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THE EFFECT OF LABOR MOBILITY ON CORPORATE INNOVATION

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Employees are increasingly becoming crucial asset for firms, especially as firms’ competitive advantage is increasingly becoming dependent on its ability to innovate constantly. We study the effect of restricted employee mobility – enabled by state’s recognition of Inevitable Disclosure Doctrine (IDD) – on firms’ innovation output. We find that following recognition of IDD although firms exhibit reduced innovation output vis-à-vis those headquartered in states that never recognized or revoked IDD, the economic value of such innovations increase. In addition, firm’s Tobin’s Q, market-to-book ration and patent value to firm’s market value increase post IDD. We conclude that reduced threat of losing intellectual properties to rivals owing to labor mobility results in firm’s taking up more valuable innovation.

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Key words: innovation; trade secrets; intellectual property; labor mobility

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1. Introduction

The significance of innovation in determining an economy's growth cannot be emphasized enough. Starting from pioneer work of Solow (1957), numerous researchers have documented significance of innovation in an economy's prosperity and growth (Reinganum 1989; Wong, Ho, and Autio 2005; Scherer 1986). Not only economy, intellectual property is a critical revenue generating asset for a firm and plays a crucial role in determining its competitive advantage and performance vis-à-vis its rivals in product market (Shapiro and Hassett 2005). This trend is increasingly becoming more prominent with time owing to intensifying competition across the globe and has led to emergence of human capital as a key asset for a firm (Zingales 2000). Retaining such advantage not only depends on retaining and attracting high quality human capital, but also refraining key employees from moving to rival firms.

Given a firm's workforce lies at the center of its innovation ability, it is of utmost importance that we understand how firms innovation output responds to labor market forces. In this paper, we are particularly interested in studying the effect of labor mobility on innovation output. Labor mobility could be both advantageous as well as disadvantageous for firms. On one hand, it facilitates firms to poach employees from other firms. On the other hand, it makes firms vulnerable to theft of intellectual property by employees. Cooper (2001) documents that the job-hopping phenomenon restrains firms' ability to protect their proprietary information, which might turn out to be quite expensive for subject firms. In addition, Mincer and Jovanovic (1979) document if workers' mobility is high in an industry, firms will be more inclined to spend sub-optimal amount on workers' training and welfare.

In sum, a firm's competitive advantage arising from innovation critically hinges on protection of its intellectual property in the form of trade secrets[1]. Therefore, improving our understanding of the impact of labor market frictions, facilitated by regulatory intervention, in this context is not only pertinent but is also essential. Manso (2011) shows that the optimal contract between firm and employees plays a key role in fostering innovation not

[1] A firm might fire employees following completion of an innovation in order to avoid sharing royalties with him leading to involuntary separation of worker. In contrast, a worker might steal firm's trade secret and join the incumbent's rivalry – voluntary separation. Since, in this context, trade secret are the central theme, it is important to establish the importance of the class of worker separation.

only by exhibiting tolerance for short-term failures but also creates incentives for successful research in the long-run. In real world, however, contracts between firms and employees are inherently incomplete. This, in turn, implies that during the times of conflict, the employment contract might not suffice as reference to address the conflict and thus settle their disagreement in a court of law. In other words, incompleteness of employment contract leaves a significant room for the role played by regulatory framework and its interpretation and/or intervention.

Labor laws can complement incompleteness of employee-employer contract by offering a significant protection to the employees. A series of work, such as Hart and Moore (1990), Hart (1995), etc., argue that incomplete contracts lead up to holdup issues. Countries' dismissal laws offers some relief by preventing employers from arbitrarily discharging employees and thus limiting firm's ability to hold up key employees following a successful innovation Acharya, Baghai, and Subramanian (2013). However, having a law in place is not enough, i.e. unless its enforcement is ensured by the authorities, the law alone might fail to achieve its intended objective. For instance, Bhattacharya and Daouk (2002) document that cost of equity doesn't respond to introduction of insider trading laws alone, but decreases significantly after the first prosecution.

Prima facie, reduced workers' mobility and improved protection of intellectual property should result in higher expense of employee training and innovation output by firms. However, the researchers have documented conflicting results. For instance, Garmaise (2011) finds that stricter enforcement of non-compete agreements result in reduced capital expenditure per employee. Contigiani, Hsu, and Barankay (2018) document that higher trade-secret protection, enabled by implementation of Inevitable Disclosure Doctrine (IDD), results in reduced innovation output by firms. On the flip side, Jeffers (2017) document positive effect of enforceability of non-compete agreements on investment rates at existing knowledge-based firms. Png (2017) finds the positive effect of Uniform Trade Secrets Act (UTSA), which equips firms to protect their trade-secrets and intellectual property, on R&D expense for larger firms and firms operating in high-tech industries. Do these finding, in conjunction, imply that better trade-secret results in sub-optimal decision making by firms, i.e. incurring higher R&D expense while reducing innovation output?

This research question lies at the heart of this paper. At this point let's consider an example from the real world. A patent granted to IBM in 2001 for a "system and method for providing reservations for restroom use." This patent describes a system to allow passengers on an airplane to reserve a spot in the bathroom queue. The patent has subsequently been of such little value to IBM that the firm has stopped paying the annual renewal fee to the USPTO, and the patent has now lapsed. Our method would identify this patent as having little economic value – the return over the 3-day window is slightly negative, and there is no change in the trading volume. By contrast, citation counts indicate that this patent presented a considerable scientific advance – the patent has received 21 citations, which places it in the top 20% of the patents granted in the same year[2].

This is an extremely relevant incidence in light of the fact that only 5% of all active patents are ever licensed is ever commercialized[3] and that most companies use less than a quarter of invention they own[4]. These observations raises question on using total number of patent grants as the benchmark for measuring firms' innovation output. In other words, we should be cautious of putting equal weight on each innovation. In addition, Manso, Balsmeier, and Fleming (2017) argue that patent count and R&D expense do not capture a crucial dimension of firms' innovative strategies.

This, in conjunction, presents a potential pitfall in relying extensively on patent count and patent citation as sacrosanct measures of innovation. These are particularly important given relation between patent citations and the private value of a patent can be theoretically ambiguous. Hall, Jaffe, and Trajtenberg (2005) and Nicholas (2008) argue that forward citations are also correlated with the private value of patents based on a regression of a firms Tobin's Q on its stock of citation-weighted patents. On the other hand, Abrams et al. (2013) cast doubt on these earlier findings by proposing a model of defensive patenting. Using a proprietary dataset that includes estimates of patent values based on licensing revenues, they document an inverse-U relation between citations and patent values. Therefore, in order to distinguish scientifically important innovation patents, which are consequential for firm profitability, from the others we use patent value as measured by Kogan et al. (2017). Using total economic values of patents in addition to patent count and

[2] As presented in Kogan et al. (2017).
[3] The Real Patent Crisis is Stifling Innovation by Daniel Fisher [Source: Forbes, Jun 18, 2014].
[4] A Better Way from 'R'to 'D' by Edward Jung [Source: Project Syndicate, Apr 27, 2017].

citation helps us distinguish economically consequential innovations from inconsequential ones, i.e. we are going to emphasize on the quality of innovations instead of quantity. This also helps us analyze whether increased R&D expense, owing to better trade-secret protection (Png 2017), results in more valuable innovation or lower innovation, as proposed by Contigiani, Hsu, and Barankay (2018).

In this paper, we study the effect of adoption of Inevitable Disclosure Doctrine (IDD) by various states in the USA – as a *quasi-natural* experiment – on firm innovation. Under IDD, a firm's suit can rest on the mere threat of irreparable harm. To obtain an injunction, the firm must only establish that the employee had access to its trade secrets, the employee's will inevitably require her to use or disclose the trade secrets, and the disclosure of the trade secrets would produce irreparable economic harm to its business. The importance of IDD is underscored by states' courts' preference to implement it even in the absence of a non-compete and/or non-disclosure agreement between firm and employees and without requiring the firm to establish any wrongdoing on the part of employees.

Adoption of IDD leads to reduced mobility of not only key executives, who have access to the firm's trade secrets (Klasa et al., 2017) but also of scientists and engineers (Png and Samila, 2013). Moreover, Kim and Marschke (2005) argue that risk of scientists' departure poses a threat to the incumbent firm, which in turn reduces firm's R&D expenditure as well as its propensity to innovate. On the grounds of better legal protection of intellectual properties, firms might feel less threatened and be more willing to invest on research in order to fuel innovation and reinforce their competitive advantage. In other words, firms can establish boundaries that guarantee safe circulation of internal ideas, which can be reinforced with legal framework of a country and thus IDD recognition would result in higher innovation.

We primarily use difference-in-difference method to estimate the effect of reduced workers' mobility, enabled by IDD recognition, on various aspects of firm innovation. Given such protection of trade secrets come under the purview of employment laws and not corporate laws, the relevant jurisdiction is usually the one in which the employee works, i.e. where the office of the incumbent firm is located (Pentelovitch 2003; Malsberger 2004). Furthermore, Howells (1990) and Breschi (2008) show that large firms locate their R&D

facilities close to the company's headquarters and do not disperse them geographically. Therefore, in context of patent filing and grants and employment law, we refer to firm's headquarter state to capture the effect of state laws and legislations on firm's innovation output. Therefore, firms headquartered in states recognizing IDD constitute treatment group whereas firms headquartered in states not recognizing IDD constitute control group.

We establish that parallel trend holds true for IDD in the context of innovation (please refer to Fig. 1). Following this we compare and contrast the effect of IDD adoption on patent value with the popular input and output measures of innovations, i.e. R&D expense and, patent count and citations, respectively. In addition, we also estimate the impact of IDD recognition on various market response, viz. firm's growth opportunities, measured as market-to-book ratio, firm value, measured by Tobin'n Q, and the ratio of firm's total patent value to its market capitalization. We find that IDD results in reduced number of patents granted and patent citation – in line with Contigiani et al. (2017) – and increased value of R&D expense – consistent with Png (2018).

Patent value measure, as estimated by Kogan et al. (2017), allows us to study this question at a more granular level than Hall et al. (2005), while using a broader sample than Abrams et al. (2013). Kogan et al. (2017) relate the total number of citations a patent receives in the future to the estimated value of the patent, the change in the stock price at the grant date. The total dollar value of innovation produced by a given firm in a year is a sum of all the values of patents that were granted to that firm. We find that the economic value of patents of patent value to firm's market value, firm's growth opportunities and Tobin's Q increase post adoption of IDD. These effects are both statistically as well as economically significant.

In addition, we exploit a set of cross sectional heterogeneity, *viz*. industry cash-flow volatility, competition and research intensity, which might help us establish the validity of aforementioned results. Cuñat and Melitz (2012) document that firms operating in industries with more volatile cash flows are more likely to need to adjust employment in response to cash flow fluctuation. Using DIDID (difference-in-difference), we find that the cash-flow volatility reinforces the positive effect of labor mobility restriction on innovation. This implies that impact of reduced mobility on innovation for firms facing high cash-flow volatility exhibit higher innovation output – number of patents, patent citation and patent value – post adoption of IDD.

In addition, researchers have argued high product market competition results in high cash-flow volatility, which in turn is captured by high stock volatility (Gaspar and Massa 2006; Irvine and Pontiff 2009; Chay and Suh 2009). In addition, intense domestic product market competition creates employment opportunities (Nickell 1999; Gersbach 1999; Chen and Funke 2008), thereby exacerbating job-hopping of employees and hence transfer of intellectual properties to the rival firms. We, therefore, estimate the moderating role of domestic competition on the effect of IDD on innovation using DIDID. Consistent with the impact of industry cash-flow volatility, we document that intense competition and research intensity reinforce the positive effect of labor mobility restriction on all three measures of innovation.

A firm that has high research intensity run a high risk of job-hopping and hence transfer of intellectual property, may exhibit less likelihood of spending in research. In response to higher protection of trade-secrets, facilitated by IDD, these firms exhibit higher innovation. In addition, we test for a series of robustness tests in as much as to corroborate that the result that we observe here are not spurious. We run a set of placebo tests, to see the effect of IDD on innovation output is not spurious, by checking whether the results hold true if we change the year of IDD adoption. These results pass through. In addition, we also run a sub-sample test where we compare only the states with significant patent filings with control group. We also estimate the strength of all the above results by dropping California, since this state has the highest number of patents (please refer to Fig. 3). However, for brevity we do not present these results here.

This paper makes a significant contribution to the growing literature at the intersection of finance and labor economics, given growing importance of innovation and regulatory changes in the backdrop changing regulations. We document that if workers are restricted to move across firms freely, firms are more inclined to undertake more valuable innovation, which has a positive implications for firm valuation. This effect is particularly pronounced for firms operating in more competitive industries and those that are subject to high cash flow volatility. These findings contrast the conclusions of Contigiani et al. (2018) and we are inclined to conclude that higher trade secret protection encourages firms to undertake more risk. This paper also offers an explanation for apparent conflicting findings of Png (2017) and Contigiani et al. (2018). We propose that with reduced labor mobility across firms, firms incur higher R&D expense and invest in fewer but more valuable projects.

The rest of the paper has been organized as follows. Section II discusses the background of inevitable disclosure doctrine (IDD) and establishes the importance of studying the regulation in this contest, whereas section III describes data and descriptive statistics. Subsequently section IV presents main empirical models and result of the paper and section VI concludes the paper.

2. Background of Inevitable Disclosure Doctrine

The protection of trade secrets mainly come under the purview of state laws and legislations. Inevitable Disclosure Doctrine (IDD) is a legal doctrine that states that a firm's former employee can be prevented from working for a rival firm if this would "inevitably" lead the employee to divulge the firm's trade secrets to the rival (Klasa et al. 2017b). Under Uniform Trade Secret Act (UTSA) section 1(4), a *trade secret* is defined as information that: (i) derives independent economic value from not being generally known to, and not being readily ascertainable by proper means, by other persons who can obtain economic value from its disclosure or use, and (ii) if the subject of efforts that are reasonable under the circumstance to maintain its secrecy.

The crucial issue for a piece of information to be determined as trade-secret is whether the information sought to be protected is, in fact in law, *confidential*. Consequently, misappropriation occurs when the trade secret is acquired by (i) improper means (e.g., theft or breach of a duty to maintain secrecy) or (ii) disclosure without express or implied consent by a person who acquired the trade secret under circumstances giving rise to a duty to maintain its secrecy or limit its use.

The key legal concept in understanding the applicability of the IDD is "threatened misappropriation", which occurs when an employee who has knowledge of a firm's trade secrets goes to work for a direct competitor in a similar position. The IDD is a legal doctrine based on a strong interpretation of the concept of threatened misappropriation which does not immediately follow from the general principles in trade secrets law (e.g., as codified in the UTSA). It maintains that, if the new employment would inevitably lead to the disclosure of the firm's trade secrets to a competitor and cause the firm irreparable harm, then upon the firm's request state courts can prevent the employee from working for the firm's competitor or can allow it but limit the responsibilities the worker can undertake.

2.1. Distinction between UTSA and IDD

There are, however, a few key differences between UTSA and IDD[5]. One key difference is "continuous use" requirement under UTSA, i.e. any information that derives independent economic value from not being generally known and includes information that is not actually in use is considered a trade secret under UTSA but not IDD. Second, IDD might now allow common cost-shifting provisions of UTSA. The UTSA allows the owner of a trade secret to obtain an injunction against "threatened disclosure" of a trade secret as well as its actual disclosure.

This distinction is a departure from common law where the plaintiff must demonstrate a reasonable likelihood of success on the merits to obtain an injunction. In the employment context, courts have interpreted the UTSA's "threatened disclosure" language to create a sort of *de facto* noncompete. In addition, the recognition of the IDD by a state court and the adoption of the UTSA in the same state are different legal events. Several state courts recognized the IDD before the state adopted the UTSA (some states recognized the IDD but never adopted the UTSA). In contrast, several states adopted the UTSA but their courts did not recognize the IDD (Klasa et al. 2017).

The adoption of the IDD by a state court enhances the protection of trade secrets for firms located in the state by reducing the risk that departing employees who know their firm's trade secrets will reveal them to rival companies (in any state) or use them to start a rival company. Under the IDD, a firm's suit can rest on the mere threat of irreparable harm. To obtain an injunction, the firm must only establish that (i) the employee had access to its trade secrets, (ii) the employee's duties at the new employer would be so similar to those she had at the firm that in performing them she will inevitably use or disclose the trade secrets, and (iii) the disclosure of the trade secrets would produce irreparable economic

[5] Commercial and Business Litigation Winter 2016. Vol. 17. No. 2. By Gregory S. Bombard.

harm to its business. However, the firm need not establish actual wrongdoing by the employee or disclose the actual details of the underlying trade secrets in the lawsuit.

2.2. A Case in Point: Pepsi Co. Inc. vs. Redmond[6]

The Seventh Circuit's decision in PepsiCo, Inc. v. Redmond is considered the prominent case discussing inevitable disclosure after the adoption of the UTSA. PepsiCo brought an action seeking a preliminary injunction against its employee, William Redmond, Jr. (Redmond), from accepting a position with PepsiCo's competitor, Quaker. Redmond, who had been employed with PepsiCo for ten years, had access to PepsiCo's financial goals and its strategic planning for the upcoming year; consequently, although he signed a confidentiality agreement stating he would not disclose confidential information, PepsiCo was concerned about the secrecy of its trade secrets. This was mainly due to Redmond's lack of candor regarding accepting the position at Quaker. The district court granted an injunction against Redmond from assuming his position with Quaker for a period of five months, and granted a permanent injunction preventing him from using or disclosing PepsiCo's trade secrets.

Noteworthy, lawsuits related to employment contracts are filed in the context of employment law, and thus the relevant jurisdiction for a lawsuit seeking to protect a firm's trade secrets when employees switch employers is typically the state where the former employee worked (Malsberger 2004; Garmaise 2011). As a result, the IDD protects a firm's trade secrets even if the new employer of a firm's former worker is in another state whose courts have not adopted IDD.

Employment contracts sometimes contain a non-disclosure agreement (NDA) and/or a covenant not to compete (CNC). These are designed to protect the firm's trade secrets in cases when employees wish to switch jobs or start competing firms. This enables the firm to bolster its suit by including a claim of breach of contract. The protection offered by NDAs is somewhat limited because violations must be detected and proved before the firm can initiate legal action against a former employee, i.e. establish a case of bad faith or wrong doing on employees' part. Further, even if the firm can prove that an employee violated an NDA, by that time the harm has already been done (Klasa et al. 2017).

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[6] A State-by-State Analysis of Inevitable Disclosure: A Need for Uniformity and a Workable Standard. Marquette Intellectual Property Law Review. Vol. 16. Iss. 1.

On the other hand, covenant not to compete (CNC) are most effective when workers seek to switch jobs within a state (Garmaise 2011). CNCs are much less effective when workers try to switch to a new job in another state because the geographical area where a firm's former employee may not compete is typically limited to a state or a part of a state (Malsberger 2004). The importance of IDD is underscored by states' courts' preference to implement it even in the absence of a non-compete and/or non-disclosure agreement between firm and employees. This overrides even if there is no evidence of actual wrongdoing on employee's part (Klasa et al. 2017).

3. Data and Sample Description

In this study we use both firm-level parameters as well as macroeconomic variables to test the robustness of the hypothesis presented above. We have collected these parameters from various sources.

3.1. Firm level parameters

The firm-level parameters come from Compustat North American Industrial Annual database. However, we restrict my sample to only those firms for which CRSP identifier, i.e. *permno*, is available. The sample includes around 130,000 firm-year observations for US firms spanning from 1950 to 2011. We drop the firms with zero or missing book value, and industries that have less than 5 observations in a year. In addition, we also drop the firms that don't report their headquarters (HQ) or are headquartered outside USA. In other words, the sample only consists of patent assignees that are located in USA. We use North American Industry Classification System (NAICS) three-digit-code for classification of industries.

Building on Kogan et al. (2017), We use number of patents granted, total citations-weighted patents[7] (TCW) and patent value as primary measures of firm's innovation output. Patent citations are more reflective of the scientific value of the innovation. For instance, one patent may represent only a minor scientific advance – and thus receive few citations – but be particularly successful at restricting competition and thus generate sizeable private benefits. Furthermore, dollar value of patents allows us to study questions

[7] Citation-weighted patent counts are computed as $\Sigma_j 1 + C_j/\overline{C_J}$, where C_j is the number of citations to patent j and $\overline{C_J}$ is the mean number of cites to patents granted in the same year as patent j.

in the context of innovation at a more granular level than Hall et al. (2005), while using a broader sample than Abrams et al. (2013) (Kogan et al. 2017). They relate the total number of citations a patent receives in the future to the estimated value of the patent, the change in the stock price at the grant date. The total dollar value of innovation produced by a given firm in a year is a sum of all the values of patents that were granted to that firm. Patent value (TSM) is thus helpful in distinguishing between innovations that are scientifically important and those that have a large impact on firm profits. We obtain these parameters from Noah Stoffman's website[8] and use *permno* to merge it with Compustat dataset. Table 1 summarizes the descriptive statistics of firm-level parameters. All the ratios, i.e. market-to-book, book leverage and gross profit – net sales minus cost of goods sold scaled by inflation – are winsorized at 1% and 99% levels.

3.2. State-level and macroeconomic parameters

Howells (1990) and Breschi (2008) show that large firms locate their R&D facilities close to the company's headquarters and do not disperse them geographically. In addition, protection of trade secrets come under the purview of employment laws and not corporate laws, the relevant jurisdiction is usually the one in which the employee works, i.e. where the office of the incumbent firm is located (Pentelovitch 2003; Malsberger 2004). Therefore, referring to state headquarters would be able to capture the effect of state laws and legislations on firm's innovation output, especially in context of employees and patent filings.

As mentioned by Heider and Ljungqvist (2015), firm's state HQ data provided by Compustat is quite static in nature and hence is not very reliable to capture state-level variation. We, therefore, use EDGAR to get firm's state HQ data, precisely we obtain the state mentioned under "Business Address" for SEC filing and we backfill this data from until 1989. Firms for which EDGAR doesn't provide state HQ data, we retain Compustat data; and where we do not have either, we use firm's state of incorporation. For macroeconomic parameters, viz. consumer price index (CPI) inflation U.S Bureau of Labor Statistics.

[8] We obtain the data from Noah Stoffman's website (Indiana University). We would like to extend our gratitude to Noah Stoffman to make the data available as for we have immensely benefited from it.

4. Empirical Framework and Results

Herein we use difference-in-difference in the form of non-linear models to estimate the effect of IDD recognition on innovation. Since all measures of innovation is non-negative, we use Tobit model for innovation measures, viz. numbers of patent grant, total citation-weighted patent (TCW), patent value (TSM) and R&D to sales ratio[9]. More precisely, we use log(1+Patent Grant), log(1+TCW) and log(1+TSM) as innovation measures, which allows us to compare the changes in overall trend in innovation following adoption of IDD. Also, for the same reason and in line with Acharya et al. (2013), we replace missing R&D with zero. In addition, we also test for market's response, such as firm's Tobin's Q, market to book ratio and Patent Value to market capitalization, to this regulatory change.

$$Innovation_{it} = \alpha_i + \beta * IDD_{st} + \boldsymbol{\omega} * \boldsymbol{Z} + \epsilon_{ist} \quad (1)$$

Here, α_i is firm fixed effects. IDD is a binary variable that takes 1 when a state has adopted IDD and zero if the state has never adopted IDD and when it has rejected IDD in later years. In other words, it captures the interaction effects of treatment and post period, i.e. it captures the difference-in-difference estimate. Thus our main coefficients of interests here is β. We also include relevant firm characteristics to control for the effects arising from these on firm's innovation. Since firm size comes with significant advantages, e.g. by having better access to capital and attract talent by giving them higher remuneration, etc., it substantially influences firm's research and innovation abilities.

Therefore, we control for it by including natural logarithm of total asset. In addition, following Kogan et al. (2017) we include gross profit – sales minus cost of goods sold deflated by inflation (CPI). Given importance of employees in this context, following Acharya, Baghai, and Subramanian (2014), We also control for number of employees. Given source of capital significantly affects firm's ability to determine its investment, we control for firm's book leverage. Table 2 summarizes the tobit estimates[10] corresponding to

[9] Typically there is a lag of two to three years between patent filing and patent granted. Therefore, we also estimate equation (1) for two and three year lead of innovation. We, however, do not report the results for brevity.

[10] The number of observations in logit results are significantly fewer than those in descriptive statistics table. The reason is 7,692 groups, i.e. 64,843 observations, are dropped because of all positive or all negative outcomes.

equation (1). β is statistically negative, i.e. with the adoption of inevitable disclosure doctrine although patent grant and citations decrease, patent value and market's estimates of firm value increase. This suggests that firms that are headquarters in the states adopting IDD are more likely to invest in value-increasing innovations vis-à-vis those headquartered in the states not adopting IDD. The effects of other firm level parameters, such as firm size and leverage, on successful innovation are also along the expected lines.

However, given the identification in this paper predominantly relies upon difference-in-difference, it is crucial to establish parallel trend first. It is important to note here that IDD adoption is staggered across time and time-trend of patents granted is too significant to be ignored as exhibited in Fig 1. Therefore, before estimating parallel trend, we have to control for effects arising from years. By controlling for year fixed effects, we ensure ridding firm innovation of the yearly trends. Fig 2 plots average residual patents for the two groups after controlling for year fixed effects. Herein we plot average number of patents granted in treatment and control groups, i.e. state-year levels, before and after treatment – adoption of IDD by the state. We use adoption of IDD as reference point, i.e. year 0. Since IDD adoption by state varies across time, we use median IDD adoption year, i.e. 1994, as treatment reference year for control states. This, we believe, establishes parallel trend between treatment and control groups before treatment thereby passing litmus test for carrying out difference-in-difference analyses in the paper using tobit model, as presented in equation (1).

Furthermore, to ascertain underlying mechanism of IDD affecting firm-innovation, we exploit cross-sectional heterogeneity across various dimensions using DIDID (difference-in-difference-in-difference) model as presented in equation (2). Moulton (1990) and Donald and Lang (2007) argue that economic shocks may affect all individuals in a state on an annual basis. This annual changing response could generate higher correlation of standard errors if both economic conditions and labor laws of a state effect firm's decisions, especially when the event we study is staggered across time, as happens with IDD adoption. Therefore, to correct for such correlation, We cluster standard errors at state-year level (Bertrand, Duflo, and Mullainathan 2004).

$$Innovation_{it} = \alpha_i + \alpha_{s*t} + \beta * I_{IDD} * I_{cross-sectional\,variable} + \boldsymbol{\omega} * \boldsymbol{Z} + \epsilon_{ist} \quad (2)$$

We include state-year fixed effects in order to control for effects arising from each state-year variation. We use employee research intensity, industry cash flow volatility and industry competition to construct $I_{cross-sectional\,variable}$, where $I_{cross-sectional\,variable}$ is an indicator variable that takes 1 when these variables is high, i.e. above median and zero otherwise.

4.1. Research Intensity

I test the compare the strength of the impact across firms with high and low research intensity. Whether reduced incentives to innovate following restricted labor mobility arises from firm-level and employee-level preferences, these effects are stronger for firms with high research intensity. If a firm's R&D to sales ratio is above median, I classify it as high research intensity firms and if the ratio is below media, I classify firm as low research intensity firm. The estimates for research intensity is summarized in Table 3.

Since we have firm fixed effects, the coefficient of research intensity does not load on innovation per se, except for PV/Mcap measure of innovation. This coefficient is positive, as reported in column (4). This is consistent with our expectation that firm with high research intensity has higher number of patents granted. However, our main coefficient of interest here is that of IDD*High Research Intensity, which is positive and statistically significant. We find that the firms with high research intensity benefit more from IDD adoption and hence show higher innovation output post IDD adoption. These results are consistent across all four measures of innovations we use herein.

4.2. Industry cash-flow volatility

The reason for analyzing industry cash-flow volatility is two pronged. First, firms operating in industries with more volatile cash flows are more likely to need to adjust employment in response to cash flow fluctuations (Cuñat and Melitz 2012). Second, firms operating in more competitive industries are faced with higher volatility in their cash-flows (Gaspar and Massa 2006; Valta 2012), which in return might act as a strong motivation for firms to keep innovating. Therefore, high cash-flow should result in undermining the negative effect of restrained labor mobility on firm innovation.

Following Serfling (2016), we estimate industry cash flow volatility as the average cash flow volatility across all firms in the same three-digit NAICS industry and year. A firm's cash flow volatility is the standard deviation of the ratio of income before extraordinary items plus depreciation and amortization to book assets over the preceding 10 years. We create an indicator variable that is set to one if its value is above the sample median and zero otherwise. Estimates are summarized in Table 4. As expected β, the DIDID coefficient, corroborates the effect of IDD on firm patent value and undermining the effect of IDD on patent grants and total citation weighted patents thereby rendering support for our above argument.

4.3. Industry Competition

Researchers have long argued intense domestic product market competition creates employment opportunities (Nickell 1999; Gersbach 1999; Chen and Funke 2008), thereby exacerbating job-hopping of employees and hence transfer of intellectual properties to the rival firms. Firms operating in more intense competition stand to benefit more from the IDD adoption that inhibits employees from freely moving across competing firms. Also, high (domestic) product market competition results in high cash-flow volatility, which in turn results in high stock volatility (Gaspar and Massa 2006; Irvine and Pontiff 2009; Chay and Suh 2009). We, therefore, estimate the moderating role of domestic competition on the effect of IDD on innovation using DIDID in line with equation (2). These results are summarized in Table 5. Consistent with the impact of industry cash-flow volatility, we document that intense competition reinforces the positive effect of labor mobility restriction on all three measures of innovation.

5. Robustness tests

In order to establish the strength of the results and that these observations are not spurious, we corroborate our findings with a battery of robustness tests as discussed in the subsections below. Starting from a set of placebo tests, we run a subsample analyses and use additional measures of innovation to reinforce our findings.

5.1. Falsification tests

Since we rely upon *difference-in-difference* method, in addition to establishing parallel trend between treat and control groups, we run two sets of placebo test as recommended by Roberts and Whited (2013). Following Almeida et al. (2009) we estimate difference in difference results, as presented in equation (3).

$$Innovation_{it} = \alpha_i + \alpha_s + \alpha_t + \beta * I_{treatment} + \boldsymbol{\omega} * \boldsymbol{Z} + \epsilon_{ist} \tag{3}$$

We estimate equation (3) by imposing the assumption that IDD were adoption two and three years ago instead of actual year of adoption; theses estimates are reported in Tables 6 and 7, respectively. Columns (1)-(3) summarize the results for the subsample where we have non-zero observations for patents granted, i.e. only those firms which have produced any innovation. Whereas columns (4)-(6) summarize the result for the entire sample. We find the estimates to be statistically insignificant for both cases when year of IDD adoption was moved by 2 and 3 years. These set of falsification tests corroborate that the results obtained earlier are not spurious and it is indeed the adoption of IDD that drives the impact of innovation.

5.2. States with prominent patent grants

As reported in Table 8, distribution of patents granted differ significantly across states during 1950-2011. Some states have much higher number of successful patent application than the others. This might suggest that some states have more support for innovation than the others. In order to test robustness of the effects estimated above and have a better control-set, We drop the firms headquartered in the states with less than 1% of total patents granted (approximately 390) in the sample period. The estimates for equation (1) corresponding to this restricted sample are reported in Table 8. The results are statistically significant as well as consistent with the main results of the paper. The DID coefficients for IDD adoption is negative and statistically significant and the effect of IDD in these states are of higher magnitude in comparison with those of entire sample reported in Table 2.

6. Conclusion

In this paper, we study the effect of restricted labor mobility, enabled by recognition of IDD, on firm's innovation output. Staggered adoption of IDD provides a good empirical setting to establish the causal effect of workers' mobility on innovation. As has been hypothesized in Section I, we document that although the number of patents granted reduced following IDD adoption, the patent value and hence the firm value increase post adoption of IDD. Firms, legally empowered by IDD and protected from trade-secret theft, are more willing to undertake value increasing innovation projects. Since innovation is costly and employees cannot join competing firms as free as before IDD recognition, firms might decide to go more aggressive on innovation output.

This paper also offers to bridge the gap in the existing literature by offering an explanation for *prima facie* conflicting findings. We document that if workers are restricted to move across firms freely, firms are more inclined to undertake more valuable innovation, which has a positive implications for firm valuation. This effect is particularly pronounced for firms operating in more competitive industries and those that are subject to high cash flow volatility. These findings contrast the conclusions of Contigiani et al. (2018) and we are inclined to conclude that higher trade secret protection encourages firms to undertake more risk. This paper also offers an explanation for apparent conflicting findings of Png (2017) and Contigiani et al. (2018). We propose that with reduced labor mobility across firms, firms incur higher R&D expense and invest in fewer but more valuable projects.

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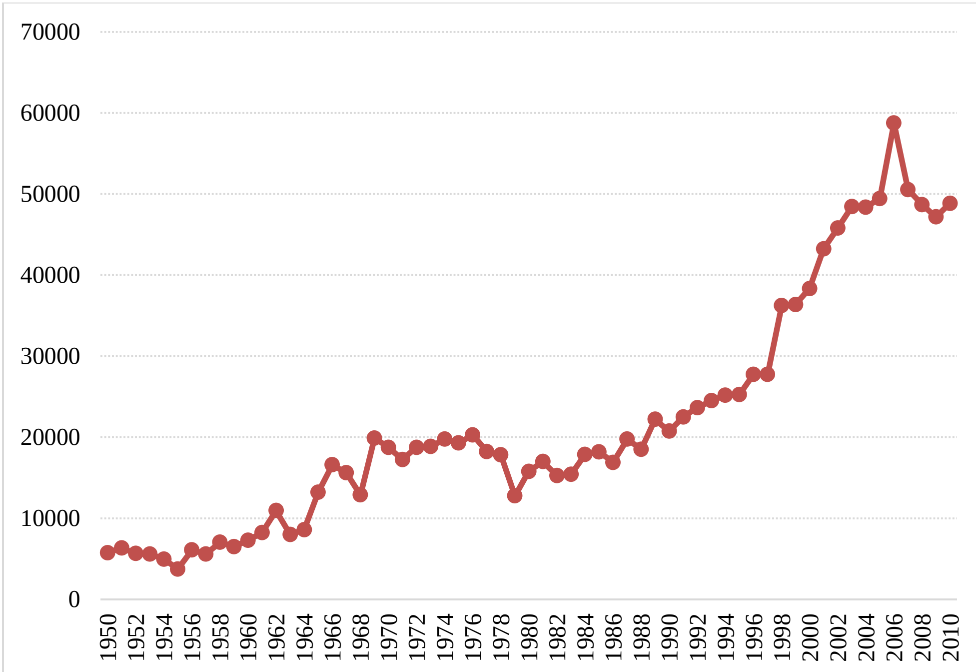

Fig. 1. No. of patents

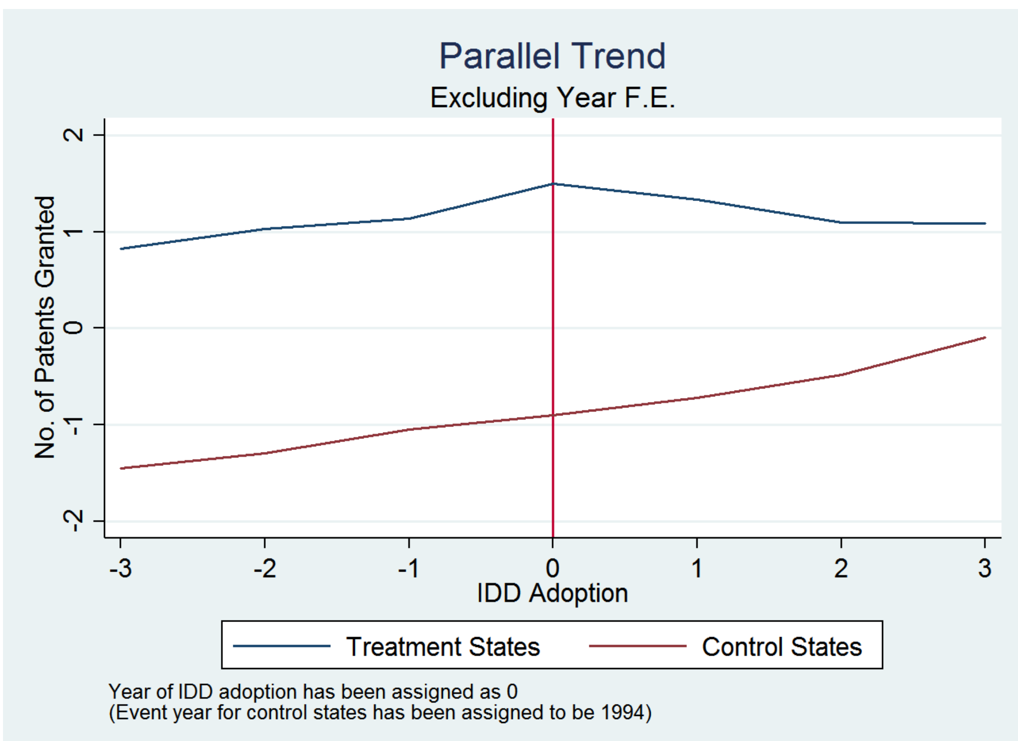

Fig. 2. Innovation Comparison between Treatment and Control Groups

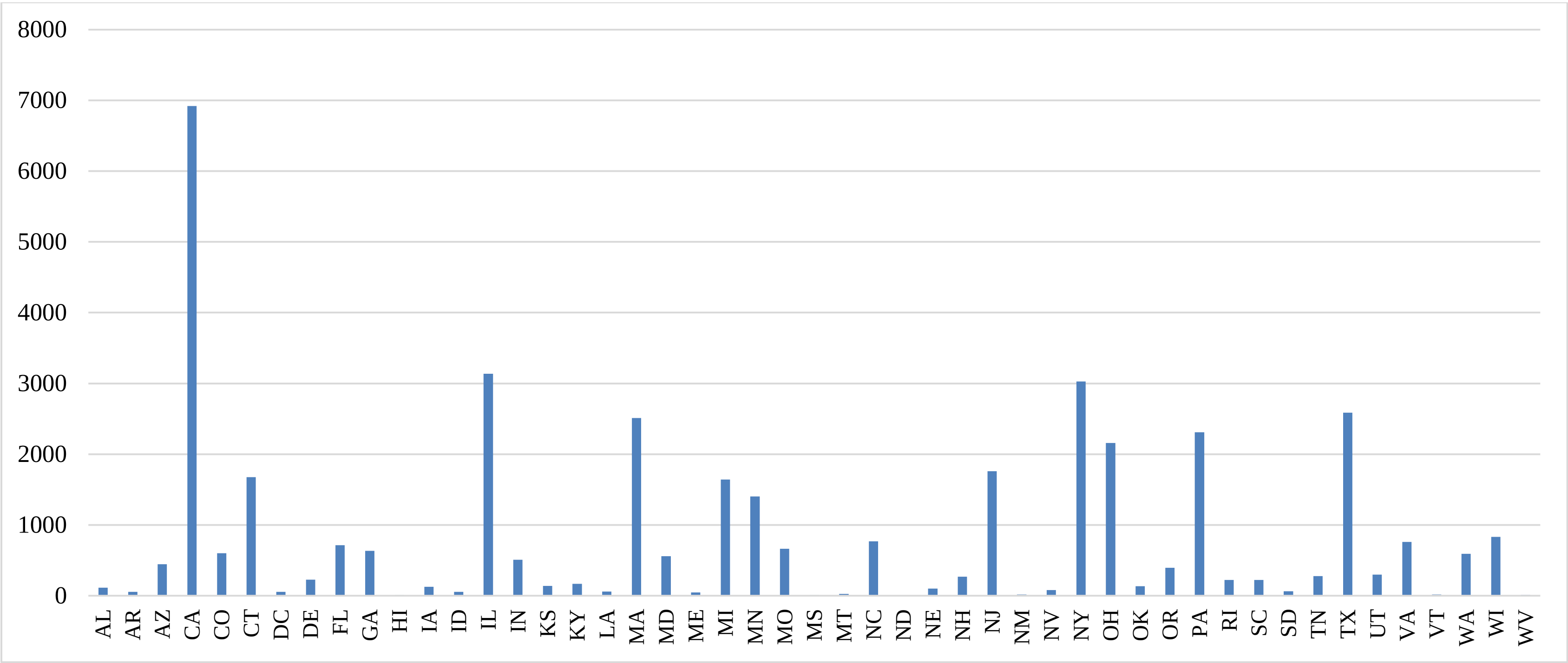

Fig. 3. Statewise Distribution of Number of Patents

Table 1. Descriptive Statistics

					Quantiles			
	N	**Mean**	**S.D.**	**Min**	**0.25**	**Mdn**	**0.75**	**Max**
Patents granted	135965	6.02	39.64	0	0	0	1	2045
CW patents	135965	13.36	90.46	0	0	0	1.07	4555.69
Total Assets (In mm)	135965	3121.39	33179.07	0.02	33.51	148.77	794.58	2.30E+06
Net Sales (In mm)	135965	1279.11	6973.55	-4234.47	28.38	120.51	525.3	4.40E+05
CoGS (In mm)	135957	875.48	5151.29	-366.64	16.78	73.4	338.19	3.50E+05
No. of Employees (In '000)	135965	6.95	29.69	0	0.18	0.88	3.9	2200
Market-to-book	135965	2.55	3.3	0.23	0.94	1.57	2.75	23.22
Gross profit	135957	3444.99	65868.29	-4.90E+05	194.74	1020.82	4930.91	2.40E+05
Book Leverage	135965	0.33	0.25	0	0.1	0.31	0.52	0.93
IDD	135965	0.4	0.49	0	0	0	1	1
CPI	135965	0.04	0.03	0	0.03	0.03	0.04	0.13
Public Policy (WDL)	135965	0.52	0.5	0	0	1	1	1
Implied Contract (WDL)	135965	0.52	0.5	0	0	1	1	1
Good Faith (WDL)	135965	0.17	0.38	0	0	0	0	1

Table 2. Tobit Estimate – Impact of IDD on innovation measures and market response

	(1) log(1+No. of Patents)	(2) log(1+TCW)	(3) R&D to Sales	(4) log(1+TSM)	(5) Market-to-Book	(6) Tobin's Q	(7) log(1+PV/MCap)
IDD	-0.0418***	-0.0631***	0.00183***	0.0490***	0.114***	0.0847***	0.0259***
	(0.00533)	(0.00688)	(0.000390)	(0.00725)	(0.0172)	(0.0113)	(0.00614)
log(Total Assets)	0.0364***	0.0248***	0.00720***	0.226***	-0.484***	-0.307***	0.208***
	(0.00308)	(0.00397)	(0.000242)	(0.00422)	(0.00958)	(0.00625)	(0.00357)
Market-to-Book	-0.00128	-0.000529	0.000441***	0.0367***			-0.0145***
	(0.000911)	(0.00118)	(6.62e-05)	(0.00124)			(0.00105)
log(Gross Profit)	0.00255	0.00266	-0.00407***	0.0210***	0.469***	0.290***	-0.00733***
	(0.00231)	(0.00298)	(0.000173)	(0.00315)	(0.00736)	(0.00482)	(0.00268)
Book Leverage	-0.0835***	-0.119***	-0.00568***	-0.273***	1.736***	-0.669***	-0.215***
	(0.0104)	(0.0134)	(0.000759)	(0.0142)	(0.0333)	(0.0218)	(0.0120)
log(No. of Employees)	0.0981***	0.128***	-0.00438***	0.0453***	-0.222***	-0.135***	0.0518***
	(0.00284)	(0.00366)	(0.000233)	(0.00382)	(0.00873)	(0.00566)	(0.00321)
Constant	0.208***	0.418***	0.0273***	-0.962***	0.879***	1.654***	-0.639***
	(0.0152)	(0.0196)	(0.00142)	(0.0205)	(0.0470)	(0.0307)	(0.0172)
Observations	113,178	113,178	112,591	113,178	113,178	113,178	113,178
Number of permno	10,768	10,768	10,631	10,768	10,768	10,768	10,768
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald Chi-sq	4010	3074	1093	15349	6812	6614	14929
p-val	0	0	0	0	0	0	0
Sigma U	0.680	0.878	0.100	0.874	1.841	1.175	0.715
Sigma E	0.489	0.631	0.0341	0.670	1.622	1.066	0.570
Rho	0.659	0.659	0.897	0.630	0.563	0.548	0.612

Table 3. IDD Adoption and Cross-sectional Heterogeneity across Firm's Research Intensity

	(1) **PV to MCap**	(2) **log(1+TSM)**	(3) **log(1+TCW)**	(4) **log(1+No. of Patents)**
IDD*High Research Intensity	11.13***	0.291***	0.0369*	0.0527***
	(1.353)	(0.0277)	(0.0218)	(0.0179)
log(Total Assets)	9.798***	0.316***	0.126***	0.109***
	(0.621)	(0.0126)	(0.00739)	(0.00597)
Market-to-Book	-0.823***	0.0304***	-0.00505***	-0.00440***
	(0.0997)	(0.00230)	(0.00177)	(0.00141)
Gross Profit	3.29e-06	3.13e-08	-1.29e-07**	-5.83e-08
	(1.16e-05)	(1.18e-07)	(6.09e-08)	(5.04e-08)
Book Leverage	-4.331***	-0.229***	-0.0294*	-0.0154
	(0.911)	(0.0185)	(0.0173)	(0.0140)
log(No. of Employees)	-1.742***	0.00727	0.0674***	0.0517***
	(0.357)	(0.00658)	(0.00581)	(0.00463)
High Research Intensity	0.399	0.0113	0.0443***	0.0246**
	(0.906)	(0.0183)	(0.0155)	(0.0125)
Observations	118,973	118,973	118,973	118,973
R-squared	0.563	0.822	0.819	0.833
Adj-Rsq	0.512	0.802	0.798	0.814
Firm FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Table 4. IDD Adoption and Cross-sectional Heterogeneity across Industry Cash-Flow Volatility

	(1) **PV to MCap**	(2) **log(1+TSM)**	(3) **log(1+TCW)**	(4) **log(1+No. of Patents)**
IDD*High Ind CF Volatility	2.113***	0.0835***	0.0411***	0.0390***
	(0.668)	(0.0159)	(0.0131)	(0.0106)
log(Total Assets)	10.95***	0.311***	0.129***	0.112***
	(0.769)	(0.0141)	(0.00888)	(0.00719)
Market-to-Book	-0.813***	0.0285***	-0.00717***	-0.00622***
	(0.109)	(0.00256)	(0.00208)	(0.00166)
log(Gross Profit)	-0.724*	0.00753	0.00681	0.00576
	(0.439)	(0.00691)	(0.00549)	(0.00423)
Book Leverage	-5.190***	-0.241***	-0.0373**	-0.0257*
	(0.925)	(0.0194)	(0.0182)	(0.0145)
log(No. of Employees)	-1.865***	-0.000697	0.0594***	0.0447***
	(0.422)	(0.00768)	(0.00590)	(0.00478)
High Ind CF Vol	0.124	-0.0127	-0.0294***	-0.0260***
	(0.513)	(0.0111)	(0.00953)	(0.00773)
Observations	109,973	109,973	109,973	109,973
R-squared	0.582	0.828	0.825	0.839
Adj-Rsq	0.532	0.807	0.804	0.820
Firm FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Table 5. IDD Adoption and Cross-sectional Heterogeneity across Industry Competition

	(1) **PV to MCap**	(2) **log(1+TSM)**	(3) **log(1+TCW)**	(4) **log(1+No. of Patents)**
IDD*High Competition	3.048***	0.0804***	0.0210	0.0156
	(0.744)	(0.0192)	(0.0169)	(0.0136)
log(Total Assets)	10.73***	0.306***	0.126***	0.110***
	(0.750)	(0.0139)	(0.00872)	(0.00705)
Market-to-Book	-0.782***	0.0282***	-0.00731***	-0.00626***
	(0.107)	(0.00250)	(0.00203)	(0.00162)
log(Gross Profit)	-0.749*	0.00718	0.00714	0.00580
	(0.426)	(0.00676)	(0.00536)	(0.00414)
Book Leverage	-5.195***	-0.235***	-0.0385**	-0.0268*
	(0.917)	(0.0191)	(0.0179)	(0.0143)
log(No. of Employees)	-1.934***	-0.00355	0.0585***	0.0437***
	(0.408)	(0.00752)	(0.00576)	(0.00466)
High Competition	-4.143***	-0.0200	-0.00597	0.00106
	(0.689)	(0.0164)	(0.0144)	(0.0118)
Observations	112,053	112,053	112,053	112,053
R-squared	0.581	0.827	0.824	0.838
Adj-Rsq	0.531	0.806	0.803	0.819
Firm FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Table 6. Falsification (or Placebo) Test – I

	Sub Sample – Firms with Patent Grants	**Entire Sample – All Firms**				
	(1) log(TSM)	**(2) log(TCW)**	**(3) log(No. of Patent)**	**(4) log(1+TSM)**	**(5) log(1+TCW)**	**(6) log(1+No. of Patents)**
IDD Adoption (T-2)	0.00947	-0.0254	0.00901	0.00906	-0.0149	-0.0107
	(0.0311)	(0.0286)	(0.0266)	(0.0181)	(0.0162)	(0.0124)
log(Total Assets)	1.185***	0.332***	0.330***	0.277***	0.143***	0.119***
	(0.0359)	(0.0379)	(0.0333)	(0.0116)	(0.0116)	(0.00879)
		-				
Market-to-Book	0.173***	0.0350***	-0.0365***	0.0222***	-0.0139***	-0.0116***
	(0.00750)	(0.00647)	(0.00585)	(0.00235)	(0.00262)	(0.00194)
Gross Profit	-1.01e-07	6.10e-07*	7.26e-07**	4.76e-06***	5.22e-07*	6.79e-07**
	(3.34e-07)	(3.41e-07)	(3.35e-07)	(4.18e-07)	(3.02e-07)	(2.72e-07)
Book Leverage	-1.242***	-0.0651	-0.0787	-0.246***	-0.0220	-0.0236
	(0.0555)	(0.0594)	(0.0525)	(0.0214)	(0.0268)	(0.0196)
log(No. of Employees)	0.0735**	0.0936***	0.0965***	-0.0326***	0.0421***	0.0260***
	(0.0356)	(0.0357)	(0.0315)	(0.00775)	(0.00839)	(0.00620)
Observations	13,610	13,610	13,610	42,597	42,597	42,597
R-squared	0.940	0.826	0.852	0.886	0.855	0.875
Adj-Rsq	0.933	0.805	0.835	0.873	0.839	0.861
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Falsification Test – II

	Sub Sample – Firms with Patent Grants			Entire Sample – All Firms		
	(1) **log(TSM)**	**(2)** **log(TCW)**	**(3)** **log(No. of Patent)**	**(4)** **log(1+TSM)**	**(5)** **log(1+TCW)**	**(6)** **log(1+No. of Patents)**
IDD Adoption (T-3)	-0.00427	-0.0361	3.95e-05	-0.00788	-0.0179	-0.0138
	(0.0277)	(0.0264)	(0.0255)	(0.0151)	(0.0144)	(0.0108)
log(Total Assets)	1.185***	0.332***	0.330***	0.277***	0.143***	0.119***
	(0.0359)	(0.0378)	(0.0333)	(0.0116)	(0.0116)	(0.00878)
Market-to-Book	0.173***	-0.0350***	-0.0366***	0.0222***	-0.0139***	-0.0115***
	(0.00750)	(0.00646)	(0.00585)	(0.00235)	(0.00261)	(0.00193)
Gross Profit	-1.01e-07	6.17e-07*	7.26e-07**	4.76e-06***	5.26e-07*	6.82e-07**
	(3.33e-07)	(3.39e-07)	(3.35e-07)	(4.17e-07)	(3.01e-07)	(2.71e-07)
Book Leverage	-1.242***	-0.0648	-0.0787	-0.246***	-0.0220	-0.0236
	(0.0555)	(0.0594)	(0.0525)	(0.0214)	(0.0268)	(0.0196)
log(No. of Employees)	0.0737**	0.0942***	0.0966***	-0.0325***	0.0421***	0.0260***
	(0.0356)	(0.0357)	(0.0316)	(0.00775)	(0.00839)	(0.00620)
Observations	13,610	13,610	13,610	42,597	42,597	42,597
R-squared	0.940	0.826	0.852	0.886	0.855	0.875
Adj-Rsq	0.933	0.805	0.835	0.873	0.839	0.861
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. State-wise Distribution of Granted Patents (1950-2011)

State	Patents Granted	State	Patents Granted
AL	114	MT	24
AR	57	NC	771
AZ	445	ND	3
CA	6918	NE	100
CO	599	NH	270
CT	1674	NJ	1760
DC	57	NM	19
DE	229	NV	79
FL	715	NY	3029
GA	633	OH	2159
HI	8	OK	137
IA	128	OR	394
ID	54	PA	2309
IL	3138	RI	223
IN	509	SC	223
KS	140	SD	62
KY	167	TN	279
LA	61	TX	2585
MA	2512	UT	299
MD	560	VA	762
ME	48	VT	18
MI	1644	WA	594
MN	1404	WI	832
MO	664	WV	13
MS	9		

Table 9. Tobit Estimate for Subsample – States with Significant Patent Grants

	(1) log(1+TSM)	(2) log(1+TCW)	(3) log(1+No. of Patents)
IDD	0.0591***	-0.0529***	-0.0350***
	(0.00712)	(0.00674)	(0.00522)
log(Total Assets)	0.211***	0.0209***	0.0320***
	(0.00415)	(0.00390)	(0.00302)
log(Gross Profit)	0.0202***	0.00274	0.00301
	(0.00311)	(0.00293)	(0.00227)
Book Leverage	-0.253***	-0.106***	-0.0754***
	(0.0140)	(0.0132)	(0.0102)
log(No. of Employees)	0.0413***	0.121***	0.0934***
	(0.00376)	(0.00359)	(0.00279)
Market-to-Book	0.0356***	-0.000391	-0.00108
	(0.00123)	(0.00116)	(0.000897)
Constant	-0.908***	0.399***	0.199***
	(0.0202)	(0.0193)	(0.0149)
Observations	110,648	110,648	110,648
Firm FE	Yes	Yes	Yes
Number of permno	10,742	10,742	10,742
Wald Chi-sq	13950	2770	3644
p-val	0	0	0
Sigma U	0.855	0.861	0.666
Sigma E	0.654	0.613	0.476
Rho	0.631	0.663	0.662

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Влияние трудовой мобильности на корпоративные инновации [Электронный ресурс] : препринт WP9/2019/06 / А. Чакраверти, Н. Гонг, Х. Сингх ; Нац. исслед. ун-т «Высшая школа экономики». – Электрон. текст. дан. (500 Кб). – М. : Изд. дом Высшей школы экономики, 2019. – (Серия WP9 «Исследования по экономике и финансам»). – 35 с. (На англ. яз.)

Работники все в большей степени становятся критически важным активом для компаний, а их конкурентные преимущества все в большей степени зависят от способности к инновациям. Мы изучаем влияние ограничений на мобильность сотрудников (ограничений, связанных с признанием штатом Доктрины неизбежного раскрытия (ДНР)) на инновационный продукт компаний. Установлено, что после признания штатом ДНР экономическая ценность инноваций увеличивается, несмотря на то, что инновационный продукт компаний (по сравнению с компаниями, штаб-квартиры которых находятся в штатах, никогда не признававших или отказавшихся от признания ДНР) уменьшается. Кроме того, после признания ДНР увеличиваются Тобиновская Q, отношение рыночной к бухгалтерской стоимости компании и стоимость патентов компании. Мы делаем вывод, что уменьшение угрозы утери интеллектуальной собственности из-за ухода работников в компании-конкуренты приводит к тому, что компании занимаются более ценными инновациями.

Препринты Национального исследовательского университета «Высшая школа экономики» размещаются по адресу: http://www.hse.ru/org/hse/wp

Препринт WP9/2019/06
Серия WP9
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Аркаджа Чакраверти, Нинг Гонг, Харминдер Сингх

Влияние трудовой мобильности
на корпоративные инновации

(*на английском языке*)

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