Human Capital Driven Acquisition: Evidence from the Inevitable Disclosure Doctrine*

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Abstract: We present evidence that the desire to gain human capital is an important motive for corporate acquisitions. Our tests exploit the staggered recognition of the Inevitable Disclosure Doctrine (IDD) by U.S. state courts, which prevents employees with trade secret knowledge from working for other firms. We find a significant increase in the likelihood of being acquired for firms headquartered in states that recognize such a doctrine relative to firms headquartered in states that do not. Our result is stronger for firms with greater human capital and for firms whose employees have better ex-ante employment mobility. We show that the IDD is positively associated with the retention of target firms' key technicians, employees, and top executives after an acquisition. We also show that the IDD is positively associated with synergy creation, acquirers' announcement returns, and acquirers' long-run stock and operating performance. Overall, our result indicates that corporate acquisitions can be used as a means for firms to overcome labor market frictions and gain access to valuable human capital.

Keywords: Acquisition; Human Capital; Labor Market Friction; Inevitable Disclosure Doctrine

JEL Classification: G34, J24, J62, M51, M54

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Acquisitions are going to be an alternative to normal recruiting that people really haven't considered before.

Bernard Wysoki Jr. Wall Street Journal 06 Oct 1997 A1

1. Introduction

Anecdotal evidence suggests that obtaining human capital is a key driver of mergers and acquisitions (M&As), and that many M&As occur due to acquirers' intention to acquire target firms' human capital. For example, Facebook CEO Mark Zuckerberg once stated, "Facebook has not once bought a company for the company itself. We buy companies to get excellent people."[1] Despite a few circumstantial examples, there is little empirical evidence on this matter. In this paper, we fill this gap and present evidence that the desire to gain human capital is an important motive for corporate acquisitions.

Our test exploits the staggered adoption of the Inevitable Disclosure Doctrine (IDD) by U.S. state courts, which prevents a firm's workers who have knowledge of their firm's trade secrets from working for another firm. We predict that a state's recognition of the IDD could increase the likelihood of firms in that state being acquired for the following three reasons. First, the IDD prevents the potential acquirer from poaching the target firm's employees directly from the labor market, making corporate acquisition a more effective alternative for the acquirer to obtain the target's human capital. Second, the IDD helps the acquirer retain employees of the target company after the acquisition, and reduces the risk of post-acquisition employee turnover. Third, the IDD strengthens the protection of a target firm's trade secrets and intellectual property and enhances the value of its intangible assets (which is inseparably linked with human capital), which in turn makes the target firm more attractive to potential acquirers.

This setting of employing the staggered recognition of the IDD by U.S. state courts is highly appealing from an empirical standpoint for two reasons. First, the motivation behind the IDD centers around state courts' determination to enhance the protection of trade secrets for firms located in the state by reducing the risk that departing employees will reveal a firm's trade secrets to other firms. As the IDD was not adopted with the intention of promoting M&As, potential effects on M&As are likely to be an

[1] http://www.huffingtonpost.com/2010/10/19/mark-zuckerberg-we-buy-co_n_767338.html

unintended consequence of these policies. Second, the staggered adoption of the IDD in several U.S. states enables us to identify its effects in a difference-in-differences framework. Because multiple shocks affect different firms exogenously at different times, we can avoid the common identification difficulty faced by studies with a single shock: the potential biases and noise coinciding with the shock that directly affect corporate acquisitions (Roberts and Whited, 2013).

Using a panel of 123,212 U.S. public firms from 1980 to 2013 and a difference-in-differences approach, we show that, on average, firms headquartered in states that recognize the IDD experience an increase in the likelihood of being acquired by approximately 0.8 percentage point relative to firms headquartered in states that do not recognize such a doctrine. This effect is economically important, considering that the unconditional probability for a firm to be acquired is around 5 percentage points in our sample. These results are robust to controlling for various firm and state characteristics.

The assumption central to a causal interpretation of the difference-in-differences estimation is that, in the absence of treatment, treated and control firms would have parallel trends both before and after the policy change. This assumption is inherently untestable, because we don't observe the treated firms in the absence of treatment. However, we can obtain peripheral evidence by examining pre-treatment trends. Our tests show that these firms' pre-treatment trends are indeed indistinguishable. Moreover, most of the impact of the IDD on acquisition likelihood occurs after the state policy change takes effect, which suggests a causal effect.

However, it is possible that the recognition of the IDD is triggered by unobserved local business conditions that in turn increase M&A activities (although we have controlled for various state characteristics, such as state GDP growth, population, unemployment rate, etc., in the regression). To mitigate this concern, we exploit the fact that economic conditions are likely to be similar in neighboring states, whereas the effects of the IDD stop at state borders. This discontinuity in the IDD allows us to difference away any unobserved confounding factors as long as they affect both the treated state and its neighbors. By comparing treated firms to their immediate neighbors, we can better identify how much of the observed change in firms' likelihood of being acquired is due to the IDD rather than other shocks to

local business conditions. When we difference away changes in local business conditions by focusing on treated and control firms closely located on either side of a state border, we continue to find a significant increase in firms' likelihood of being acquired after their states recognize the IDD. These results suggest that our results do not seem to be driven by unobserved local economic shocks.

To provide further evidence that the effects of the IDD on corporate acquisitions are indeed tied to human capital, we apply a triple difference-in-differences approach to examine heterogeneous treatment effects. We find that the treatment effects are stronger for firms with greater human capital and for firms whose employees have better *ex ante* employment mobility. These cross-sectional variations in the treatment effects further increase our confidence in the presence of a human capital channel.

We next investigate the retention of targets' employees following the acquisition. We find that the IDD is associated with greater retention of target firm's inventors, employees, and top managers in the post-acquisition period. This evidence further supports the view that obtaining human capital is an important motive in such IDD-related acquisitions.

Finally, we examine the valuation effect of such human capital-driven acquisitions. Considering that these IDD-related acquisitions are motivated to overcome labor market frictions and gain access to valuable human capital, they are likely associated with positive valuation effects. Consistent with this view, we find that the IDD is associated with greater synergy creation, acquirers' higher announcement returns, and acquirers' better long-run stock and operating performance after the acquisition. Using patents co-produced by both the acquiring firm's and its target firm's employees to measure human capital collaboration, we provide suggestive evidence that the IDD is associated with greater cooperation among the target's and acquirer's employees in the post-acquisition period.

Our paper relates to the surging literature on the effect of labor laws and labor market conditions on M&A activity. For example, John et al. (2015) find acquirers from strong labor rights states have lower announcement returns, partially because such acquirers pursue deals not in the best interest of their shareholders. In an international setting, Dessaint et al. (2017) show that increases in employment protection significantly reduce takeover activity and synergy gains, and they conclude that labor

restructuring is an important driver of takeover and source of synergy gains. Chatt et al. (2017) find that U.S. state laws that increase firing costs have a negative impact on M&A activity, and their findings indicate that post-merger employee turnover is an important source of synergy gains. Alimov (2015) shows that tighter employment protection regulations in the target firm's country help attract more foreign acquirers, especially when acquirers' countries have more flexible labor market regulations. Complementing these studies that focus on employee protection, our study focuses on the restriction of labor mobility and provides evidence that state laws that increase labor market frictions have important effects on M&A activity.

It is worth noting that our study is closely related to Ouimet and Zarutskie (2016), which use detailed Census data and find positive post-merger employment outcomes in cases where acquirers are more likely to seek skilled labor. Although our paper complements theirs in showing that obtaining human capital is an important motive in acquisitions, our paper extends theirs in the following three ways. First, their paper mainly examines how employees in target firms—conditional on an M&A deal occurring—are retained and paid in the post-acquisition period, and their paper does not examine why an acquisition deal occurs in the first place. In contrast, our paper examines not only the *ex post* effect of an acquisition but also the *ex ante* likelihood for an acquisition to occur. We show that the labor market frictions of obtaining employees drive an M&A deal to occur in the first place. Second, even for the post-acquisition outcome variables, their paper mainly examines the retention and wage changes of the target firm's employees in the post-acquisition period. However, our paper examines a wider range of post-acquisition outcomes, including valuation effect, operating performance, firm innovation, retention of target firms' inventors and top executives, etc. Third, their paper focuses on the language used by the target firms to describe employees in their 10-K statements, and documents a positive correlation between the use of the word "skilled" by the target firms in the pre-acquisition period and post-acquisition employment outcomes. In contrast, our study exploits the staggered adoption of the IDD and can provide a relatively clearer identification on the causal effect of labor market frictions on acquisitions.

2. Background on Trade Secrets and the IDD

A trade secret is defined as any valuable business information that is not generally known and is subject to reasonable efforts to preserve confidentiality. Examples include software, techniques, business plans, designs, details about customers and suppliers, etc. In U.S. public firms, trade secrets have been estimated to be worth $5 trillion and account for two-thirds of the value of firms' intangible assets (U.S. Chamber of Commerce, 2014). Misappropriation of trade secrets occurs when the trade secret is acquired by improper means (e.g., theft or breach of a duty to obtain the secret) or by disclosure without consent by the person who obtained the secret under situations giving rise to a duty to maintain the secret or limit its use.

State courts adopt the IDD to enhance the legal protection of trade secrets for firms located in the state when an employee will inevitably use or disclose knowledge of such trade secrets in her new employment. The IDD maintains that if this new employment would inevitably lead to the disclosure of the firm's trade secrets to competitors and cause the firm irreparable harm, then state courts can prevent the employee from working for the firm's competitor or can limit the worker's responsibility in the new firm. Under the IDD, a firm's suit can be based on the threats of irreparable harm (even though the actual harm has not occurred), as long as the firm can provide evidence that (1) the departing employee had access to its trade secrets, (2) the employee's duty in the new firm would inevitably make her disclose the trade secrets, and (3) the disclosure of the trade secrets would lead to irreparable economic harm to the firm. Furthermore, the firm does not need to establish any actual wrongdoing by the employee or disclose the actual details of the underlying trade secrets in the lawsuit. As shown by Malsberger (2004) and Garmaise (2011), the relevant jurisdiction for a trade secret-related lawsuit is typically in the state where the job-hopping employee's former employer is located. Thus, the IDD prevents the job-hopping employee from working in a new firm even if the new firm operates in a state without adopting the IDD.

The legal case between PepsiCo and Mr. William Redmond is a classic example in which the court applied the IDD. In 1994, PepsiCo sought an injunction against its former employee, William Redmond, from working for Quaker, a competitor of PepsiCo. PepsiCo's products "PowerAde" and "Fruitopia" competed with Quaker's "Gatorade" and "Snapple" brands, and Redmond had a senior-level marketing

position at PepsiCo. In that position, Redmond had knowledge of PepsiCo's strategic plans, price structure, distribution system, marketing plan, and other trade secrets; and he was hired by Quaker for a similar position. PepsiCo argued that, no matter how hard he tried, Redmond could not help but use PepsiCo's trade secrets in his new position, and that disclosing these trade secrets would give Quaker an unfair advantage. Though there was no evidence that Redmond took any physical materials from PepsiCo, the court found the situation to be a clear case of inevitable disclosure and prohibited Redmond from taking the position.

The details of the IDD adoptions are collected from Klasa et al. (2018). As shown in Table 1, New York was the first U.S. state to adopt the IDD (in 1919). By the end of our sample period, 21 states adopted IDD once, 3 of which rejected their previously adopted IDD a few years after the initial adoption.

Klasa et al. (2018) describe a few key differences between the IDD and employment contracts with a non-disclosure agreement (NDA) and/or a covenant not to compete (CNC). First, an NDA or CNC usually has specific geographic restrictions; the scope of enforceable CNC/NDA is often within a county or a city, or within a 10- or 50-mile radius around the place of business. In contrast, the IDD typically can be enforced within a much broader geographic scope. Second, the IDD allows state courts to grant an injunction if allowing employment at the rival firm would inevitably lead to a future violation of NDAs (before the actual violation of NDAs), which greatly enhances the enforceability of NDAs because detecting and proving an *ex post* violation of an NDA is costly. Finally, the IDD allows courts to grant an injunction even if the job-hopping employee did not sign an NDA or CNC with her previous company.

Finally, it is also worth pointing out that the change in a state's IDD policy can largely be regarded as exogenous in our context of corporate acquisition tests. When considering the adoption of the IDD, state courts mainly aim to achieve a balance between the companies' interests of stronger protection of trade secrets and the employees' interests of labor market freedom (Godfrey, 2004; Harris, 2000). In other words, given that the primary purpose of the IDD policy change is either to better protect firms' trade secrets or to better protect employees' employment freedom, the change in firms' likelihood of being acquired is likely to be an unintended consequence of these policy changes. Moreover, unlike other state laws whose adoption

can be influenced greatly by interest groups, such as labor unions and companies, the adoption of the IDD largely depends on judicial decisions based on the merits of the specific case. Further, state judges who make the judicial decision are deemed to be independent of the state and federal government and largely immune to lobby groups and political pressure (Klasa et al., 2018). In summary, the staggered adoption of the IDD is unlikely to be triggered by factors that drive corporate acquisition activities.

3. Hypothesis Development

We expect that a state's recognition of the IDD increases its local firms' likelihood of being acquired for the following three reasons: (1) the acquirer makes an acquisition to obtain the target's key employees to whom the acquirer would not otherwise have access due to IDD restrictions on hiring, (2) acquisitions become more advantageous because the risk of post-acquisition employee turnover is reduced by IDD restrictions, and (3) IDD protection of trade secrets and intellectual property make the target firm's intangible assets (which are inseparably linked with human capital) more attractive to the acquirer.

Typically, there are two ways for a firm to obtain human capital: hiring from the labor market (labor market approach) and acquiring via corporate acquisition (acquisition approach). Compared to the former approach, the latter is advantageous when it is difficult for the firm to directly poach its desired talent from the labor market (for example, a desired talent is closely tied to another firm and is unwilling or not allowed to switch jobs legally). The IDD increases labor market frictions for the potential acquirer to hire talent directly from the state's local firms and thus makes acquisition a relatively more effective way for the acquirer to obtain target firms' human capital. Moreover, there could be a team-specific component of human capital (trust, customs, shared culture, and the like), and the value of a firm's human capital is not necessarily contained within specific individuals but embedded in relationships, teamwork, and networking among individuals (see, e.g., Kogut and Zander, 1992; Ranft and Lord, 2000; Ouimet and Zarutskie, 2016). That is, to make full use of a firm's human capital, one needs to obtain not only the individual experiences of the team members, but also the collective experience of the team as a whole. This further makes the

acquisition approach advantageous because acquisitions (instead of hiring talent one by one from other firms) is more effective to bring in full teams of employees.

Second, following the completion of the acquisition, the target firm's employees (who are desired by the acquirer) can choose to leave and are not acquired in the same way the new owner gains control of the target firm's physical assets. The IDD restricts the departure of the desired target's employees during the post-acquisition period. Considering that the target firm's knowledge is usually stored in the experience of its employees, the departure of employees immediately reduces the target firm's knowledge base and increases the risk of knowledge leaking to other firms, which decreases the effectiveness of using acquisition as a means of obtaining human capital (Ashkenas et al., 1998; Buchholtz et al., 2003). Even if the acquisition is not entirely for human capital, as long as voluntary labor mobility negatively contributes to the post-acquisition success, a lower likelihood of employee turnover in the post-acquisition period will make the acquisition more valuable to the acquirer.

Third, by providing better protection of a firm's trade secrets and intellectual property, the IDD increases the value of firms' intangible assets (which is inseparably linked with human capital) and the firms' competitive advantage in the product market (Qiu and Wang, 2018). This could in turn make these firms better targets and increase their likelihood of being acquired. In summary, after a state adopts the IDD, we expect that companies headquartered in this state are more likely to be acquired subsequently.

4. Sample Formation and Variable Construction

From CRSP-Compustat merged dataset, we start with all U.S. public firms traded on NYSE, AMEX, or NASDAQ. To focus on more economically important companies, we require that our sample firms have a book value of total assets above $10 million. We obtain a firm's historical headquarters state information from different sources. For the period before 1987, we use hand-collected data by Bai et al. (2020)[2]; for the period between 1987 and 2007, we obtain this information from Compact Disclosure (which starts in 1987);

[2] Bai et al. (2020) hand-collected firms' historical headquarters data (starting from 1969) from the Moody's Manuals (later Mergent Manuals) and Dun & Bradstreet's Million Dollar Directory (later bought by Mergent).

for the period after 2007, we obtain the data from the CSRP-Compustat Merged database.[3] The assumption underlying our tests is that because the IDD usually applies to the state where an employee works, the best approximation available to use is the headquarters location. A large body of literature shows that firms usually locate their core business activities and R&D facilities close to their headquarters (e.g., Howells, 1990; Pirinsky and Wang, 2006; Breschi, 2008). Therefore, it is reasonable to assume that a significant portion of the firm's key employees, who know their firm's trade secrets, work in the same state as the firm's headquarters. Nevertheless, we acknowledge that lack of detailed data on employee location is a limitation of this study. Readers should be aware of this limitation when deciding how our findings might be generalized.

Our dependent variable is the *Acquisition* indicator variable, which equals one if the firm is the target of an acquisition in a given year, and zero otherwise. Information on acquisitions is obtained from Thomson Financial's SDC Database. We retain an acquisition deal only if the deal is completed and the acquirer owns 100% of the target firm after the deal's completion. Given that the SDC database might be less reliable before 1980, we start our sample in 1980. Our final sample consists of 123,212 firm-year observations (11,122 unique firms) from 1980 to 2013.

We control for a vector of firm characteristics that may affect a firm's likelihood of being acquired, and these controls are motivated by prior literature (e.g., Song and Walkling, 2000). These variables include firm size, asset tangibility, leverage, R&D expenditures, ROA, Tobin's *Q*, and excess stock return. We also account for various state-level variables in our regressions. Since larger and richer states may have more active M&A activities, we control for state GDP growth rate and state population. We further control for state business combination laws, which reduce the threat of hostile takeovers and thus affect the firm's likelihood of being acquired. We control for the state's enforceability of the covenants not to compete (CNC) policy, which limits the mobility of informed workers in the labor market. We also include the state establishment entry rate, the state establishment exit rate, and the state unemployment rate to capture the

[3] We have 11,122 unique firms in our sample. Over our sample period of 1980-2013, 89.7% of these firms never relocated, 9.2% of them have relocated once, and 1.1% of them have relocated two or more times.

local economic conditions. Wrongful discharge laws (in particular, the good-faith exception), implemented at the state level, have been shown to impact firms' ability to dismiss employees,[4] which may influence labor restructuring in the post-acquisition period. Thus, we control for the adoption of these laws. Data on state GDP growth is obtained from the Bureau of Economic Analysis, and data on state population is obtained from the U.S. Census Bureau. Information regarding state business combination laws is collected from Giroud and Mueller (2010). Data for CNC enforceability is obtained from Garmaise (2011). State business entry and exit rates are obtained from the Business Dynamics Statistics database of the U.S. Census Bureau. Finally, state unemployment rates are obtained from the U.S. Bureau of Labor Statistics Local Area Unemployment Statistics Series. Data on the good-faith exception is collected from Autor et al. (2006). All explanatory variables are lagged by one year. We winsorize all continuous variables at the 1st and 99th percentiles. Detailed variable definitions are provided in the Appendix.

Table 2 provides summary statistics. The *Acquisition* indicator has a mean value of 0.05, indicating that, on average, 5% of our sample firms become the target in an acquisition deal. Our median sample firms have book value assets of $461.67 million, are moderately levered with a book leverage ratio of 11.22%, and have 17.09% of total assets in the form of tangible assets. In terms of performance, sample firms perform well with a median ROA of 3.10%, sales growth of 8.91%, and Tobin's *Q* of 1.29. As to state characteristics, the average state has a population of 13.47 million, a GDP growth rate of 5.72%, and an unemployment rate of 6.33%. On average, the establishment entry and exit rates are 12.04% and 10.50%, respectively. Almost half of the states have adopted business combination laws, and about a quarter of the states have adopted wrongful discharge laws (good-faith exception).

[4] Legal scholars distinguish three distinct wrongful discharge laws: the good-faith exception, the public-policy exception, and the implied-contract exception. Among them, the good-faith exception is considered by many legal scholars as the most far-reaching (Kugler and Saint-Paul, 2004; Acharya et al., 2014). In untabulated analysis, we additionally control for the public-policy exception and the implied-contract exception, and our inference is unchanged.

5. Empirical Results

5.1 Baseline Regression

Several U.S. state courts recognized the IDD in different years during the sample period. Thus, we can compare the before-after effect of the change in the IDD in affected states (the treatment group) to the before-after effect in states in which such a change was not effected (the control group). This is a difference-in-differences test design in multiple treatment groups and multiple time periods as employed by Acharya et al. (2014), Klasa et al. (2018), and Imbens and Wooldridge (2009). We implement this test through the following linear probability regression[5]:

$$Acquisition_{i,t} = \alpha + \beta_1 IDD_{s,t-1} + \beta_2 Firm\ Characteristics_{i,t-1} + \beta_3 State\ Characteristics_{s,t-1} + Firm\ FE + Region \times Year\ FE + \varepsilon_{i,t}\ , \qquad (1)$$

where *i* indexes firm, *s* indexes the state in which the firm's headquarters is located, and *t* indexes the year. The dependent variable is an indicator variable that takes the value of one if the firm is acquired in year *t*, and zero otherwise. The variable *IDD* is a dummy variable that equals one if the IDD is in place in state *s* in a given year, and zero otherwise.[6] We include a set of control variables that may affect a firm's likelihood of being acquired, as discussed in Section 4. The firm fixed effects allow us to control for time-invariant differences in the likelihood of being acquired across firms. Following Acharya et al. (2014), we also control for regional time trends through the interaction of region dummies with year dummies.[7] These interactions enable us to nonparametrically account for time-varying differences between geographic

[5] Considering that we have a large number of fixed effects, a non-linear model (such as a logit or probit model) is impractical and likely to produce biased estimates due to the incidental parameter problem (Lancaster, 2000). Moreover, the marginal effects in a linear probability model are easier to compute and interpret relative to non-linear models, especially for interaction terms. Nevertheless, in an untabulated analysis, we re-estimate our tests based on a logit or probit model and obtain the same inference.

[6] It is possible that an acquisition takes place at the beginning of the year, while the IDD is adopted at the end of the same year. In this case, the acquisition is actually prior to the IDD adoption even they occur in the same year. To avoid such complication, we take a lead-lag regression specification by lagging the IDD by one year.

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

regions of the U.S. in corporate acquisitions and in the recognition of the IDD. Given that our treatment is defined at the state level, we cluster standard errors by state.

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

Table 3 presents the regression results. The coefficient estimates on *IDD* are positive and statistically significant in all columns. In column (1), we only include *IDD*, *Firm FE*, and *Region*×*Year FE* as the independent variables; and the coefficient estimate on the *IDD* indicator is 0.008 and significant at the 5% level, suggesting a positive effect of the policy change on the firm's likelihood of being acquired.

In columns (2) and (3), we additionally control for various firm and state characteristics and obtain similar results. For example, we control for the full set of firm and state characteristics in column (3) and find that the coefficient estimate on the *IDD* indicator is 0.008 and significant at the 5% level. The economic magnitude is also sizeable: the adoption of the IDD leads to an increase in the firm's likelihood of being acquired by approximately 0.8 percentage points, relative to the unconditional probability of 5 percentage points (i.e., an increase of 16%).[8]

Our *IDD* indicator variable captures both the recognition of the IDD (the most frequent event that dominates our sample) and the three rejections of the IDD by states that had recognized the IDD in prior years. We then separately study the impact of adoptions and rejections of the IDD on the likelihood of being acquired. In column (4), we replace the *IDD* indicator with the *IDD adoption* indicator, which equals one after the IDD is adopted and zero otherwise, and the *IDD rejection* indicator, which equals one after the state reverses its previously adopted IDD and zero otherwise. The coefficient estimate on the *IDD adoption*

[8] It is worth noting that if some of the control variables, such as leverage, are also affected by the IDD, our estimation may be biased (Angrist and Pischke, 2009). However, the coefficient on the *IDD* indicator in column (1) of Table 3 (where we do not control for any firm characteristics) is the same as that in column (3) (where we include a long list of firm characteristics as controls). This result indicates that our results are less likely to suffer from this endogenous controls problem.

indicator is 0.010 and significant at the 5% level, indicating that the adoption of the IDD leads to an increase in the firm's likelihood of being acquired by 1 percentage point. The coefficient estimate on the *IDD rejection* indicator is -0.003 but statistically insignificant. This is probably because such a test is based on only three rejection events and thus has less statistical power (Klasa et al., 2018). Hence, our results are largely driven by the adoption events of the IDD over our sample period.

The validity of a difference-in-differences estimation depends on the parallel trends assumption: absent the IDD, treated firms' likelihood of being acquired would have evolved in the same way as that of control firms. Column (5) presents the pre-trend between the treated group and the control group. The specification follows Atanassov (2013) and Acharya et al. (2014). We re-estimate column (3) by replacing the *IDD* indicator with the six indicator variables: IDD^{-2}, IDD^{-1}, IDD^{0}, IDD^{1}, IDD^{2} and IDD^{3+}. These variables indicate the year relative to the adoption of the IDD. In particular, IDD^{-2} indicates that it is two years before the IDD adoption; IDD^{-1} indicates that it is one year before the IDD adoption; IDD^{0} indicates the year in which the IDD is adopted; IDD^{1} indicates that it is the year after the IDD adoption; IDD^{2} indicates that it is two years after the IDD adoption; IDD^{3+} indicates that it is three or more years after the IDD adoption.[9] We exclude observations in Florida, Michigan, and Texas (the three rejection states) after these states reversed their adoption of the IDD to avoid their effects on the post IDD variables.

The coefficients on the IDD^{-2} and IDD^{-1} indicators are especially important because their significance and magnitude indicate whether there is any difference between the treatment group and the control group prior to the adoption of the IDD. The coefficients on these two indicators are not significantly different from zero, suggesting that the parallel trend assumption of the difference-in-differences approach is not violated. The impact of the IDD starts to show up two years after the adoption: the coefficients on the IDD^{2} and IDD^{3+} indicators become significantly positive. Overall, Table 3 shows that the IDD leads to a significant increase in firms' likelihood of being acquired.

[9] We do not include the indicator IDD^{-3+} (an indicator variable to flag three or more years prior to the IDD adoption) in column (5), because the sum of IDD^{-3+}, IDD^{-2}, IDD^{-1}, IDD^{0}, IDD^{1}, IDD^{2}, and IDD^{3+} equals one (there will be the multicollinearity problem if we include all these seven indicators in the regression). Given that IDD^{-3+} is omitted, the period of IDD^{-3+} serves as the benchmark period in the regression.

5.2 Unobservable Confounding Local Business Conditions

Although we have accounted for *observable* local business conditions in the regression, some *unobservable* local economic shocks may be associated with both the recognition of the IDD and corporate acquisition activities. In this section, we difference away unobservable local business conditions by focusing on treatment firms that are on one side of a state border and their neighboring control firms on the other side of the state border.

In particular, we exploit the discontinuity of the IDD and examine the change in the likelihood of being acquired in the treatment firms on the state border relative to their neighboring control firms. The logic is as follows. Suppose that the IDD is driven by unobserved changes in local business conditions, and that it is these changes (not the IDD) that spur corporate acquisitions in reality. Then both firms in treated states and their neighbors in untreated states just across the state border would spuriously appear to react to the policy changes, because economic conditions, unlike state laws, have a tendency to spill across state borders (Heider and Ljungqvist, 2015). In this case, the change in acquisition likelihood in treated firms should be no different from that in neighboring control firms that are located just across the state border.

To examine this possibility, we match each treated firm with replacement to a control firm that is in the same industry (based on the 2-digit SIC code), is in an adjacent state without recognizing the IDD, and is closest in firm size. Obviously, a treated firm may not necessarily share the same local economic conditions with its control firm in the adjacent state if the treated firm is in the middle of a large state. To alleviate this concern, we further require that the distance between the treated firm and its matched untreated firm be within a certain range (such as 40 to 100 miles). If the distance is beyond this range, we drop this pair from our sample. By doing so, we increase our confidence that our treated firm and control firm are truly close to each other geographically and thus face similar local economic shocks. Then, we re-estimate Equation (1) by focusing on this sub-sample of firms across state borders.

Table 4 presents the results. In column (1), we require that the distance between the treated firm and its neighboring control firm be within 40 miles. This requirement reduces the sample to 19,476 firm-year observations; yet, we still find a positive and significant coefficient on the *IDD* indicator. As a robustness check, we require the distance between the treated firm and its neighboring control firm to be within 50, 60, 80, and 100 miles in columns (2)–(5), respectively; we continue to find that the likelihood of firms being acquired is significantly increased after recognition of the IDD. The magnitude of coefficient on *IDD* ranges from 0.009 to 0.012, which is comparable to that reported in the baseline regression in column (3) of Table 3 (0.008). Overall, these results suggest that unobserved local business conditions are unlikely to drive our results.

5.3 The IDD and State-level Acquisition Intensity

In this section, we examine the effect of the IDD on the aggregate state-level M&A activity. Specifically, following Dessaint et al. (2017), we aggregate deal numbers and deal volumes at the state level, and examine the effect of the IDD on deal numbers and volumes in treated states relative to the control states. Although we only focus on public firms in our baseline firm-level analysis, state-level analyses allow us to examine both public and private targets.

The sample is based on 1,734 state-year observations. We consider all completed acquisition deals where the acquirer owns 100% of the target after acquisition and the deal value is at least $50 million. *Deal number* is the number of firms being acquired in a state, and *Deal volume* is the sum of M&A deal value in which the state's firms are acquired. In columns (1) and (2), we focus on public target firms; in columns (3) and (4) we focus on private target firms. Following our baseline regression, we control for time-varying state characteristics, *Region* × *Year FE* and *State FE*. The coefficients on *IDD* are positive and significant at the 5% or 1% level in all columns, indicating that the IDD increases firms' likelihood of being acquired at the aggregate state level.

5.4 Triple Difference-in-differences Tests

To provide further evidence that the effects of the IDD on acquisitions are tied to the human capital mechanism, in this section we implement triple difference-in-differences tests to examine the heterogeneous treatment effects.

First, if the enhanced likelihood of a firm being acquired after the IDD adoption is due to bidding firms' desire to acquire human capital, we expect this treatment effect to be stronger for target firms that possess more human capital. Following Coff (2002), we measure human capital intensity as the number of knowledge workers as a proportion of all workers in the industry. We obtain employment data from the Integrated Public Use Microdata Series database (IPUMS-USA, see Ruggles et al., 2010). Based on the IPUMS occupational codebook, we define knowledge workers to be those with an occupational code (1990 basis) below 200. This definition includes occupations such as managers, scientists, engineers, computer programmers, IT professionals, and so forth. The IPUMS provides Current Population Survey (CPS) data on individual workers' occupational code, industry, state, etc., on an annual basis. From the IPUMS CPS data, we calculate the proportion of knowledge workers in the total workforce for a given 2-digit SIC industry in a given year, and then assign that measure to each focal firm in our sample.[10] We then define the *High human capital intensity* indicator as one if the proportion of knowledge workers among all workers is above the sample median, and zero otherwise. We re-estimate Equation (1) by adding the interaction term of *IDD* × *High human capital intensity* and the *High human capital intensity* indicator.

Table 6 column (1) presents the results. The coefficient on *IDD* × *High human capital intensity* is 0.012 and significant at the 5% level, while the coefficient on the *IDD* indicator is 0.003 and statistically insignificant. This indicates that the treatment effect is significant for firms with a high level of human capital, and is virtually absent for firms with little human capital.

[10] The CPS data does not provide SIC industry information directly, so we manually link the 1990 industry code to 2-digit SIC code. The five industries with the highest human capital intensity are Educational Services, Legal Services, Membership Organizations, Social Services, and Real Estate. The five industries with the lowest human capital are Agricultural Production – Livestock, Apparel and Accessory Stores, General Merchandise Stores, Automotive Dealers & Service Stations, and Agricultural Production – Crops.

Second, human capital is particularly important for high R&D industries (Zingales, 2000). Thus, we expect the treatment effects to be stronger for high R&D industries. We define a *High R&D* indicator as one if the industry level R&D expenditure is above the sample median, and zero otherwise. We then re-estimate Equation (1) by adding the interaction term of *IDD* × *High R&D* and the *High R&D* indicator. The coefficient on *IDD* × *High R&D* is positive and significant at the 5% level, while the coefficient on *IDD* indicator itself is not significantly different from zero. This result indicates that the treatment effect is significant for high R&D firms, whereas it is virtually absent in low R&D firms.

Considering that the impact of the IDD on a firm's likelihood of being acquired is due to increased labor market frictions to hire talent directly, we expect the treatment effects to be stronger for firms whose employees have higher *ex ante* mobility in the labor market.

Oyer and Schaefer (2005) and Aldatmaz et al. (2018) argue that employee stock options help retain employees. Hence, employees with low stock options are expected to have higher mobility in the labor market (i.e., these employees are more likely to switch jobs *ex ante*), and we expect the treatment effect to be more pronounced for those firms whose employees have a lower level of employee stock options.

We first follow Call et al. (2016) to calculate the value of a firm's annual employee stock option grant.[11] Next, considering that unvested stock options are particularly effective in retaining employees and that the typical vesting period for employee options is three years (Crimmel and Schildkraut, 2001; Oyer and Schaefer, 2005), we then calculate a firm's unvested employee option grant as the sum of the value of employee options granted in the current and previous year scaled by the book value of total assets. Then, we define the *Low option grant* indicator as taking the value of one if the firm's unvested employee stock option grant is below the sample median, and zero otherwise. We re-estimate Equation (1) by adding the

[11] Specifically, starting in 2004, Compustat started to report the fair value of employee stock options granted (data item: OPTFVGR). Thus for the period 2004–2013, we directly obtain the data from Compustat. For the period 1992–2003, we infer this value from ExecuComp. ExecuComp reports the value of options granted to each top executive both as the dollar value (data item: BLKSHVAL) and as the percentage among all employee option grants (data item: PCTTOTOPT). From each executive's record, we infer the firm's total value of employee options as BLKSHVAL divided by PCTTOTOPT. We then use the average inferred value obtained from the top-five executives as the value of the firm's annual employee stock options granted. Since ExecuComp starts in 1992, the sample period for this test is 1993–2013.

interaction term of *IDD* × *Low option grant* and the *Low option grant* indicator. As reported in column (3), the coefficient on *IDD* × *Low option grant* is positive and significant at the 5% level, while the coefficient on the *IDD* indicator itself is not significantly different from zero. This result indicates that the treatment effect is significant for firms with a low level of unvested employee stock options (whose employees are more likely to switch jobs *ex ante*), whereas it is virtually absent for firms with a high number of unvested employee option grants.

Lastly, Deng and Gao (2013) and Gao et al. (2015) show that employees have better employment mobility when there are a large number of industry peer firms available in the local labor market. Following their studies, we use the number of firms in the same 2-digit SIC industry and same state as another proxy for the *ex ante* labor market mobility. We expect the treatment effect to be stronger when there are a large number of industry peer firms nearby. To examine this prediction, we define the *Many rivals* indicator as one if the number of firms in the same industry and same state is above the sample median, and zero otherwise. In column (4), we re-estimate Equation (1) by adding the interaction term of *IDD* × *Many rivals* and the *Many rivals* indicator. The coefficient on *IDD* ×*Many rivals* is positive and significant at the 10% level, while the coefficient on *IDD* is not significantly different from zero. This result indicates that the treatment effect is significant for firms surrounded by many industry peers (and thus their employees are more likely to switch jobs *ex ante*), whereas it is virtually absent for firms surrounded by few industry peers.

Taken together, the effects of the IDD on a firm's likelihood of being acquired are stronger for firms with greater human capital, and for firms whose employees have better employment mobility *ex ante*. These results suggest that obtaining human capital via M&As is likely the mechanism through which a state's recognition of the IDD influences its local firms' likelihood of being acquired.

5.5 Cross-industry vs. Within-industry Acquisitions

In this section, we differentiate between within-industry and cross-industry acquisitions. Within-industry acquisitions are more likely to be driven by economy of scale or cost saving considerations; whereas in cross-industry acquisitions, firms enter new markets, learn new technologies and areas where they do not have pertinent experience or expertise, and thus may particularly value the target's human

capital (Matsusaka,1993; Ranft and Marsh, 2008). For this reason, we expect a stronger treatment effect in cross-industry acquisitions.

In Table 7, we re-estimate Equation (1) by separately examining cross-industry and within-industry acquisitions. In column (1), the dependent variable, *Cross-industry acquisition*, takes a value of one if the target firm is acquired in a cross-industry acquisition (i.e., the acquirer and the target are from different industries), and zero otherwise. The coefficient on *IDD* is 0.007 and significant at the 5% level, indicating that the IDD significantly increases a firm's likelihood of being acquired in cross-industry acquisitions.

In column (2), the dependent variable, *Within-industry acquisition*, takes a value of one if the target firm is acquired in a within-industry acquisition (i.e., the acquirer and the target are from the same industry), and zero otherwise. The coefficient on *IDD* is only 0.001 and is not significantly different from zero. Overall, Table 7 shows that our treatment effect is mainly driven by cross-industry acquisitions, which is consistent with the view that IDD-related acquisitions are for a human capital purpose.

5.6 More Evidence on Post-Acquisition Human Capital Retention

To provide evidence that the IDD indeed increases the retention of target firms' human capital in the post-acquisition period, we conduct additional analyses in Table 8. In order to track target firms' employees, we focus on completed acquisition deals in which the acquirer owns 100% of the target firm after the acquisition deal and in which both the target and the acquirer are in the CRSP-Compustat merged database for all tests in this section.

First, we examine the retention of target firms' inventors after an acquisition is completed. Inventors produce patents and thus can be regarded as one group of key technicians in a firm. We collect individual inventor data from the Harvard Business School Patent Dataverse, which provides information on both inventors (i.e., employees who produce the patents) and assignees (i.e., companies that own the patents). We can thus track the employment records of inventors in the target firms during the post-acquisition period. Our inventor data is available from 1976 to 2013. To ensure that we can track the employment of the target firms' inventors before and after the acquisition, we restrict our selection to acquisition deals announced from 1981 to 2008 (five years after the start and five years before the ending

of our data period). We identify a total of 20,282 inventors who work for the target firms before the acquisition, and define the dependent variable *Innovator retained* as an indicator variable that equals one if the inventor is retained and works for the acquirer after the acquisition, and zero otherwise.[12] We exclude inventors whose residential state differs from the target firm's headquarters. The regression specification is a linear probability model, and we control for bidder characteristics, target characteristics, deal characteristics and a set of fixed effects.[13] The *IDD* indicator variable takes the value of one if the target firm's headquarters is located in a state that has the IDD in place at the time of the acquisition, and zero otherwise. The mean value of *Innovator retained* is 0.13, which means, on average, 13% of the inventors in the target firm are retained and continue to work for the acquirer after the deal.

Column (1) reports the result. The coefficient on the *IDD* indicator is 0.064 and significant at the 5% level, indicating that the IDD is associated with a higher likelihood of target firms' inventors being retained by 6 percentage points, as compared to the unconditional probability of 13 percentage points. If the acquisition associated with the IDD is driven by acquiring human capital from the target firm, the inventor retention likelihood should be even higher for more productive inventors. To examine this prediction, we measure an inventor's productivity using the number of patents she produces during five years prior to the acquisition. In column (2), we additionally control for *Ln (Past 5 year patent)* and its interaction term with *IDD*, where *Ln (Past 5 year patent)* is the natural logarithm of the total number of patents the inventor produced within 5 years prior to the acquisition. The coefficient on the interaction term, *IDD* × *Ln (Past 5 year patent)*, is positive and significant at the 5% level, which indicates that the positive relation between the IDD and the likelihood of an inventor being retained is more pronounced for more productive inventors.

[12] We identify an inventor as "working for the target before the acquisition" if the inventor has filed at least one patent in the target firm within five years prior to the acquisition. Similarly, we identify an inventor as "working for the acquirer after the acquisition" if the inventor has filed at least one patent in the acquiring firm within five years after the acquisition.

[13] Bidder (target) characteristics include bidder's (target's) size, asset tangibility, sales growth, leverage, R&D expenditures, ROA, and Tobin's Q. Deal characteristics include all stock payment indicator, friendly deal indicator, and tender offer indicator. We also include target state fixed effects, bidder state fixed effects, target industry fixed effects, bidder industry fixed effects, and year fixed effects.

It is worth noting that there are certain limitations to the above test. First, the variable *Innovator retained* requires an inventor to file a new patent within five years after the acquisition; for this reason, it could be picking up higher research productivity at the new firm rather than just retention. Second, trade secrets and patents may work as substitutes (Png, 2017a). Since the adoption of the IDD may weaken the need for the external protection of patents, firms may wish to avoid the disclosure and other costs of patent applications (e.g., Dass et al., 2018). To mitigate these limitations, in column (3) we examine the retention of all employees, regardless of whether they file patents or not. Specifically, we focus on the changes in combined total employment before and after the acquisition. As workforce restructuring may persist for several years after the acquisition (Dessaint et al., 2017), we measure post-acquisition employment three years after the acquisition. The dependent variable *Change in combined number of employees* is calculated as the Ln (number of the acquirer's employees three years after the acquisition) − Ln (sum of acquirer's employees and target firm's employees one year prior to the acquisition). We exclude M&A deals in which the acquirer makes multiple acquisitions within such a window. In total, we identify 1,441 acquisition deals with sufficient data to calculate the dependent variable. The regression specification is the same as that in column (1). The coefficient on *IDD* is positive and significant at the 5% level, indicating that the IDD is associated with higher total employee retention.

The test in column (3) also has a limitation in that it does not distinguish between workers who have and who do not have knowledge of trade secrets. To mitigate this shortcoming, in column (4) we examine the retention of top executives of target firms in the post-acquisition period, considering that these executives are likely to know firms' trade secrets. We search the SEC Edgar database for these top executives' personal information, then run an additional search for their employment history in the post-acquisition period to determine how many are retained by the acquirer. As the Edgar database begins its coverage in 1994, we restrict our selection to acquisition deals from 1995 to 2013. We are able to identify and find post-acquisition employment information of 6,230 executives of target firms. The regression specification is the same as that in column (1), except that the dependent variable is *Executive retained*.

This indicator variable takes the value of one if the target's executive is retained by the acquirer after the acquisition, and zero otherwise.[14] The mean value of *Executive retained* is 0.36, which indicates that, on average, 36% of executives from the target firms are retained and continue to work for the acquirer after the deal. The coefficient on the *IDD* indicator is 0.096 and significant at the 5% level, indicating that the IDD is associated with a higher likelihood of target firms' executives being retained by 9.6 percentage points, as compared to the unconditional probability of 36 percentage points. Although none of the above tests alone are perfect, together they provide some supporting evidence that the IDD is associated with greater retention of target firms' human capital.

5.7 Market Valuation and Post-Acquisition Performance

In this section, we examine the valuation effect of IDD-related acquisitions. In particular, we focus on the combined announcement CAR (a proxy to measure the synergy), the target firm's CAR, the acquirer's CAR, the acquirer's long-run buy-and-hold stock return after the acquisition, and the acquirer's operating performance after the acquisition.

If IDD-related acquisitions are motivated to overcome labor market frictions and gain access to valuable human capital, they are likely associated with positive valuation effects. In column (1) of Table 9, we measure synergy using the combined announcement CAR. The dependent variable *Combined CAR3* is the weighted average of the target and the acquirer's three-day cumulative abnormal returns around the deal announcement. Following standard event study methods, the abnormal returns are estimated based on the market model using CRSP value-weighted index returns. The parameters are estimated within an (−200, −60) event window relative to the announcement date. The weights are the market values of the target and the bidder two days prior to the announcement.

The *IDD* indicator variable takes the value of one if the target firm's headquarters is located in a state that has the IDD in place at the time of the acquisition, and zero otherwise. The coefficient estimate

[14] Our definition of target firms' executives includes the Chairman of the Board and all executive officers listed in the target firms' annual reports, proxy statements, and other documents filed with the SEC one year prior to the deal announcement. Executives above the age of 65 are excluded to avoid potential effects of retirement. Executives who work for the merged entity on a temporary basis (shorter than one year) are not considered as retained.

on the *IDD* indicator is 0.004 and is significant at the 10% level, indicating that the IDD is associated with a larger synergy of 0.4 percentage points relative to the sample average synergy of 1.6 percentage points. This result suggests that the IDD is associated with greater synergy creation.

In column (2), the dependent variable is *Target CAR3* and the coefficient estimate on *IDD* is 0.010 but statistically insignificant, implying that the IDD is not associated with a higher announcement return for the target firm. A possible explanation is as follows. Klasa et al. (2018) show that firms experience positive abnormal returns when their state adopts the IDD. Thus, it is possible that the price of the "increased protection" or "increased difficulty for key employees to move" has already been reflected in the target firms' valuation prior to the acquisition rather than reflected in target firms' announcement returns.

In column (3), the dependent variable is *Bidder CAR3* and the coefficient on *IDD* is 0.004 and significant at the 5% level. This result indicates that IDD-related acquisitions create value for the acquirers, as these firms overcome labor market frictions and obtain desired human capital via acquisitions. Considering that the average market capitalization of the acquirer is 10.3 billion dollars, the IDD is associated with an increase of 41.2 million dollars (=0.004×10.3 billion) for the acquirer.

In column (4), we further examine the acquirer's long-run buy-and-hold abnormal return. The dependent variable *Bidder BHAR3* is calculated by subtracting the compound return of the CRSP value-weighted market index from the compound return of the bidder firm over the three-year period following the acquisition. The coefficient estimates on *IDD* is positive and significant, indicating that IDD-related acquisitions create value for acquirers in the long run.

In Table 10, we further examine acquiring firms' innovation activity and operating performance following an acquisition. Specifically, following the standard difference-in-differences test design in event studies as employed by Hong, Hung, and Lobo (2014) and Seru (2014), we investigate the change in acquirers' innovation activity and operating performance from five years before to five years after the acquisition. *Post-Acquisition* is an indicator variable that takes the value of one if it is in the post-acquisition period, and zero otherwise. The *IDD* indicator is not included in the regression because we control for deal

fixed effects. The coefficient estimate on *Post-Acquisition × IDD* captures the treatment effect of acquiring an IDD target compared to that of acquiring a non-IDD target.

In Table 10 columns (1) and (2), we examine combined firms' innovation output (measured by the number of patents and patent citations) before and after an acquisition. We obtain patent and citation information from the USPTO Patentsview database, and use the application year of a patent as the time of its invention to measure a firm's innovation output (Hall et al., 2005). In column (1), the dependent variable is *Ln (1+ Patent)*. For the period before the acquisition, *Patent* is the sum of patents applied for (and subsequently awarded) by the acquirer and the target; for the period after the acquisition, *Patent* is the number of patents applied for (and subsequently awarded) by the combined firm. The dependent variable in column (2) is *Ln (1+ Citation)*. For the period before the acquisition, *Citation* is the sum of citation counts received by patents applied for by the acquirer and the target; for the period after the acquisition, *Citation* is the citation counts received by patents applied for by the combined firm. We follow Hall et al. (2005) to adjust for the duration of patent citations by technology classes. The coefficients on *Post-Acquisition* are negative and significant, consistent with Seru's (2014) findings that acquirers experience a decrease in innovation after the acquisition. In both columns, the coefficients on *Post-Acquisition × IDD* are positive and significant, and are of similar magnitudes to those on the *Post-Acquisition* indicator, indicating that the IDD partially (if not fully) limits the negative effect of acquisitions on innovation.

In column (3), the dependent variable is *ROA*. For the period before the acquisition, *ROA* is the weighted average ROA based on the acquirer's and target's total assets; for the period after the acquisition, *ROA* is the ROA of the combined firm. The coefficient on *Post-Acquisition × IDD* is positive and significant, indicating that the IDD is associated with better operating performance of acquiring firms in the post-acquisition period. Overall, Table 10 suggests that human capital-driven acquisitions lead to greater innovation outputs and better operating performance for the acquiring firms.

Finally, we shed light on how acquirers utilize the human capital they obtained from the target firm. One possibility is that acquirers explore complementarity and foster more collaboration between their

employees and their target firm's employees.[15] It is usually difficult to observe employee activity using publicly available data. To proxy for employee collaboration, we examine the patents coproduced by inventors previously from the target firm and inventors previously from the acquirer. We investigate whether targets' and acquirers' inventors cooperate more after IDD-related acquisitions. In Table 11 column (1), the dependent variable *Number of co-invented patents* is the number of the acquirer's patents co-invented by both the target and acquiring firms' inventors scaled by the acquirer's total number of patents within three years after the acquisition. The coefficient on *IDD* is positive and significant at the 5% level, indicating that the IDD is associated with greater collaboration between employees who formerly worked for the two separate organizations. In column (2), the dependent variable *Citations to co-invented patents* is the number of citations of these co-invented patents scaled by the acquirer's total number of patent citations within three years after acquisition. We also find a positive and significant coefficient on the *IDD* indicator.

Notably, considering that trade secrets likely work as a substitution for patents, using patenting activities may underestimate the collaboration of the target's and acquirer's employees. Nonetheless, Table 11 provides some suggestive evidence that in human capital-driven acquisitions, acquirers explore complementarity and foster more collaboration between targets' employees and their own employees as a way of deploying the obtained human capital.

5.8 Robustness Check and Additional Investigation

First, due to data availability, we focus on Compustat firms in this article. Many firms in Compustat may have a large workforce, and it may be costly to take over an entire firm with its workforce and physical assets simply to obtain key employees. A more suitable sample for our test might be small firms. However, using Compustat firms should have worked against us in regard to finding a significant effect of the IDD on firms' likelihood of being acquired. That is, the effect of the IDD reported in this study is likely

[15] We thank an anonymous referee for suggesting this test. Another possible way for acquirers to utilize targets' human capital is that acquirers deploy the targets' employees to develop new products or new technologies that represent a departure from the targets' previous strategies. However, due to data limitations, we are unable to directly test this prediction. This could be an interesting question for future research.

underestimated. In Table IA1 of the Internet Appendix, we examine whether our finding is stronger for smaller firms (among Compustat firms, some are relatively smaller than others). Specifically, we use the book value of total assets, market value of total assets, sales, and number of employees to measure firm size. In all columns, the coefficients on the interaction term between the IDD and firm size measures are negative and significant. This result indicates that the IDD's effect is indeed stronger for smaller firms.

Second, the IDD is enforceable only at a physical worksite rather than at a firm's headquarters. Such measurement errors might bias the results. As reported in Table IA2 of the Internet Appendix, we conduct a robustness check by focusing on a sample of small firms headquartered in the central area of a certain state. For this type of firm, the firm's physical worksite is more likely to be in the same state as the firm's headquarters, as Chen, Harford, and Lin (2017) suggest that small firms usually have worksites concentrated in one area. In particular, we restrict our focus to the subsample of firms whose size is below the sample median and whose headquarters are at least 50 miles, 100 miles, 150 miles, or 200 miles away from state borders in columns (1) to (4) of Table IA2, respectively. We re-estimate Equation (1) and find that our inference is unchanged.

Third, the last state that adopted the IDD was Kansas in 2006, and the M&A activity observed post-crisis might be driven by other motives. As a robustness check, we restrict the sample period to before 2007 and re-estimate Equation (1). As reported in Table IA3 of the Internet Appendix, our inference is unchanged.

Fourth, as CNCs have been shown empirically to reduce employee mobility (Garmaise, 2011; Jeffers, 2017), we would expect to see a similar effect on firms located in states that enforce CNCs. However, we do not find a significant effect of the CNC index on the likelihood of a firm being acquired in Table 3, which is probably because we control for firm fixed effects and there is little within-firm variation in the CNC index from Garmaise (2011).[16] However, Jeffers (2017) shows that CNC enforcement changes more frequently after 2009. We thus utilize her data and empirically explore whether the changes in CNC enforcement also affect the likelihood of a firm being acquired. Following Jeffers (2017), we define *Jeffers'*

[16] Over our sample period, only three states experienced any changes in the CNC enforcement index.

CNC as an indicator variable that equals one if there is an increase in CNC enforceability relative to the 2008 level, and zero otherwise. In Table IA4 of the Internet Appendix, we re-estimate Equation (1) for the period 2008–2014 and replace the *IDD* indicator with the *Jeffers' CNC* indicator. As shown in column (3) of Table IA4, the coefficient on *Jeffers' CNC* is positive and significant, indicating that an increase in a state's CNC enforcement leads to a higher likelihood of firms being acquired in that state.

Fifth, the Uniform Trade Secrets Act (UTSA) also provides better trade secret protection by expanding the definition of trade secrets (Png, 2017b). However, UTSA does not limit labor mobility directly: Png (2012) shows that inventor mobility is not affected by the enactment of UTSA. Nonetheless, it is an interesting empirical question to investigate: Does a state's adoption of UTSA also make the state's local firms more susceptible to acquisition? We re-estimate Equation (1) by replacing the *IDD* indicator with the *UTSA* indicator. As reported in Table IA5, we do not find any significant effect of UTSA on a firm's likelihood of being acquired. This result suggests that it is reduced labor mobility, instead of mere trade secret protection, that affects acquisition activities.

Sixth, so far we have focused on completed acquisition deals, in which the acquirer owns 100% of the target firm after the acquisition. As a robustness check, we include all announced deals (no matter if they are completed or not) and our inference is unchanged (see column (1) of Table IA6). Moreover, we also include all completed partial or full acquisitions (i.e., the acquirer does not necessarily own 100% of the target firm), and our inference is unchanged (see in column (2) of Table IA6). For mergers of equals, information about "the target firm" collected from SDC may be less accurate. In column (3) of Table IA6, we re-estimate Equation (1) by removing all mergers of equals (i.e., the book value of total assets of target firms is within [90%, 110%] of that of acquirers prior to the deal announcement). Our inference is unchanged. In column (4) of Table IA6, we conduct a robustness check based on a conditional logit regression. Specifically, for each target firm, we match it to a hypothetical target firm that is in the same industry, that is closest in firm size in the year prior to the acquisition, and that has not been acquired within five years around the acquisition of the true target firm. Using both the actual target firms and their matched hypothetical control firms, we run a conditional logit regression. The dependent variable takes the value of

one if the actual target firm is acquired in a given year, and zero otherwise; the independent variables are the ones used in column (3) of Table 3 (but firm fixed effects are dropped as we no longer have panel data). We continue to find a positive and significant coefficient on the *IDD* indicator.

Seventh, the IDD might affect overall acquisition intensity in treated states (i.e., not only the likelihood of being acquired but also the likelihood of making acquisitions). If so, it would not be surprising to observe an effect on the probability of being a target, as acquisitions might concentrate geographically. To investigate this possibility, we examine whether the likelihood of being an acquirer also increases following the adoption of the IDD. The regression specification is the same as that in column (3) of Table 3, except that we use different dependent variables. In column (1) of Table IA7, the dependent variable *Acquirer* is an indicator variable, which takes the value of one if the firm makes at least one acquisition in a given year, and zero otherwise. In column (2), *Number of acquisition deals* is the number of acquisitions the firm makes in a given year. In column (3), *Acquisition value* is the sum of transaction values the firm makes in a given year scaled by the firm's book value of total assets. The coefficient on the *IDD* indicator is not significantly different from zero across all three columns, indicating that the IDD does not have any significant effect on local firms' propensity of being an acquirer. Thus, our main results are unlikely due to an increase in the overall acquisition intensity following the state's adoption of the IDD.

Eighth, as shown in column (2) of Table 9, the IDD has no effect on a target firm's premium (measured by target CAR3). In Table IA8, we conduct a robustness check on this test by using three alternative measures of target premium. Specifically, following Bargeron et al. (2008) and Officer et al. (2010), we measure acquisition premiums using *Premium BHAR* (targets' accumulative abnormal return during trading day (−43, +126) around the deal announcement), *Premium 4 week* (the percentage difference between the offer price and the target share price four weeks prior to the announcement), and *Deal value to sales* (the ratio of deal value to target sales). Similar to the results in column (2) of Table 9, we do not find any significant relation between the IDD and target premiums.

6. Conclusions

In this paper, we investigate whether obtaining human capital is an important motivation for corporate acquisitions, by exploiting exogenous shocks from the staggered recognition of the Inevitable Disclosure Doctrine (IDD) by U.S. state courts. The recognition of this doctrine (1) increases the cost for the acquirer to directly poach the target firm's employees from the labor market, (2) decreases the likelihood of departure of the target firm's employees following the acquisition's completion, and (3) enhances the value of the target firm's intangible assets (which is inseparably linked with human capital), which makes the target firms more attractive to potential acquirers. Thus, we predict that a state's recognition of the IDD could increase the likelihood of being acquired for firms in that state.

Consistent with this prediction, we find a significant increase in the likelihood of being acquired for firms in states that recognize the IDD, relative to firms in states that do not. In support of a causal interpretation of our findings, our timing test indicates that the firm's likelihood of being acquired changes after the recognition of the IDD. Further examination of treated firms and their neighboring untreated firms across the state border indicate that our results are unlikely driven by unobserved local confounding factors. Further, we present cross-sectional variations in the treatment effect, suggesting that the treatment effect is related to obtaining human capital in the labor market: the treatment effect is more pronounced for firms with greater human capital and for firms whose employees have better employment mobility *ex ante*. We also find that the IDD is positively associated with the retention of target firms' key technicians, employees, and top executives, indicating that our main finding is indeed tied to obtaining target firms' human capital. Finally, we show that the IDD is positively associated with synergy creation, acquirers' announcement returns, and acquirers' long-run stock and operating performance after the acquisitions, suggesting that human capital-driven acquisitions create value for acquirers. Overall, our findings are consistent with the view that corporate acquisitions can be used as an effective means for firms to overcome labor market frictions and gain access to valuable human capital.

Reference

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

Aldatmaz, Serdar, Paige Ouimet, and Edward D. Van Wesep, 2018. The option to quit: The effect of employee stock options on turnover. *Journal of Financial Economics* 127, 136-151.

Alimov, Azizjon, 2015. Labor market regulations and cross-border mergers and acquisitions, *Journal of International Business Studies* 46, 984-1009.

Angrist, Joshua, and Jorn-Steffen Pischke, 2009. Mostly harmless econometrics: An empiricist's companion, Princeton University Press.

Ashkenas, Ronald, DeMonaco Lawrence, and Suzanne Francis, 1998. Making the deal real: How GE capital integrates acquisitions, *Harvard Business Review* 76, 165-176.

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

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

Bai, John Jianqiu, Douglas Fairhurst, and Matthew Serfling, 2020. Employment protection, investment, and firm Growth, *Review of Financial Studies* 33, 644-688.

Bargeron, Leonce, Frederik Schlingemann, Rene Stulz, and Chad Zutter, 2008. Why do private acquirers pay so little compared to public acquirers? *Journal of Financial Economics* 89, 375-390.

Breschi, Stefano, 2008. Innovation-specific agglomeration economies and the spatial clustering of innovative firms, Handbook of research on innovation and clusters 167-192.

Buchholtz, Ann, Barbara Ribbens, and Irene Houle, 2003. The role of human capital in post-acquisition CEO departure, *Academy of Management Journal* 46, 506-514.

Call, Andrew C., Simi Kedia, and Shivaram Rajgopal, 2016. Rank and file employees and the discovery of misreporting: The role of stock options. *Journal of Accounting and Economics* 62, 277-300.

Chatt, Robert, Matthew Gustafson, and Adam Welker, 2017. Firing frictions and the US mergers and acquisitions market, Tulane University working paper.

Chen, Tao, Jarrad Harford, and Chen Lin, 2017. Financial flexibility and corporate cash policy, Nanyang Technological University working paper.

Coff, Russell, 2002. Human capital, shared expertise, and the likelihood of impasse in corporate acquisition, *Journal of Management* 28, 107-128.

Crimmel, Beth Levin, and Jeffrey L. Schildkraut, 2001. Stock option plans surveyed by NCS, *Compensation and Working Conditions* 6, 3-21.

Dass, Nishant, Vikram K. Nanda, and Steven Chong Xiao, 2018. Intellectual property protection and financial markets: Patenting vs. secrecy, Georgia Institute of Technology working paper.

Deng, Xin, and Huasheng Gao, 2013. Nonmonetary benefits, quality of life, and executive compensation, *Journal of Financial and Quantitative Analysis* 48, 197-218.

Dessaint, Olivier, Andrey Golubov, and Paolo Volpin, 2017. Employment protection and takeovers, *Journal of Financial Economics* 125, 369-388.

Gao, Huasheng, Juan Luo, and Tilan Tang, 2015. Effects of managerial labor market on executive compensation: Evidence from job-hopping, *Journal of Accounting and Economics* 59, 203-220.

Garmaise, Mark, 2011. Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment, *Journal of Law, Economics & Organization* 27, 376-425.

Giroud, Xavier, and Holger Mueller, 2010. Does corporate governance matter in competitive industries? *Journal of Financial Economics* 95, 312-331.

Godfrey, Eleanore, 2004. Inevitable disclosure of trade secrets: Employee mobility v. employer's rights, *Journal of High Technology Law* 3, 161-179.

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

Harris, Jonathan, 2000. The doctrine of inevitable disclosure: A proposal to balance employer and employee interests, *Washington University Law Review* 78, 325-345.

Heider, Florian, and Alexander Ljungqvist, 2015. As certain as debt and taxes: Estimating the tax sensitivity of leverage from exogenous state tax changes, *Journal of Financial Economics* 118, 684-712.

Hong, Hyun A, Mingyi Hung, and Gerald Lobo, 2014. The impact of mandatory IFRS adoption on IPOs in global capital markets, *The Accounting Review* 89, 1365-1397.

Howells, Jeremy, 2009. The location and organization of research and development: New horizons, *Research Policy* 19, 133-146.

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

Jeffers, Jessica, 2017. The impact of restricting labor mobility on corporate investment and entrepreneurship, University of Chicago working paper.

John, Kose, Anzhela Knyazeva, and Diana Knyazeva, 2015. Employee rights and acquisitions, *Journal of Financial Economics* 118, 49-69.

Klasa, Sandy, Hernan Ortiz-Molina, Matthen Serfling, and Shweta Srinivasan, 2018. Protection of trade secrets and capital structure decisions, *Journal of Financial Economics* 128, 266-286.

Kogut, Bruce, and Udo Zander, 1992. Knowledge of the firm, combinative capabilities and the replication of technology, *Organization Science* 3, 383-397.

Kugler, Adriana, and Gilles Saint-Paul, 2004. How do firing costs affect worker flows in a world with adverse selection? *Journal of Labor Economics* 22, 553-584.

Lancaster, Tony, 2000. The incidental parameters problem since 1948, *Journal of Econometrics* 95, 391-414.

Malsberger, Brian, 2004. Covenants not to compete: a state-by-state survey, *Bloomberg BNA.*

Matsusaka, John G, 1993. Takeover motives during the conglomerate merger wave, *The RAND Journal of Economics*, 357-379.

Officer, Micah, Oguzhan Ozbas, and Berk Sensoy, 2010. Club deals in leveraged buyouts, *Journal of Financial Economics* 98, 214-240.

Ouimet, Paige, and Rebecca Zarutskie, 2016. Acquiring labor, University of North Carolina working paper.

Oyer, Paul, and Scott Schaefer, 2005. Why do some firms give stock options to all employees? An empirical examination of alternative theories, *Journal of Financial Economics* 76, 99-133.

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

Png, Ivan PL 2012. Trade secrets, non-competes, and inventor mobility: Empirical evidence, *Academy of Management Proceedings* 1, 15945.

Png, Ivan PL, 2017a. Secrecy and patents: Theory and evidence from the Uniform Trade Secrets Act, *Strategy Science* 2, 176-193.

Png, Ivan PL, 2017b. Law and innovation: Evidence from state trade secrets laws. *Review of Economics and Statistics* 99, 167-179.

Qiu, Buhui, and Teng Wang, 2018. Does knowledge protection benefit shareholders? Evidence from stock market reaction and firm investment in knowledge assets, *Journal of Financial and Quantitative Analysis* 53, 1341-1370.

Ranft, Annette, and Michael Lord, 2000. Acquiring new knowledge: The role of retaining human capital in acquisitions of high-tech firms, *Journal of High Technology Management Research* 11, 295-319.

Ranft, Annette L., and Sarah J. Marsh, 2008. Accessing knowledge through acquisitions and alliances: An empirical examination of new market entry, *Journal of Managerial Issues*, 51-67.

Roberts, Michael, and Toni Whited, 2013. Endogeneity in empirical corporate finance, in George Constantinides, Milton Harris, and Rene Stulz, eds. Handbook of the Economics of Finance Volume 2, Elsevier.

Ruggles, Steven, Trent Alexander, Katie Genadek, Ronald Goeken, Matthew Schroeder, and Matthew Sobek, 2010. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota.

Seru, Amit, 2014. Firm boundaries matter: Evidence from conglomerates and R&D activity, *Journal of Financial Economics* 111, 381-405.

Song, Moon, and Ralph Walkling, 2000. Abnormal returns to rivals of acquisition targets: A test of the acquisition probability hypothesis, *Journal of Financial Economics* 55, 143-171.

U.S. Chamber of Commerce, 2014. The case for enhanced protection of trade secrets in the trans-pacific partnership agreement.

Zingales, Luigi, 2000. In search of new foundations, *Journal of Finance* 55, 1623-1653.

Appendix. Variable Definitions

Variable	Definition
Acquisition	Indicator variable which equals one if the firm is acquired in an M&A deal in a given year, and zero otherwise.
Bidder BHAR3	Bidder's three year buy-and-hold abnormal return, calculated by subtracting the compound return of the CRSP value-weighted market index from the compound return of the bidder firm over the three-year period after the deal announcement.
Bidder CAR3	Acquirer's cumulative abnormal return during trading day (−1, +1) around the deal announcement.
Business combination laws	Indicator variable which equals one if a state has adopted the business combination laws, and zero otherwise.
Change in combined number of employees	Calculated as Ln (number of the acquirer's employees three years after the acquisition) — Ln (sum of acquirer's employees and target's employees one year prior to the acquisition).
Combined CAR3	Weighted average of the target and the bidder cumulative abnormal returns during trading day (−1, +1) around the deal announcement. The weights are the market values of the target and the bidder two days prior to the announcement.
Cross-industry acquisition	Indicator variable which equals one if the firm is acquired by a bidder from a different industry in a given year, and zero otherwise.
Citation	Sum of citation counts received by patents applied for by the acquirer and the target.
Citations to co-invented patents	Number of citations to co-invented patents scaled by the total number of citations to patents applied for by the acquirer within three years after acquisition.
CNC index	Index constructed by Garmaise (2011), indicating state enforceability of covenants not to compete (CNCs).
Deal number	Number of firms being acquired in the state.
Deal volume	Sum of M&A deal value (in billion dollars) in which the state's firms are acquired.
Excess return	Difference between a firm's annual return and the annual return of CRSP value-weighted market index.
Executive retained	Indicator that takes the value of one if the executive is retained by the acquirer after the acquisition, and zero otherwise.
Fixed assets	Book value of property, plant, and equipment divided by the book value of total assets (Compustat Item: PPENT/AT).
High human capital intensity	Indicator variable which equals one if the fraction of knowledge workers among all workers in the firm's industry is above the sample median, and zero otherwise.
High R&D	Indicator variable which equals one if the average R&D expense scaled by book value of assets in the firm's industry is above the sample median, and zero otherwise.
IDD	Indicator variable which equals one if the state recognizes the IDD, and zero otherwise.
IDD adoption	Indicator variable which equals one beginning the year when the state first recognizes the IDD, and zero otherwise.
IDD rejection	Indicator variable which equals one after the state reverses its previously adopted IDD, and zero otherwise.

Innovator retained	Indicator that takes the value of one if the inventor is retained by the acquirer after the acquisition, and zero otherwise
Leverage	Book value of long-term debt divided by the book value of total assets (Compustat Item: DLTT/AT).
Low option grant	Indicator variable which equals one if the firm's unvested employee stock option grant is below the sample median, and zero otherwise.
Many rivals	Indicator variable which equals one if the number of firms in the same industry and same state is above the sample median, and zero otherwise.
Number of co-invented patents	Number of patents applied for by the acquirer and co-invented by target's and acquirer's inventors within three years after acquisition scaled by the total number of patents applied for by the acquirer during the same period.
Patent	Number of patents applied for and subsequently awarded by the firm.
Past 5 year patent	Number of patents the inventor produced within 5 years prior to the acquisition.
Post-Acquisition	Indicator variable which equals one if it is in the post-acquisition period, and zero otherwise.
ROA	Return on assets, measured as net income over book value of total assets (Compustat Item: NI/AT).
R&D	R&D expenditure divided by the book value of total assets (Compustat Item: XRD/AT, missing values of XRD are set to zero).
Sales growth	Percent increase of sales from the previous year (Compustat Item: $SALE_t/SALE_{t-1} - 1$).
State establishment entry	Establishment entry rate in the firm's headquarters state.
State establishment exit	Establishment exit rate in the firm's headquarters state.
State GDP growth	Annual growth rate of the GDP in the firm's headquarters state.
State population	Total population in the firm's headquarters state.
State unemployment rate	Unemployment rate in the firm's headquarters state.
Target CAR3	Target's cumulative abnormal return during trading day (−1, +1) around the deal announcement.
Tobin's Q	Book value of total assets minus book value of equity plus market value of equity, divided by book value of total assets (Compustat Item: (AT-CEQ+PRCC_F×CSHO)/AT).
Total assets	Book value of total assets (Compustat Item: AT).
Within-industry acquisition	Indicator variable which equals one if the firm is acquired by an acquirer from the same industry, and zero otherwise.
Wrongful discharge laws	Indicator variable which equals one if the state recognizes the good-faith exception associated with the wrongful discharge laws, and zero otherwise.

Table 1. List of the Adoption Years of the IDD by State

This table presents the years in which U.S. state courts adopted the Inevitable Disclosure Doctrine (IDD). The data is obtained from Klasa et al. (2018).

State	Adoption Year
New York	1919
Florida	1960 (reversed in 2001)
Delaware	1964
Michigan	1966 (reversed in 2002)
North Carolina	1976
Pennsylvania	1982
Minnesota	1986
New Jersey	1987
Illinois	1989
Texas	1993 (reversed in 2003)
Massachusetts	1994
Indiana	1995
Connecticut	1996
Iowa	1996
Arkansas	1997
Washington	1997
Georgia	1998
Utah	1998
Missouri	2000
Ohio	2000
Kansas	2006

Table 2. Summary Statistics

The sample consists of 123,212 firm-year observations during the 1980−2013 period, obtained from the CRSP-Compustat merged database. All sample firms are U.S. public firms traded on NYSE, AMEX, or NASDAQ. Variable definitions are provided in the Appendix. All dollar values are in 2013 dollars. All continuous variables are winsorized at the 1st and 99th percentiles.

	Mean	Std. Dev	P25	Median	P75
Acquisition	0.05	0.22	0.00	0.00	0.00
IDD	0.45	0.50	0.00	0.00	1.00
Total assets ($million)	3439.50	10.00	119.25	461.67	1926.10
ROA	0.47%	17.13%	0.31%	3.10%	7.21%
Excess return	4.69%	55.90%	-27.40%	-2.72%	24.07%
Tobin's Q	1.80	1.46	1.03	1.29	1.94
Sales growth	19.70%	56.02%	-0.02%	8.91%	23.35%
Leverage	17.14%	18.66%	0.95%	11.22%	27.91%
R&D	3.48%	8.06%	0.00%	0.00%	2.96%
Fixed assets	24.92%	24.69%	3.91%	17.09%	38.21%
State population (million)	13.47	10.25	5.45	10.80	19.01
State GDP growth	5.72%	3.29%	3.75%	5.52%	7.65%
Unemployment rate	6.33%	1.99%	4.89%	5.97%	7.54%
State establishment entry	12.04%	2.07%	10.60%	11.80%	13.30%
State establishment exit	10.50%	1.44%	9.50%	10.40%	11.40%
Business combination laws	0.49	0.50	0.00	0.00	1.00
CNC index	0.33	0.18	0.25	0.42	0.42
Wrongful discharge laws	0.27	0.44	0.00	0.00	1.00

Table 3. The Inevitable Disclosure Doctrine and the Likelihood of Being Acquired

This table reports the difference-in-differences tests that examine the impacts of the Inevitable Disclosure Doctrine (IDD) on a firm's likelihood of being acquired. The dependent variable *Acquisition* is an indicator variable, which takes the value of one if the firm is acquired in a given year, and zero otherwise. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. *IDD adoption* is an indicator variable which equals one beginning the year when the state first recognizes the IDD, and zero otherwise. *IDD rejection* is an indicator variable which equals one after the state reverses its previously adopted IDD, and zero otherwise. In column (5), we exclude firm-year observations after IDD rejections. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable =*Acquisition*				
	(1)	(2)	(3)	(4)	(5)
IDD	0.008**	0.008***	0.008**		
	(0.016)	(0.010)	(0.012)		
IDD adoption				0.010**	
				(0.013)	
IDD rejection				-0.003	
				(0.686)	
IDD^{-2}					0.004
					(0.577)
IDD^{-1}					-0.003
					(0.759)
IDD^{0}					0.011
					(0.108)
IDD^{1}					0.007
					(0.196)
IDD^{2}					0.013**
					(0.018)
IDD^{3+}					0.012**
					(0.049)
Ln (Total assets)		-0.001	-0.001	-0.001	-0.001
		(0.533)	(0.535)	(0.530)	(0.673)
ROA		0.008*	0.008*	0.008*	0.008
		(0.077)	(0.076)	(0.077)	(0.105)
Excess return		0.001	0.001	0.001	0.001
		(0.368)	(0.374)	(0.379)	(0.591)
Tobin's Q		-0.009***	-0.009***	-0.009***	-0.009***
		(0.000)	(0.000)	(0.000)	(0.000)
Sales growth		-0.014***	-0.014***	-0.014***	-0.014***

		(0.000)	(0.000)	(0.000)	(0.000)
Leverage		0.011*	0.011*	0.011*	0.010
		(0.091)	(0.092)	(0.090)	(0.139)
R&D		0.075***	0.075***	0.075***	0.076***
		(0.000)	(0.000)	(0.000)	(0.000)
Fixed assets		0.022***	0.022***	0.022***	0.024***
		(0.001)	(0.001)	(0.001)	(0.001)
State GDP growth			0.000	0.000	0.000
			(0.605)	(0.704)	(0.256)
Ln (State population)			-0.002	-0.003	-0.003
			(0.433)	(0.311)	(0.385)
State unemployment rate			-0.001	-0.001	-0.001
			(0.230)	(0.243)	(0.394)
State establishment entry			-0.000	-0.000	-0.002*
			(0.844)	(0.797)	(0.069)
State establishment exit			0.001	0.002	0.001
			(0.271)	(0.259)	(0.336)
Business combination laws			-0.000	0.000	-0.002
			(0.937)	(0.988)	(0.657)
CNC index			-0.017	-0.023	-0.029
			(0.219)	(0.135)	(0.184)
Wrongful discharge laws			0.000	0.001	-0.001
			(0.960)	(0.935)	(0.885)
Constant	0.046***	0.062***	0.093*	0.108**	0.126**
	(0.000)	(0.000)	(0.094)	(0.049)	(0.036)
Region × Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No
Observations	123,212	123,212	123,212	123,212	116,654
R-squared	0.162	0.165	0.165	0.165	0.168

Table 4. Treated Firms and Neighboring Control Firms across State Borders

This table reports the difference-in-differences tests that examine whether the IDD's impacts on a firm's likelihood of being acquired are confounded by unobserved changes in local business conditions. For each treated firm, we match with replacement to a control firm that is in the same industry, in a neighboring state without adopting the IDD, closest in firm size, and the distance between the treated firm and control firm is no more than 40, 50, 60, 80, and 100 miles in columns (1)-(5), respectively. The dependent variable *Acquisition* is an indicator variable, which takes the value of one if the firm is acquired in a given year, and zero otherwise. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable =*Acquisition*				
	(1) Within 40 miles	(2) Within 50 miles	(3) Within 60 miles	(4) Within 80 miles	(5) Within 100 miles
IDD	0.012**	0.010*	0.009*	0.011**	0.010**
	(0.036)	(0.065)	(0.090)	(0.039)	(0.034)
Other control	Same as column (3) of Table 3				
Observations	19,476	20,396	22,295	25,750	29,633
R-squared	0.133	0.132	0.131	0.134	0.135

Table 5. State-level Acquisition Intensity

This table reports the difference-in-differences tests that examine the IDD's impacts on state-level acquisition intensity. The sample is based on 1,734 state-year observations. In columns (1) and (2), we focus on public target firms; in columns (3) and (4), we focus on private target firms. *Deal number* is the number of firms being acquired in a state in a given year. *Deal volume* is the sum of M&A deal value in which the state's firms are acquired. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Public targets		Private targets	
	Ln (Deal number)	*Ln (Deal volume)*	*Ln (Deal number)*	*Ln (Deal volume)*
	(1)	(2)	(1)	(2)
IDD	0.146**	0.294***	0.215**	0.159**
	(0.020)	(0.009)	(0.049)	(0.020)
State GDP growth	0.004	0.005	0.007	0.009***
	(0.367)	(0.395)	(0.131)	(0.001)
Ln (State population)	1.375***	1.954***	1.523***	0.975**
	(0.000)	(0.000)	(0.009)	(0.011)
State unemployment rate	-0.050***	-0.066***	-0.038**	-0.017
	(0.009)	(0.006)	(0.039)	(0.200)
State establishment entry	0.034*	0.013	0.038*	0.008
	(0.073)	(0.635)	(0.072)	(0.554)
State establishment exit	0.023	-0.000	0.034*	0.008
	(0.175)	(0.991)	(0.079)	(0.567)
Business combination laws	-0.032	0.063	0.033	-0.005
	(0.639)	(0.566)	(0.731)	(0.935)
CNC index	-0.090	-0.512	0.885	0.981
	(0.872)	(0.466)	(0.536)	(0.392)
Wrongful discharge laws	-0.271***	-0.488***	-0.230***	-0.113*
	(0.008)	(0.002)	(0.009)	(0.063)
Constant	-19.882***	-27.850***	-22.797***	-14.614***
	(0.000)	(0.000)	(0.008)	(0.009)
Region×Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1,734	1,734	1,734	1,734
R-squared	0.807	0.701	0.775	0.704

Table 6. Heterogeneous Treatment Effects

This table reports the triple difference-in-differences tests to examine the heterogeneous treatment effects. The dependent variable *Acquisition* is an indicator variable, which takes the value of one if the firm is acquired in a given year, and zero otherwise. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. In column (1), the indicator variable *High human capital intensity* takes the value of one if the proportion of knowledge workers among all workers is above the sample median, and zero otherwise. In column (2), the indicator variable *High R&D* takes the value of one if the industry level R&D expense is above the sample median, and zero otherwise. In column (3), the indicator variable *Low option grant* takes the value of one if the firm's unvested employee stock option grant is below the sample median, and zero otherwise. In column (4), the indicator variable *Many rivals* takes the value of one if the number of firms in the same industry and same state is above the sample median, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable =*Acquisition*			
	(1)	(2)	(3)	(4)
IDD × High human capital intensity	0.012**			
	(0.012)			
IDD × High R&D		0.009**		
		(0.010)		
IDD × Low option grant			0.010**	
			(0.049)	
IDD × Many rivals				0.009*
				(0.069)
IDD	0.003	0.004	0.003	0.005
	(0.419)	(0.221)	(0.561)	(0.211)
High human capital intensity	-0.006**			
	(0.036)			
High R&D		0.002		
		(0.445)		
Low option grant			-0.009**	
			(0.041)	
Many rivals				0.003
				(0.482)
Other controls		Same as column (3) of Table 3		
Observations	123,212	123,212	48,945	123,212
R-squared	0.165	0.165	0.216	0.165

Table 7. Cross-industry Acquisition vs Within-industry Acquisition

This table reports the difference-in-differences tests that examine the IDD's impacts on the likelihood of within-industry and cross-industry acquisitions. In column (1), the dependent variable *Cross-industry acquisition* is an indicator variable, which takes the value of one if the firm is acquired by an acquirer from a different industry in a given year, and zero otherwise. In column (2), the dependent variable *Within-industry acquisition* is an indicator variable, which takes the value of one if the firm is acquired by an acquirer from the same industry in a given year, and zero otherwise. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cross-industry acquisition	*Within-industry acquisition*
	(1)	(2)
IDD	0.007**	0.001
	(0.012)	(0.437)
Other controls	Same as column (3) of Table 3	
Observations	123,212	123,212
R-squared	0.171	0.171

Table 8. Retention of Target Firms' Human Capital after the Acquisition

This table examines the retention of target firms' inventors, total employment, and top management in the post-acquisition period. In columns (1) and (2), the regression is at the level of individual inventors; the sample consists of 20,282 individual inventors who worked for target firms before the acquisition. The dependent variable *Innovator retained* is an indicator that takes the value of one if the inventor is retained by the acquirer after the acquisition, and zero otherwise. In column (3), the regression is at the level of acquisition deals; the sample consists of 1,441 acquisition deals with sufficient data to calculate the combined number of employees before and after the acquisition. The dependent variable *Change in combined number of employees* is calculated as Ln (number of the acquirer's employees three years after the acquisition) — Ln (sum of acquirer's employees and target firm's employees one year prior to the acquisition). In column (4), the sample consists of 6,230 individual executives who work for the target firm before the acquisition. The dependent variable *Executive retained* is an indicator that takes the value of one if the target firm's executive is retained by the acquirer after the acquisition, and zero otherwise. The *IDD* indicator takes the value of one if the target firm's headquarters state has the IDD in place at the time of the acquisition, and zero otherwise. Variable definitions are provided in the Appendix. All the bidder and target characteristics are measured at the year prior to the deal announcement. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Innovator retained		*Change in combined number of employees*	*Executive retained*
	(1)	(2)	(3)	(4)
IDD	0.064**	0.032	0.100**	0.096**
	(0.012)	(0.173)	(0.018)	(0.021)
IDD × Ln (Past 5 year patent)		0.060**		
		(0.017)		
Ln (Past 5 year patent)		0.057***		
		(0.000)		
Bidder control	Yes	Yes	Yes	Yes
Target control	Yes	Yes	Yes	Yes
Deal control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bidder state FE	Yes	Yes	Yes	Yes
Target state FE	Yes	Yes	Yes	Yes
Bidder industry FE	Yes	Yes	Yes	Yes
Target industry FE	Yes	Yes	Yes	Yes
Observations	20,282	20,282	1,441	6,230
R-squared	0.099	0.135	0.236	0.109

Table 9. IDD and Announcement Return at Acquisitions

This table examines the IDD's effect on market valuation of acquisitions. In column (1), the dependent variable *Combined CAR3* is the weighted average of the target and the bidder's cumulative abnormal returns during trading day (−1, +1) around the deal announcement. The weights are the market values of the target and the bidder two days prior to the announcement. In column (2), the dependent variable *Target CAR3* is the target's cumulative abnormal return during trading day (−1, +1) around the deal announcement. In column (3), the dependent variable *Bidder CAR3* is the acquirer's cumulative abnormal return during trading day (−1, +1) around the deal announcement. In column (4), the dependent variable *Bidder BHAR3* is the bidder's three-year buy-and-hold abnormal return, calculated by subtracting the compound return of the CRSP value-weighted market index from the compound return of the bidder firm over the three-year period after the acquisition. The *IDD* indicator takes the value of one if the target firm's headquarters state has the IDD in place, and zero otherwise. We control for bidder characteristics, target characteristics, deal characteristics, bidder industry fixed effects, target industry fixed effects, bidder state fixed effects, and target state fixed effects in all columns. Variable definitions are provided in the Appendix. All the bidder and target characteristics are measured at the year prior to the deal announcement. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Combined CAR3	*Target CAR3*	*Bidder CAR3*	*Bidder BHAR3*
	(1)	(2)	(3)	(4)
IDD	0.004*	0.010	0.004**	0.055*
	(0.061)	(0.235)	(0.035)	(0.059)
Bidder control	Yes	Yes	Yes	Yes
Target control	Yes	Yes	Yes	Yes
Deal control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bidder state FE	Yes	Yes	Yes	Yes
Target state FE	Yes	Yes	Yes	Yes
Bidder industry FE	Yes	Yes	Yes	Yes
Target industry FE	Yes	Yes	Yes	Yes
Observations	4,307	4,370	4,352	4,415
R-squared	0.169	0.187	0.132	0.176

Table 10. Post-Acquisition Performance

This table examines the IDD's effect on post-acquisition performance. The sample consists of firm-year observations from five years before to five years after each acquisition. In column (1), for the period before the acquisition, *Patent* is the sum of patents applied for by the acquirer and the target; for the period after the acquisition, *Patent* is the number of patents applied for by the combined firm. In column (2), for the period before the acquisition, *Citation* is the sum of citation counts received by patents applied for by the acquirer and the target; for the period after the acquisition, *Citation* is the citation counts received by patents applied for by the combined firm. In column (3), for the period before the acquisition, *ROA* is the weighted average ROA based on the acquirer's and target's total assets; for the period after the acquisition, *ROA* is the ROA of the combined firm. *Post-Acquisition* is an indicator variable that takes the value of one if it is in the post-acquisition period, and zero otherwise. The *IDD* indicator takes the value of one if the target firm's headquarters state has the IDD in place at the time of the acquisition, and zero otherwise. Firm characteristics include firm size, asset tangibility, sales growth, leverage, R&D expenditures, ROA, Tobin's Q, and excess stock return. For the period before the acquisition, firm characteristics are the weighted average based on the acquirer's and target's total asset. For the period after the acquisition, firm characteristics are for the combined firm. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ln (1+Patent)	*Ln (1+Citation)*	*ROA*
	(1)	(2)	(3)
Post-acquisition × IDD	0.037***	0.095***	0.004***
	(0.005)	(0.000)	(0.008)
Post-acquisition	-0.050***	-0.071***	-0.004***
	(0.000)	(0.004)	(0.005)
Firm characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Observations	34,141	34,141	34,141
R-squared	0.933	0.887	0.572

Table 11. Post-Acquisition Cooperation between Targets' and Acquirers' Inventors

This table examines the IDD's effect on the cooperation between target firms' and acquiring firms' inventors. In column (1), the dependent variable *Number of co-invented patents* is the number of patents applied for by the acquirer and co-invented by the target's and acquirer's inventors within three years after the acquisition scaled by the total number of patents applied for by the acquirer during the same period. In column (2), the dependent variable *Citations to co-invented patents* is the number of citations to co-invented patents scaled by the total number of citations to patents applied for by the acquirer within three years after the acquisition. Variable definitions are provided in the Appendix. All the bidder and target characteristics are measured at the year prior to the deal announcement. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Number of co-invented patents	*Citations to co-invented patents*
	(1)	(2)
IDD	0.009**	0.008**
	(0.027)	(0.016)
Bidder control	Yes	Yes
Target control	Yes	Yes
Deal control	Yes	Yes
Year FE	Yes	Yes
Bidder state FE	Yes	Yes
Target state FE	Yes	Yes
Bidder industry FE	Yes	Yes
Target industry FE	Yes	Yes
Observations	1,621	1,592
R-squared	0.354	0.374

Human Capital Driven Acquisition: Evidence from the Inevitable Disclosure Doctrine

Internet Appendix

Table IA1. Firm Size, the Inevitable Disclosure Doctrine, and the Likelihood of Being Acquired

This table reports the triple difference-in-differences tests that examine heterogeneous treatment effects on small firms. The regression specification is the same as that in column (3) of Table 3, except that we add the interaction between the IDD and firm size measures. In columns (1)–(4), we measure firm size by book value of total assets, market value of total assets, sales, and number of employees, respectively. The dependent variable *Acquisition* is an indicator variable, which takes the value of one if the firm is acquired in a given year, and zero otherwise. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable =*Acquisition*			
	(1)	(2)	(3)	(4)
IDD × Ln (Total assets)	-0.003**			
	(0.048)			
IDD × Ln (Market value of total assets)		-0.003*		
		(0.055)		
IDD × Ln (Sales)			-0.004**	
			(0.039)	
IDD × Ln (number of employees)				-0.007**
				(0.028)
IDD	0.030**	0.031**	0.035***	0.017***
	(0.010)	(0.014)	(0.010)	(0.000)
Ln (Total assets)	0.000			
	(0.840)			
Ln (Market value of total assets)		-0.003		
		(0.260)		
Ln (Sales)			0.010***	
			(0.000)	
Ln (number of employees)				-0.004
				(0.204)
Other controls	Same as column (3) of Table 3			
Observations	123,212	123,212	123,212	116,948
R-squared	0.165	0.165	0.166	0.168

Table IA2. The Inevitable Disclosure Doctrine and the Likelihood of Being Acquired, Small Firms in the Center Part of a State

This table reports the difference-in-differences tests that examine the impacts of the Inevitable Disclosure Doctrine (IDD) on the firm's likelihood of being acquired in subsamples of small firms whose headquarters are located in the center of their states. The regression specification is the same as that in column (3) of Table 3. We restrict the sample to firms whose size is below the sample median and whose headquarters are at least 50 miles, 100 miles, 150 miles, or 200 miles away from state borders in columns (1) to (4), respectively. The dependent variable *Acquisition* is an indicator variable, which takes the value of one if the firm is acquired in a given year, and zero otherwise. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	At least 50 miles from state border (1)	At least 100 miles from state border (2)	At least 150 miles from state border (3)	At least 200 miles from state border (4)
IDD	0.009**	0.013**	0.020**	0.021**
	(0.033)	(0.012)	(0.034)	(0.012)
Other controls		Same as column (3) of Table 3		
Observations	36,169	29,725	22,837	17,842
R-squared	0.048	0.049	0.053	0.052

Table IA3. IDD and the Likelihood of Being Acquired, Different Sample Period

This table reports the difference-in-differences tests that examine the impacts of the Inevitable Disclosure Doctrine (IDD) on the firm's likelihood of being acquired for the period of 1980 to 2007. The regression specification is the same as that in Table 3. The dependent variable *Acquisition* is an indicator variable, which takes the value of one if the firm is acquired in a given year, and zero otherwise. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable =*Acquisition*		
	(1)	(2)	(3)
IDD	0.009***	0.010***	0.010***
	(0.008)	(0.005)	(0.007)
Ln (Total assets)		-0.001	-0.001
		(0.666)	(0.665)
ROA		0.004	0.004
		(0.451)	(0.464)
Excess return		0.001	0.001
		(0.196)	(0.214)
Tobin's Q		-0.009***	-0.009***
		(0.000)	(0.000)
Sales growth		-0.014***	-0.014***
		(0.000)	(0.000)
Leverage		0.009	0.009
		(0.203)	(0.204)
R&D		0.094***	0.094***
		(0.000)	(0.000)
Fixed assets		0.029***	0.029***
		(0.000)	(0.000)
Log (State population)			0.001**
			(0.023)
State GDP growth			-0.003
			(0.343)
State unemployment rate			-0.001
			(0.510)
State establishment entry			0.001
			(0.703)
State establishment exit			0.003*
			(0.066)
Business combination law			-0.000
			(0.944)
CNC index			-0.022
			(0.216)
Wrongful discharge law			-0.002
			(0.827)
Constant	0.047***	0.059***	0.071
	(0.000)	(0.000)	(0.251)
Region×Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	100,757	100,757	100,757
R-squared	0.174	0.177	0.177

Table IA4. The Enforceability of Covenants Not to Compete and the Likelihood of Being Acquired

This table reports the difference-in-differences tests that examine the impacts of the enforceability of covenants not to compete (CNC) on the firm's likelihood of being acquired. The regression specification is the same as that in Table 3, except that we use *Jeffers' CNC* as our key independent variable. *Jeffers' CNC* is an indicator variable that equals one if there is an increase in CNC enforceability relative to the 2008 level, and zero otherwise. The data on enforceability of a CNC is obtained from Jeffers (2017), and the sample period is 2008–2014. The dependent variable *Acquisition* is an indicator variable, which takes the value of one if the firm is acquired in a given year, and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable =*Acquisition*		
	(1)	(2)	(3)
Jeffers' CNC	0.004	0.004	0.012**
	(0.476)	(0.519)	(0.037)
Ln (Total assets)		-0.010**	-0.010**
		(0.011)	(0.011)
ROA		0.010	0.010
		(0.528)	(0.532)
Excess return		-0.004	-0.004
		(0.131)	(0.128)
Tobin's Q		-0.003	-0.003
		(0.247)	(0.221)
Sales growth		-0.003	-0.003
		(0.333)	(0.402)
Leverage		-0.011	-0.012
		(0.487)	(0.477)
R&D		0.020	0.019
		(0.553)	(0.572)
Fixed assets		-0.001	-0.002
		(0.969)	(0.934)
Ln (State population)			-0.262
			(0.213)
State GDP growth			-0.001*
			(0.055)
State unemployment rate			-0.009***
			(0.000)
State establishment entry			0.010*
			(0.091)
State establishment exit			0.003
			(0.532)
Constant	-0.019***	0.056**	4.322
	(0.000)	(0.049)	(0.200)
Region ×Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	25,401	25,401	25,401
R-squared	0.034	0.035	0.036

Table IA5. The Uniform Trade Secrets Act and the Likelihood of Being Acquired

This table reports the difference-in-differences tests that examine the impacts of the Uniform Trade Secrets Act (UTSA) on the firm's likelihood of being acquired. The regression specification is the same as that in Table 3, except that we use *UTSA* as our key independent variable. *UTSA* is an indicator variable that equals one if the UTSA is enacted in the firm's headquarters state, and zero otherwise. The data on enactment of the UTSA is obtained from Castellaneta, Conti, and Kacperczyk (2017). The dependent variable *Acquisition* is an indicator variable, which takes the value of one if the firm is acquired in a given year, and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable =*Acquisition*		
	(1)	(2)	(3)
UTSA	0.004	0.004	0.004
	(0.301)	(0.278)	(0.323)
Ln (Total assets)		-0.001	-0.001
		(0.512)	(0.514)
ROA		0.008*	0.008*
		(0.076)	(0.077)
Excess return		0.001	0.001
		(0.367)	(0.373)
Tobin's Q		-0.009***	-0.009***
		(0.000)	(0.000)
Sales growth		-0.014***	-0.014***
		(0.000)	(0.000)
Leverage		0.011*	0.011*
		(0.090)	(0.089)
R&D		0.075***	0.075***
		(0.000)	(0.000)
Fixed assets		0.023***	0.023***
		(0.001)	(0.001)
Ln (State population)			0.000
			(0.539)
State GDP growth			-0.001
			(0.756)
State unemployment rate			-0.001
			(0.375)
State establishment entry			-0.000
			(0.896)
State establishment exit			0.001
			(0.288)
Business combination law			0.000
			(0.944)
CNC index			-0.023
			(0.113)
Wrongful discharge law			-0.001
			(0.851)
Constant	0.047***	0.063***	0.076
	(0.000)	(0.000)	(0.183)
Region×Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	123,212	123,212	123,212
R-squared	0.162	0.165	0.165

Table IA6. The Inevitable Disclosure Doctrine and the Likelihood of Being Acquired, Different Types of Acquisitions

This table reports the difference-in-differences tests that examine the impacts of the Inevitable Disclosure Doctrine (IDD) on the firm's likelihood of being acquired, based on various different types of acquisitions. The regression specification is the same as that in column (3) of Table 3. In column (1), the dependent variable is *Announced acquisition*, which takes the value of one if the firm is the target of an announced deal (the deal may or may not be eventually completed) in a given year and the acquirer seeks to own 100% of the target firm after the acquisition, and zero otherwise. In column (2), the dependent variable is *Partial and full acquisition*, which takes the value of one if the firm is the target of a completed acquisition (without requiring that the acquirer owns 100% of the target after the acquisition) in a given year, and zero otherwise. In column (3), we remove all mergers of equals. Mergers of equals are deals in which the book value of total assets of target firms is within [90%, 110%] of that of acquirers prior to the deal announcement. In column (4), we use a conditional logit regression. For each target firm, we match it to a hypothetical target firm that is in the same industry, that is closest in firm size in the year prior to the acquisition, and that has not been acquired within 5 years around the acquisition of the true target firm. The dependent variable takes the value of one if the actual target firm is acquired in a given year, and zero otherwise. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Announced acquisition	*Partial and full acquisition*	*Excluding mergers of equal*	*Conditional logit*
	(1)	(2)	(3)	(4)
IDD	0.006**	0.011***	0.008**	0.039**
	(0.048)	(0.006)	(0.014)	(0.015)
Other controls		Same as column (3) of Table 3		
Observations	123,212	123,212	123,212	8,148
R-squared	0.163	0.161	0.166	

Table IA7. The Inevitable Disclosure Doctrine and the Likelihood of Being an Acquirer

This table reports the difference-in-differences tests that examine the impacts of the Inevitable Disclosure Doctrine (IDD) on the firm's likelihood of being an acquirer. In column (1), the dependent variable *Acquirer* is an indicator variable, which takes the value of one if the firm makes at least one acquisition in a given year, and zero otherwise. In column (2), the dependent variable *Ln (1+number of acquisition deals)* is the natural logarithm of one plus the number of acquisitions the firm makes in a given year. In column (3), the dependent variable *Acquisition value* is the sum of transaction values of acquisition deals the firm makes in a given year scaled by the firm's book value of total assets. The indicator variable *IDD* takes the value of one if the IDD is recognized in a state, and zero otherwise. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Acquirer	*Ln (1+number of acquisition deals)*	*Acquisition value*
	(1)	(2)	(3)
IDD	-0.005	-0.014	-0.001
	(0.417)	(0.410)	(0.767)
Other controls		Same as column (3) of Table 3	
Observations	123,212	123,212	123,212
R-squared	0.256	0.334	0.146

Table IA8. The Inevitable Disclosure Doctrine and Alternative Measures of Acquisition Premium

This table examines the IDD's effect on the premium paid to the target firm. In column (1), the dependent variable *Premium BHAR* is the target firm's buy-and-hold abnormal return during the trading days (−43, +126), calculated by subtracting the compound return of the CRSP value-weighted market index from the compound return of the target firm over the given period. In column (2), the dependent variable *Premium 4 week* is provided by the SDC database as the percentage difference between the offer price and the target share price four weeks prior to the announcement date. In column (3), the dependent variable *Deal value to sales* is provided by the SDC database as the ratio of deal value to target sales. The *IDD* indicator takes the value of one if the target firm's headquarters state has the IDD in place, and zero otherwise. We control for bidder characteristics, target characteristics, deal characteristics, bidder industry fixed effects, target industry fixed effects, bidder state fixed effects, target state fixed effects, and year fixed effects in all columns. Variable definitions are provided in the Appendix. All the bidder and target characteristics are measured at the year prior to the deal announcement. All continuous variables are winsorized at the 1st and 99th percentiles. P-values based on robust standard error clustered at the state level are reported in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Premium BHAR	*Premium 4 week*	*Deal value to sales*
	(1)	(2)	(3)
IDD	-0.021	0.002	0.011
	(0.135)	(0.918)	(0.975)
Other controls		Same as Table 9	
Observations	4,415	3,811	4,249
R-squared	0.164	0.167	0.391