302	0.319	0.317	0.334	0.303	0.319	0.313	0.330	0.338	0.352
N	79,571	79,571	79,571	79,571	79,571	79,571	79,571	79,571	79,571	79,571

Table 15 Adjustments for residuals as the dependent variables and additional control variables.

Table 15 reports the difference-in-differences tests that examine the impacts of the IDD adoptions on the firm's abnormal net hiring with additional controls and the adjustment for residuals as the dependent variables. In column 1, we re-estimate our baseline regression by including additional controls, including the non-compete covenant (*NON-COMPETE*), institutional investor ownership (*INSOWN*), earnings quality (*EQUALITY*), operating cycle (*OPERCYC*), financial constraint (*KZINDEX*), slack (*SLACK*), cash to sales ratio (*CFOSALE*) and Z-score (*ZSCORE*). In column 2, we attempt to alleviate the concern of using residuals as dependent variables which can lead to biased coefficients and standard errors and cause incorrect inferences (Chen et al., 2018). We follow the solution provided by Chen et al (2018) by regressing abnormal net hiring (i.e. residuals) on the combination of all the second-step (Model 2) regressors and all the first-step (Model 1) regressors. In column 3, we include all the additional control variables and all the first step regressors to re-estimate our baseline regression. The p-values based on robust standard errors clustered by state are in parentheses. ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

	(1) *AB_NETHIRE*	(2) *AB_NETHIRE*	(3) *AB_NETHIRE*
IDD	0.0085**	0.0070**	0.0085**
	(2.42)	(2.60)	(2.48)
MTB	0.0012***	0.0009***	0.0008**
	(3.44)	(3.10)	(2.19)
SIZEPCR	-0.0779***	-0.0634***	-0.0646***
	(-5.27)	(-4.73)	(-4.48)
LIQ	0.0012	0.0051***	0.0020**
	(1.42)	(7.42)	(2.34)
LEV	0.0095	-0.0081*	-0.0083
	(1.63)	(-1.70)	(-1.42)
DIVD	0.0070	0.0098***	0.0097**
	(1.66)	(2.84)	(2.47)
TANGIBLES	-0.0357	-0.0364**	-0.0247
	(-1.45)	(-2.14)	(-1.05)
LOSS	-0.0002	0.0048**	-0.0011
	(-0.08)	(2.11)	(-0.40)
LABINT	-1.0635***	-0.0291	-1.0410***
	(-2.83)	(-0.35)	(-2.74)
INVEST	0.0049***	0.0033***	0.0040***
	(18.27)	(15.46)	(17.00)
SD_CFO	0.0280	-0.0255	0.0029
	(1.25)	(-1.05)	(0.11)
SD_SALES	-0.0031	0.0126**	0.0127
	(-0.33)	(2.06)	(1.44)
SD_NETHIRE	-0.0764***	-0.0733***	-0.0774***
	(-11.16)	(-12.56)	(-10.61)
GDP	-0.0356	-0.0471	-0.0400
	(-0.90)	(-1.23)	(-1.04)
EMPLOYMENT	-0.0191	0.0073	0.0028
	(-0.30)	(0.12)	(0.04)
POPULATION	-0.0103	-0.0059	-0.0046
	(-0.20)	(-0.12)	(-0.09)
INCOME_CAPITA	0.0874	0.0693	0.0758
	(1.45)	(1.33)	(1.30)
NON-COMPETE	-0.0016		-0.0012

	(-1.47)		(-1.06)
INSOWN	0.0024		-0.0083
	(0.30)		(-1.02)
EQUALITY	-0.0318***		-0.0400***
	(-4.43)		(-4.93)
OPCYCLE	-0.0145***		-0.0277***
	(-3.98)		(-7.81)
KZINDEX	-0.0002***		-0.0002***
	(-2.73)		(-3.28)
SLACK	0.0008		0.0010*
	(1.48)		(1.91)
CFOSALE	0.0125***		0.0032
	(5.99)		(1.43)
ZSCORE	0.0020***		0.0032***
	(4.10)		(7.66)
SALESGROWTH		0.1005***	0.0842***
		(26.67)	(14.93)
SALESGROWTH_LAG		0.0055**	0.0081**
		(2.37)	(2.07)
ROA		-0.0317***	-0.0699***
		(-3.40)	(-6.12)
⊿ROA		-0.0194***	0.0088
		(-2.91)	(1.12)
⊿ROA_LAG		0.0054	0.0164**
		(0.97)	(2.29)
RETURN		0.0073***	0.0073***
		(6.46)	(6.05)
⊿LIQ		-0.0014	-0.0031*
		(-0.90)	(-1.93)
⊿LIQ_LAG		0.0044***	0.0026
		(4.07)	(1.58)
LOSSBIN1		-0.0059	-0.0079
		(-0.92)	(-1.02)
LOSSBIN2		-0.0087**	-0.0102*
		(-2.22)	(-2.00)
LOSSBIN3		0.0006	0.0021
		(0.10)	(0.29)
LOSSBIN4		0.0028	0.0011
		(0.53)	(0.17)
LOSSBIN5		-0.0093	-0.0069
		(-1.45)	(-0.95)
Firm Fixed Effect	Y	Y	Y
Industry-by-Year Fixed Effect	Y	Y	Y
R2	0.383	0.408	0.407
N	44,103	55,640	44,103

Figure 1 Pseudo IDD adoption based on randomized treatment assignment

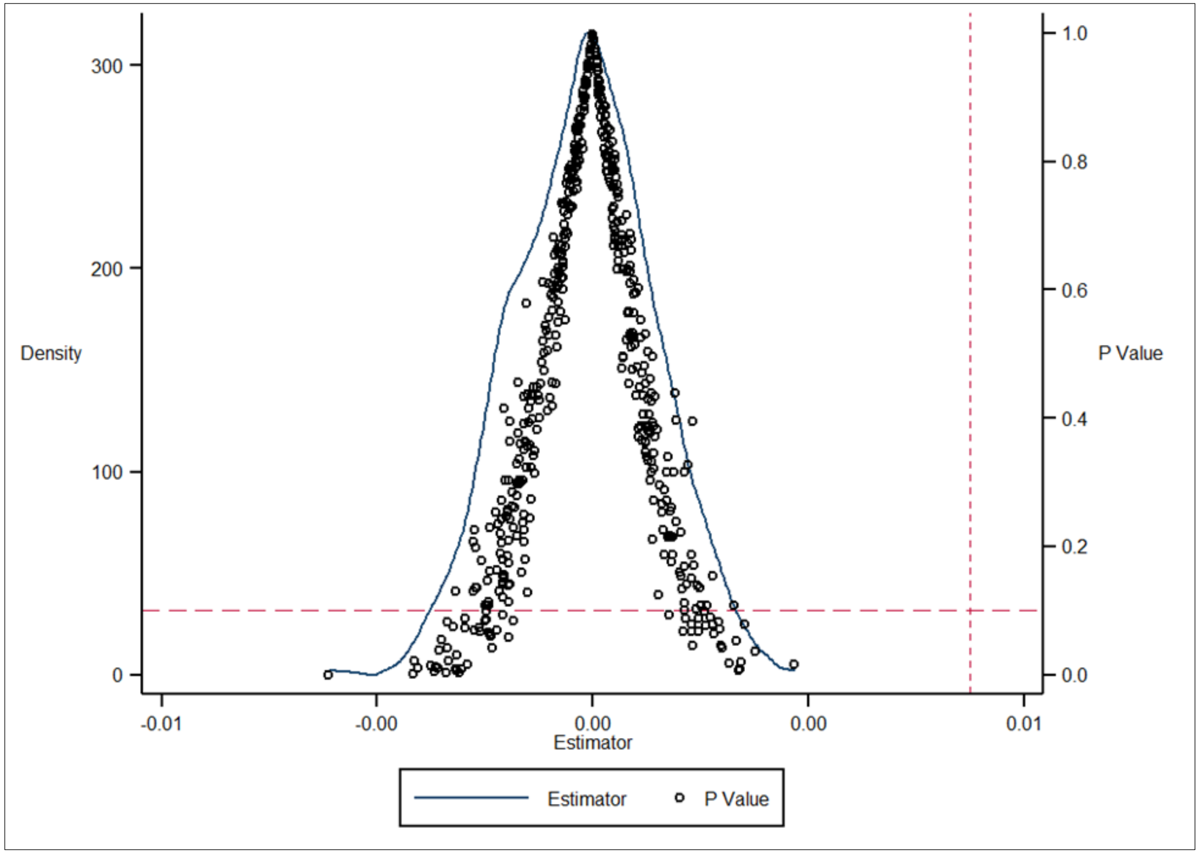
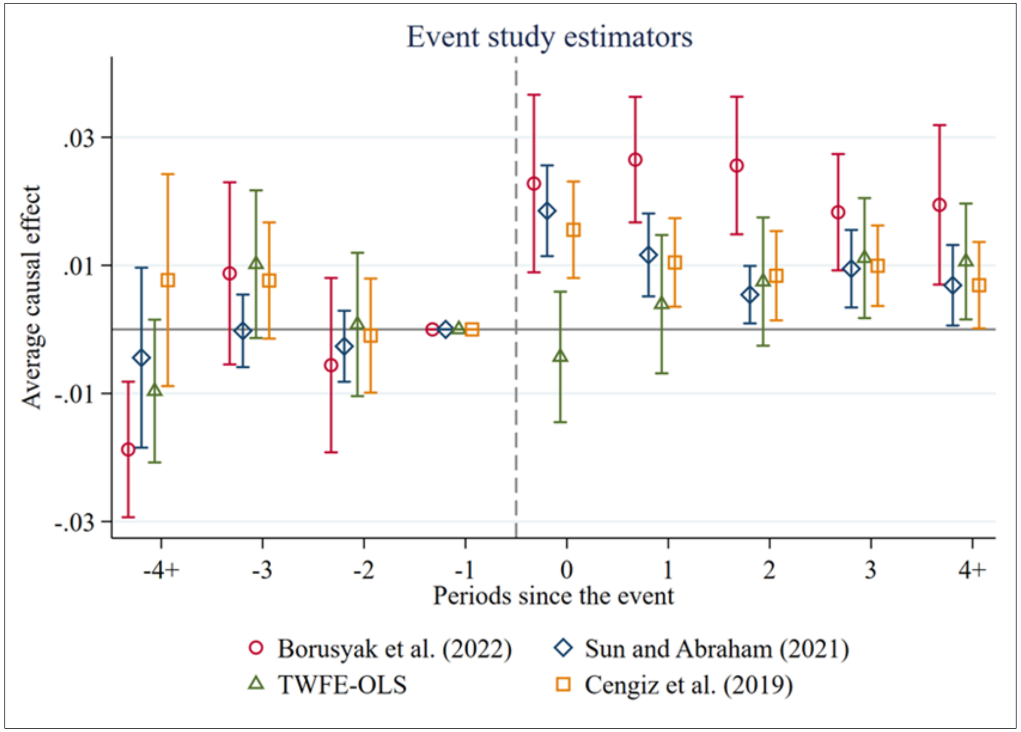


Figure 2 Parallel trends using various methods.
Figure 2 shows the parallel trends for the baseline results using methods suggested by Borusyak et al. (2022), Sun and Abraham (2021), Cengiz et al. (2019), and the staggered difference-in-differences (DiD) design (TWFE OLS).



Appendix-1

Variable definition

Variables	Description (COMPUSTAT data items in parentheses)
AB_NETHIRE	Abnormal net hiring is the absolute value of the difference between the observed level of labor investment and that justified by economic fundamentals based on Pinnuck and Lillis (2007).
ABHIRING_SIGN	Abnormal net hiring, measured as the difference between the observed level of labor investment and that justified by economic fundamentals based on Pinnuck and Lillis (2007)
OVER_LABOR	Indicator variable for over-investment in human capital equal to one if the difference between a firm's actual change in hiring and the expected level justified by economic fundamentals is positive (i.e., *ABHIRING_SIGN* >0)
UNDER_LABOR	Indicator variable for under-investment in human capital equal to one if the difference between a firm's actual change in hiring and the expected level justified by economic fundamentals is negative (i.e., *ABHIRING_SIGN* <0)
OVER_HIRING	Indicator variable for over-hiring of human capital equal to one if actual net hiring exceeds the expected amount when expected net hiring is positive.
UNDER_FIRING	Indicator variable for under-firing of human capital equal to one if actual net hiring exceeds the expected amount when expected net hiring is negative
ALT_ABHIRING1	Alternative measure of abnormal net hiring using median value of net hiring of each industry as the measure for optimal net hiring following Cella (2020)
ALT_ABHIRING2	Alternative measure of abnormal net hiring by considering labor investment as a function of sales growth and using the absolute value of the residuals as the alternative abnormal net hiring proxy following Biddle et al. (2009).
ALT_ABHIRING3	Alternative measure of abnormal net hiring by extending Pinnuck and Lillis (2007) model with extra control variables including GDP per capita, unionization level, and expenditures for acquisitions, R&D, and capital investment.
ALT_ABHIRING4	Alternative measure of abnormal net hiring by extending the Pinnuck and Lillis (2007) model with year and industry fixed effects.
ALT_ABHIRING5	Alternative measure of abnormal net hiring by extending the Pinnuck and Lillis (2007) model with year and firm fixed effect.
IDD_ADOPTION	An indicator variable which equals one if the state recognizes the IDD, and zero otherwise.
IDD_REJECTION	An indicator variable which equals one if the state rejects the IDD, and zero otherwise.
DIVD	Indicator variable coded as 1 if the firm paid dividends in year t-1 for firm i.
TANGIBLES	Property, plant and equipment at the end of year t-1, divided by total assets at year t-1, for firm i.
LOSS	Indicator variable coded as 1 if a firm I had negative ROA for year t-1 firm i.

LABINT	Labor intensity, measured as the number of employees divided by total assets at the end of year t-1 for firm i.
INVEST	Abnormal other (nonlabor) investments, defined as the absolute magnitude of the residual from the following model: $INVEST_{it} = \beta_0 + \beta_1 SALESGROWTH_{it-1} + \varepsilon_{it}$, where INVEST is the sum of capital expenditure, acquisition expenditure, and research and development expenditure, less cash receipts from the sale of property, plant, and equipment, all scaled by lagged total assets.
SD_CFO	Standard deviation of firm i's cash flows from operation from year t-5 to t-1.
SD_SALES	Standard deviation of firm i's sales from year t-5 to t-1.
SD_NETHIRE	Standard deviation of firm i's change in the number of employees from year t-5 to t-1.
GDP	Natural logarithm of the GDP of the state for the year where the firm's headquarters is located.
EMPLOYMENT	Natural logarithm of the employment number of the state where the firm's headquarters is located.
POPULATION	Natural logarithm of the total population of the state where the firm's headquarters is located.
INCOME_CAPITA	Natural logarithm of income per capita of the state where the firm's headquarters is located.

Additional variables:

LABOR SKILLS	Labor skill data is from Ghaly et al. (2017) and we use the industry average number of employees working in occupations with a JobZones index equal to 4 or 5 as a proxy for the degree of reliance on skilled-labor. JobZones data from Occupational Information Network (O*Net), available at http://www.onetonline.org/find/zone. Data on the number of employees by occupation is from Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics.
PRODUCT MARKET COMPETITION	Product market competition data is from Hoberg et al. (2014). Following Hoberg et al (2014), we use product market fluidity as the proxy for product market competition. Product market fluidity is based on product descriptions found in firms' 10–K filings and captures the degree to which a firm's products are sensitive to the evolution of rivals' products. It is defined as the similarity between a firm's vocabulary and the change in overall use of vocabulary by rivals in a given industry. A greater similarity in the business descriptions between rivals implies that a firm faces higher competitive threats, and thus a higher intensity of product market competition
NON-COMPETE	Non-compete agreements enforceability computed by Garmaise (2011).
INSOWN	Institutional shareholders at the end of year t-1 for firm i.
EQUALITY	Discretionary accrual is estimated by using the performance-adjusted modified Jones model developed by Kothari et al. (2005). We estimate the model for every industry classified by two-digit SIC code for each year and capture the residuals. The absolute value of discretionary accrual, *AB_DISC*, is used as the proxy for financial reporting quality. The large value of the absolute value of discretionary accrual, the lower level of financial reporting quality. We further multiply *AB_DISC* by -1 so that large value of *AB_DISC* indicates higher-quality of financial reporting.
OPERCYC	The natural log of the length of the firm's operating cycle, defined as sales turnover plus days in inventory in year t-1 for firm i.
KZ_INDEX	Financial constraint measure computed following Kaplan and Zingales (1997) and Lamont et al. (2001).
SLACK	Slack in year t-1 for firm i.
CFOSALE	Ratio of cash flow from operations to sales.
ZSCORE	Z-score is a measure of distress computed following the methodology in Altman (1968)

Appendix-2a Descriptive statistics of selected variables in Pinnuck and Lillies (2007).
Panel A of Appendix 2 presents the descriptive statistics for the model of Pinnuck and Lillies (2007). This table presents the number of observations, the mean, the median, the standard deviation, the values for the first and the third quartile for all the variables in Equation 1. The primary estimate of expected net hiring is based on the model of Pinnuck and Lillies (2007). NET_HIRE is the percentage change in employees. SALE_GROWTH is the percentage change in sales revenue. ROA is net income scaled by the beginning of the year total asset. RETURN is the annual stock return for year t. SIZE_R is the log of the market value of equity at the beginning of the year, ranked into percentiles. LIQ is the ratio of cash and short-term investments plus receivables to current liabilities. LEV is the ratio of long term debt to total assets at the beginning of the year.

Panel A Variable	N	Mean	Median	Std.Dev	P25	P75
NET_HIRE	201,376	0.075	0.336	-0.055	0.021	0.133
SALESGROWTH	201,376	0.175	0.585	-0.026	0.086	0.225
SALESGROWTH_LAG	201,376	0.237	0.735	-0.013	0.099	0.253
⊿ROA	201,376	0.012	0.222	-0.030	0.007	0.039
⊿ROA_LAG	201,376	0.005	0.222	-0.030	0.007	0.04
ROA	201,376	-0.035	0.324	-0.033	0.040	0.087
RETURN	201,376	0.153	0.892	-0.293	0.000	0.316
SIZE	201,376	4.731	2.379	2.959	4.581	6.387
LIQ	201,376	1.808	2.239	0.719	1.151	1.929
⊿LIQ	201,376	0.108	0.772	-0.220	-0.021	0.200
⊿LIQ_LAG	201,376	0.209	1.099	-0.208	-0.008	0.235
LEV	201,376	0.295	0.317	0.069	0.238	0.408

Appendix-2b Regression results of Pinnuck and Lillies (2007)
This table presents the results based on the model of Pinnuck and Lillies (2007) through regressing the percentage change in employees on variables capturing underlying economic fundamentals. *, **, *** indicate statistical significance at the 0.10, 0.05 and 0.001 levels.

Regression Results (Dependent Variable = *NET_HIRE*)

Panel B	(1) Expected Sign	(2) Coefficient (t-stat)
SALESGROWTH	+	0.2300***
		(69.97)
SALESGROWTH_LAG	+	0.0255***
		(14.18)
ROA	+	0.0746***
		(16.27)
⊿ROA	-	-0.1164***
		(-19.64)
⊿ROA_LAG	+	0.0503***
		(9.15)
RETURN	+	0.0351***
		(29.54)
SIZE_P	+	0.0071***
		(14.15)
LIQ	+	-0.0101***
		(-6.81)
⊿LIQ	+/-	0.0172***
		(15.09)
⊿LIQ_LAG	+	0.0572***
		(22.15)
LEV	+/-	-0.0052
		(-1.44)
LOSSBIN1	-	-0.0243***
		(-4.24)
LOSSBIN2	-	-0.0265***
		(-5.05)
LOSSBIN3	-	-0.0313***
		(-5.35)
LOSSBIN4	-	-0.0333***
		(-5.60)
LOSSBIN5	-	-0.0383***
		(-6.57)
Industry Fixed Effect		Yes
N		201,376
R2		0.213

Appendix-3

Precedent-setting legal cases adopting or rejecting the Inevitable Disclosure Doctrine.
The table lists the precedent-setting legal cases in which state courts adopted the Inevitable Disclosure Doctrine (IDD) or rejected it after adopting it.

State	Precedent-setting case(s)	Date	Decision
AR	Southwestern Energy Co. v. Eickenhorst, 955 F. Supp. 1078 (W.D. Ark. 1997)	3/18/1997	Adopt
CT	Branson Ultrasonics Corp. v. Stratman, 921 F. Supp. 909 (D. Conn. 1996)	2/28/1996	Adopt
DE	E.I. duPont de Nemours & Co. v. American Potash & Chem. Corp., 200 A.2d 428 (Del. Ch. 1964)	1964/5/5	Adopt
FL	Fountain v. Hudson Cush-N-Foam Corp., 122 So. 2d 232 (Fla. Dist. Ct. App. 1960)	1960/11/7	Adopt
	Del Monte Fresh Produce Co. v. Dole Food Co. Inc., 148 F. Supp. 2d 1326 (S.D. Fla. 2001)	5/21/2001	Reject
GA	Essex Group Inc. v. Southwire Co., 501 S.E.2d 501 (Ga. 1998)	6/29/1998	Adopt
IL	Teradyne Inc. v. Clear Communications Corp., 707 F. Supp. 353 (N.D. 111. 1989)	1989/9/2	Adopt
IN	Ackerman v. Kimball Int'l Inc., 652 N.E.2d 507 (Ind. 1995)	1995/12/7	Adopt
IA	Uncle B's Bakery v. O'Rourke, 920 F. Supp. 1405 (N.D. Iowa 1996)	1996/1/4	Adopt
KS	Bradbury Co. v. Teissier-duCros, 413 F. Supp. 2d 1203 (D. Kans. 2006)	2006/2/2	Adopt
MA	Bard v. Intoccia, 1994 U.S. Dist. LEXIS 15,368 (D. Mass. 1994)	10/13/1994	Adopt
MI	Allis-Chalmers Manuf. Co. v. Continental Aviation & Eng. Corp., 255 F. Supp. 645 (E.D. Mich. 1966)	2/17/1966	Adopt
	CMI Int'l, Inc. v. Intermet Int'l Corp., 649 N.W.2d 808 (Mich. Ct. App. 2002)	4/30/2002	Adopt
MN	Surgidev Corp. v. Eye Technology Inc., 648 F. Supp. 661 (D. Minn. 1986)	1986/10/10	Adopt
MO	H&R Block Eastern Tax Servs. Inc. v. Enchura, 122 F. Supp. 2d 1067 (W.D. Mo. 20 0 0)	2000/2/11	Adopt
NJ	Nat'l Starch & Chem. Corp. v. Parker Chem. Corp., 530 A.2d 31 (N.J. Super. Ct. 1987)	4/27/1987	Adopt
NY	Eastman Kodak Co. v. Powers Film Prod., 189 A.D. 556 (N.Y.A.D. 1919)	1919/5/12	Adopt
NC	Travenol Laboratories Inc. v. Turner, 228 S.E.2d 478 (N.C. Ct. App. 1976)	6/17/1976	Adopt

OH	Procter & Gamble Co. v. Stoneham, 747 N.E.2d 268 (Ohio Ct. App. 20 0 0)	9/29/2000	Adopt
PA	Air Products & Chemical Inc. v. Johnson, 442 A.2d 1114 (Pa. Super. Ct. 1982)	2/19/1982	Adopt
TX	Rugen v. Interactive Business Systems Inc., 864 S.W.2d 548 (Tex. App. 1993)	5/28/1993	Adopt
	Cardinal Health Staffing Network Inc. v. Bowen, 106 S.W.3d 230 (Tex. App. 2003)	2003/3/4	Adopt
UT	Novell Inc. v. Timpanogos Research Group Inc., 46 U.S.P.Q.2d 1197 (Utah D.C. 1998)	1/30/1998	Adopt
WA	Solutec Corp. Inc. v. Agnew, 88 Wash. App. 1067 (Wash. Ct. App. 1997)	12/30/1997	Adopt