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Proprietary Knowledge Protection and Product Market Performance

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Abstract

Does proprietary knowledge protection (PKP) spur or hinder the product-market performance of new firms? Exploiting the staggered adoptions of the inevitable disclosure doctrine by U.S. State Courts, which enhance PKP, we show that treated firms increase industry-adjusted sales growth by 2% compared to control firms. The effect is concentrated among small and young firms and increases with the scope of proprietary knowledge and rivals' access to external finance. PKP encourages firms to develop new products and stimulates initial public offering activity. Our results suggest that PKP alleviates predation risk associated with "deep-pocket" rivals by allowing firms to maintain competitive advantages.

Intellectual property has the shelf life of a banana.
– Bill Gates

I. Introduction

Does the protection of proprietary knowledge (trade secrets) promote the development and growth of new firms in their product market? This question is important in today's knowledge economy as policymakers face the controversial issue of whether to strengthen intellectual property (IP) rights for the purpose of fostering economic growth. On the one hand, proponents of IP protection argue that it stimulates growth by motivating economic agents to innovate.[1] Their rationale critically depends on the assumption that protection leads to tangible market share gains. On the other hand, opponents present a more nuanced view that protection can be a blunt instrument that in fact restricts new knowledge dissemination and

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[1]See Gould and Gruben (1996) and Park and Ginarte (1997), among others for cross-country evidence.

deters new entrants into an industry (Murray and Stern (2007), Huang and Murray (2009), and Williams (2013)). Their concerns reflect recent evidence showing that the benefits of IP protection appear to concentrate on large established firms (e.g., see Galasso and Schankerman (2015)), implying an adverse effect on the intensity of product market competition.[2]

Thus, in the debate about the merits of proprietary knowledge protection (PKP), the balance critically hinges on its heterogeneous effects across firm types. However, the extant literature has thus far not clearly established whether such protection generates positive product market outcomes, and if so, if this effect differs for new entrant firms (small/young) versus incumbent firms (large/mature). The ambiguity may reflect their different levels of financing frictions and competitive threats. As small/young firms tend to be knowledge-intensive, better PKP helps such firms boost the return from growing their product market presence, but doing so also requires external financing that may be constrained by the competitive (predatory) responses of large, well-resourced rivals. In a seminal theory, Bolton and Scharfstein (1990) argue that firms may not be able to enter product markets and grow if external investors are concerned about agency problems and demand tight performance milestones in exchange for continual access to financing. It is possible that PKP alleviates these financing frictions: firms can pledge a greater proportion of their future cash flows to such performance-contingent financing contracts if they are more certain that their proprietary knowledge generates substantial future returns and cannot be easily appropriated by rivals.

This, however, may not be the dominant possibility. A PKP-induced improvement in ex ante contracting efficiency can be at the expense of additional frictions in ex post monitoring. Prior theories suggest that, as firms develop valuable trade secrets, the risk of revealing such secrets in corporate disclosure is elevated (Verrecchia (1983), Dye (1986), and Lanen and Verrecchia (1987)). As such, PKP may in fact make firms less transparent and their asset values more difficult to ascertain.[3] Investors may actually end up cutting off funding too readily when knowledge-intensive firms report low profits, inviting predation by their competitors (Billett, Garfinkel, and Yu (2017)). Apart from the direct effect on a firm's external financing capacity, PKP may also create negative externalities by limiting economy-wide knowledge spillovers and labor mobility. In the setting of noncompete agreements (employment contract clauses that restrict existing employees' ability to join or found a rival firm), prior studies show that such frictions reduce the incentive of existing employees to switch employment and create new firms, and to invest in their own (portable) general skills (Garmaise (2011), Samila and Sorenson (2011), and Starr, Balasubramanian, and Sakakibara (2018)).[4] Difficulties in accessing skilled labor and external knowledge base may end up restricting new firms' ability to compete while entrenching the market positions of incumbent firms.

Our study assesses these opposing possibilities by analyzing the extent to which firms' product market outcomes improve as they are provided with stronger

[2]These opposing arguments are also part of a wider century-long debate on the merits of intellectual property rights in promoting economic and societal welfare (see Bryan (2010) for a summary).

[3]Empirical evidence suggests that increased proprietary knowledge investment results in a reduction in firm disclosures (Verrecchia and Weber (2006), Ellis, Fee, and Thomas (2012), Aobdia (2018), and Li, Lin, and Zhang (2018)) and greater disagreement about firm value (Glaeser (2018)).

[4]See McAdams (2019) for a comprehensive review of the literature on noncompete agreements.

means to keep their critical proprietary knowledge. Importantly, we seek to identify the types of firms (new or incumbent) that benefit more from having such protection and to establish the role of external financing barriers in forming this relationship.

The current lack of empirical evidence on the link between PKP and product market outcomes likely reflects an identification challenge. How well a firm protects its proprietary knowledge is not directly measurable and may be correlated with other unobservable firm characteristics, which makes causality difficult to establish. Our study addresses this issue by exploiting the staggered adoptions of the inevitable disclosure doctrine (IDD) and the subsequent rejections of the doctrine by U.S. state courts. These events provide a quasi-natural experimental setting that allows us to estimate the effect of exogenous changes in the level of PKP on product market outcomes.

The adoption of the IDD is an economically significant shock because a primary channel through which proprietary knowledge of a firm is leaked to its competitors is the mobility of knowledgeable employees (Jaffe, Trajtenberg, and Henderson (1993), Matusik and Hill (1998), and Almeida and Kogut (1999)). The doctrine limits such leakages by restricting the ability of a former employee to work for a rival firm if doing so would inevitably lead to the disclosure of the former employer's trade secrets (e.g., proprietary knowledge such as formulas, practices, production processes, designs and instruments that have inherent economic value) to the rival. Its effectiveness is underpinned by the fact that its enforcement is not contingent on employment contract clauses (such as whether a noncompete agreement is in place) and the locations of future rival firms (such as whether the rival firm is located in the same state as the former employer). The adoption of the IDD by a state court thus significantly enhances the ability of firms located in that state to protect their proprietary knowledge.

Using difference-in-differences (DiD) regression analysis, we document a positive and statistically significant treatment effect of the IDD on treated firms' product market outcomes. The magnitude of the effect is large: the adoption of the IDD by a treated firm's headquarter state on average results in a 2.3% increase (per year) in the firm's industry-adjusted sales growth.[5] This increase is equivalent to nearly one-third of the median sales growth rate for the entire sample of 7.1%. To distinguish between new and incumbent firms, we consider firm size and age differences, and find clear heterogeneity in the effect, which is about twice as large for small (below median size) firms as for large (above median size) firms, and about six times as large for young (below median age) firms as for old (above median age) firms. Our results thus indicate that PKP facilitates the growth of new entrants (rather than established firms) in their product markets.

When verifying the parallel trends assumption underpinning the DiD approach, we find that the above treatment effect is concentrated in the period after (and not before) the IDD is adopted. Moreover, the treatment effect switches to *negative* when a state court *rejects* the previously adopted IDD. A placebo test using the IDD-related ruling of a firm's neighboring state court further shows that

[5]Following the literature, we focus on firm headquarters because these locations are where core business activities occur, and where employees with access to key proprietary knowledge are likely to be concentrated (Pirinsky and Wang (2006), Klasa, Ortiz-Molina, Serfling, and Srinivasan (2018), and Qiu and Wang (2018)).

time-varying local macroeconomic and political conditions are unlikely to drive our baseline results. The documented positive relationship between PKP and product market outcomes thus appears to be causal.

Another concern is that IDD adoption may generate broader implications that are not specific to the protection of proprietary knowledge. For example, it may restrict general labor mobility that restricts firm' ability to grow and/or create additional legal risk that somehow changes firms' strategies. To address such possibilities, we delve into differences across firms to tease out those most at risk of losing proprietary knowledge due to the departure of critical knowledgeable employees to rivals. Specifically, we assess a firm's reliance on skilled labor and manager-level employees, its knowledge-generating orientation (R&D and SG&A expenditures), the similarity and fluidity of its product market (Hoberg, Phillips, and Prabhala (2014), Hoberg and Phillips (2016)), and the presence of nearby competitors and activeness of local labor market. Across all of these categories, we find that the IDD effect on product market outcomes is indeed concentrated among firms facing an inherently greater risk of losing proprietary knowledge.

Our baseline evidence suggests that PKP *alleviates* rather than exacerbates the financing-driven predation risk raised in Bolton and Scharfstein (1990). To strengthen this interpretation, we consider that firms are particularly vulnerable to predation risk when they face financially strong rivals or are themselves financially constrained. Analyzing the heterogeneity within our data, we find that the product market benefits of IDD adoption are indeed concentrated among the above categories of firms. In addition, we find that the recognition of the IDD also improves treated firms' ability to raise new equity finance, with the effect again being concentrated among smaller firms.

To consolidate our sales growth evidence, we also examine other measures and outcomes related to the process of making new market entries. First, we examine how increased PKP bestowed by the IDD allows firms to engage more intensively in new product development. We show that the IDD has a positive effect on treated firms' successful new product launches and stock price reactions to the announcements of these launches. Second, we document that IDD adoption leads to an increase in the number of firms in the same state going public. In relation to the debate surrounding the impact of knowledge protection on new firm development (e.g., see Qiu and Wang (2018); Jeffers (2019); Carlino (2021)), our evidence on initial public offerings (IPOs) thus implies that PKP encourages rather than harms entrepreneurial activity. These results, combined with our main evidence of the IDD effect concentrating among small and young firms, suggest that new entrants receive disproportionately large benefits from having their proprietary knowledge protected, and hence the concern about incumbents using PKP to consolidate their market power is perhaps unwarranted.

Our study expands a relatively scant literature on the product market effects of financing frictions. Campello (2003), (2006) focuses on capital structure and shows that its relationship with product market outcomes varies over business cycles, and maybe nonmonotonic; too high (or too low) indebtedness leads to product market underperformance. Fresard (2010) finds that large cash holdings lead to favorable product market outcomes, especially when rival firms are financially constrained. Billett et al. (2017) show that an exogenous decrease in analyst monitoring intensity (following a brokerage house closure/merger) has a negative impact on market share, especially among firms with high financing barriers. None of these studies considers the possibility that PKP can improve product market outcomes in the presence of financing frictions.

More broadly, our study contributes to the wide-ranging debate on the economic importance of various legal PKP mechanisms. Using the IDD setting, Qiu and Wang (2018) show that such protection benefits shareholders by incentivizing firms to invest in knowledge assets. Klasa et al. (2018) find evidence to suggest that the IDD allows firms to increase their financial leverage, by reducing the risk of losing proprietary knowledge to rivals. Chen, Gao, and Ma (2020) focus on M&A *target firms* and show that the IDD leads to increased acquisition activities as a means to overcome labor market frictions and obtain necessary human capital. In a different PKP setting, that of noncompete agreements, Garmaise (2011) identifies both the theoretical benefits and costs of PKP. He suggests that, by restricting labor mobility, such protection incentivizes firms to invest in firm-specific human capital of their key employees, but the employees themselves may lack the incentive to invest in their own general skills. Analyzing CEO compensation and firm investment data, Garmaise (2011) shows that the second effect is more dominant. Another important consideration in the literature is that some firm types may suffer more from the negative externalities of labor mobility restrictions than others. For example, Jeffers (2019) shows that the stronger enforcement of noncompetes leads to substantial declines in employee departures from incumbent firms and in new firm creation in knowledge-intensive sectors.

Overall, because of the different focuses and empirical settings employed in the two strands of literature discussed above, it is not possible to combine their results to infer that PKP necessarily helps firms achieve better product market outcomes. It is also unclear whether the hypothesized financing benefits of improved PKP necessarily outweigh the costs arising from its negative externalities. Our evidence thus provides new insights by directly establishing that PKP leads to favorable product market outcomes and that the relationship is plausibly causal. Another area of ambiguity in interpreting existing evidence is with respect to heterogeneity in firm characteristics. The previous studies have not explicitly established whether knowledge protection benefits new firms or incumbent firms. Thus, another contribution of our study is in showing that the effect is more pronounced among new entrants. This distinction is particularly relevant to the previously mentioned debate on the broad economic impact of strengthening IP protection, implying that PKP makes industries more competitive and eventually improves consumer welfare.

II. Hypothesis Development

It is a well-established theoretical notion that financing and competitiveness are intimately linked. In a seminal theory, Bolton and Scharfstein (1990) argue that the entry of new firms can be restricted by the predatory behavior of "deep-pocket" incumbents. More specifically, they analyze a staged financing scenario involving a "shallow-pocket" firm (the entrant) negotiating the financing terms for its market entry investment with an investor in date 0. The contract stipulates that the entrant does *not* receive all the required funds upfront. In date 1, the entrant can receive the fund needed for its second-period investment only if it declares a higher than minimum amount of profit that can be returned to the investor. Making funding contingent in this way helps the investor address potential agency problems by creating a credible threat of terminating the contract if the entrant's performance at date 1 is poor. This termination threat, however, is costly in a competitive environment. Another firm (the incumbent) can incur a predation cost to reduce the entrant's chance of earning a high profit in date 1, effectively making it harder for the entrant to secure additional financing from the investor and allowing the incumbent firm to maintain its monopoly.

We argue that PKP is an important condition that enables firms to break out of the Bolton and Scharfstein (1990) financing-predation wedge. Consider a variation of the above scenario, in which the entrant develops some profit-boosting proprietary knowledge in date 0, but it is not protected. The risk that other firms copy and tunnel profits from the same knowledge can discourage the entrant firm from entering the product market as it may lack the financing capacity to fight off a costly predatory response from the incumbent. If instead, the entrant's proprietary knowledge is strongly protected, the firm is more certain about its profit in date 1. This allows it when negotiating on the financing contract at date 0, to agree to declare more profit in favor of the investor on date 1 to secure the additional financing for its investment in the second period. Thus, strong PKP can help the entrant successfully enter the product market despite the predatory threat from the incumbent. Our argument is consistent with the multi-stage nature of the Bolton and Scharfstein (1990) model, as PKP is about the protection of *future* profit-generating capacity.

However, this hypothesized benefit needs to be weighed up against potential costs. First, PKP may create negative externalities that impede a firm's ability to compete in the product market, by preventing it from internalizing the potential spillover benefits from knowledge developed by other firms. For example, Galasso and Schankerman (2015) examine an important protection mechanism (patents) and show that they have an adverse effect on downstream innovation. Garmaise (2011) provides theory and evidence that PKP through noncompete agreements creates a disincentive for existing employees to invest in their own general (transferable) skills, which in turn has a negative effect on firm productivity and performance. Starr, Frake, and Agarwal (2019) show that noncompetes generate externalities in the form of labor market frictions, making it difficult for firms to hire new employees. McAdams (2019) also suggests that restricting worker mobility through noncompetes may hinder the development of startups by preventing knowledgeable workers from founding or joining new firms and bringing their proprietary knowledge over. Importantly, evidence on both patents (Galasso and Schankerman (2015)) and non-competes (Starr et al. (2018), Jeffers (2019), and Carlino (2021)) suggests that the negative externalities of PKP may weigh more on new and small firms, as they are more dependent on knowledge spillovers. Thus, while it is plausible that PKP may facilitate the product market entry and growth of such firms (as we argue), its *net* effect may be the consolidation of product market positions of large established firms.

Second, although PKP may improve ex ante contracting efficiency as argued above, such protection may have a negative effect on ex post monitoring. This is because the effort to develop valuable proprietary knowledge actually raises the cost of disclosing information to investors as such disclosure may unintentionally benefit their competitors. PKP may also restrict industry-wide information discovery (by investors) due to restricted labor mobility. A "shroud of secrecy" may thus envelop firms that are motivated to develop proprietary knowledge because of the improved PKP.[6] If investors overall care more about firms' continuous activity disclosures rather than profit milestones, financing may not be forthcoming, and these firms may not be able to produce favorable outcomes in the presence of intense product market competition, as demonstrated by Billett et al. (2017).

To summarize, it remains ambiguous whether PKP has a net positive impact on product market performance and, if yes, what type of firms (new or incumbent) benefits more from having such protection. The opposing hypotheses outlined above motivate a rigorous and thorough empirical analysis of the product market effects of increasing PKP.

III. Data and Variable Construction

A. IDD Indicator

The IDD is a common law concept that substantially strengthens the protection of trade secrets. The doctrine effectively prevents a firm's former employees from working for its competitors if this inevitably leads to the disclosure of the firm's trade secrets to its competitors (see Hyde (2003) for a detailed discussion). With the adoption of the IDD by a state court, a firm headquartered in that state can obtain an injunction to prohibit a former employee from working at a competing firm, thereby preventing the potential leakage of its trade secrets.

We focus on the IDD as a form of PKP because of its significant economic implications. Evidence shows that the adoption of the IDD effectively restrains knowledgeable employees' mobility to rival firms and, hence, limits cross-firm knowledge spillovers (Png and Samila (2015)). Filing patents is another form of knowledge protection but its use can be limited. Specifically, many different types of nontechnical proprietary knowledge (e.g., customer lists) cannot be patented, and even for patented intellectual property, there is a risk that the patents themselves can create public information that is in fact expropriated by rivals (Garmaise (2011)). Proprietary knowledge can also be protected through non-compete agreements, but these contract clauses have limitations (e.g., in terms of applicable geographic areas and time periods) and can be difficult to enforce.

Focusing on the IDD adoption and rejection events also provides us with a research design advantage. While some protection can be achieved through patents and non-compete agreements, these mechanisms reflect endogenous choices of

[6] Indeed, a number of empirical studies document that these firms tend to engage more in selective public market disclosure (Verrecchia and Weber (2006), Ellis et al. (2012), and Aobdia (2018)) and experience declines in corporate transparency measures (Glaeser (2018), Li et al. (2018)).

firms and do not provide a good instrument for inferring the effect of improved knowledge protection. The laws in relation to the enforceability of non-compete agreements vary across states but are largely time-invariant (Garmaise (2011)). In contrast, IDD precedent-setting cases are plausibly exogenous events. Unlike the passage of state laws, which might be subject to lobbying by special interest groups and to political pressure created by certain economic conditions, adoptions and rejections of the IDD are based on court rulings on specific precedent-setting cases. These rulings mainly depend on the nature of the relevant cases and the character of the justices, which are arguably exogenous to firms' decision-making processes (Qiu and Wang (2018)).

Our construction of the IDD indicator variable is consistent with Qiu and Wang (2018) who compile the list of precedent-setting IDD adoptions and rejections through 2014 based on extant legal studies as well as a comprehensive review of IDD-related court cases in the LexisNexis database.[7] In particular, over the 1960–2014 period, the authors identify in total 34 primary IDD court-ruling events by U.S. states, of which 24 are adoptions and 10 are rejections of the previously adopted IDD laws. Similar to Klasa et al. (2018) and Qiu and Wang (2018), the IDD is converted back to zero value from the year of rejection onward. All the events and their timing are listed in Supplementary Table A1.

B. Measures of Product Market Outcomes

We follow Fresard (2010) and Billett et al. (2017) to use three alternative measures of product market outcomes (PMO). The first is firm-level sales growth (SG), computed as the percentage change in sales from year $t-1$ to year t. The second and third measures are a firm's sales growth minus its industry median sales growth from year $t-1$ to year t, with industries defined using 4-digit SIC codes (MSG_SIC) or the Fama–French 49 industry classification (MSG_FF), respectively. The last two measures capture the relative market share gain by a focal firm, as its sales growth is benchmarked against those of its rival firms.

C. Sample Selection and Descriptive Statistics

We start our sample selection with all Compustat U.S. firms over the period of 1980 to 2016. Our sample period begins 2 years before Pennsylvania (PA) state adopts the IDD in 1982 and ends 2 years after North Carolina (NC) rejects the IDD in 2014. We follow the sample selection criteria of Billett et al. (2017) and exclude financial and utility firms (SIC codes 6000–6999 and 4900–4999) and industry-years with less than 10 observations (under both the 4-digit SIC and Fama–French 49 industry classification). We further require each firm-year observation to have headquarter state information, nonnegative sales revenue, nonnegative total assets, and other data to compute all variables in the baseline regression model. It is important to note that other studies in the same area (Campello (2003), (2006), Fresard (2010)) impose similar criteria to maintain reasonable stability in the PMO

[7]Klasa et al. (2018) utilize a list of IDD adoption and rejection cases up to 2006, containing 21 precedent-setting cases. Qiu and Wang (2018) extend the list to 2014 with 34 such events.

TABLE 1
Summary Statistics of Key Variables

The sample period in Table 1 is from 1980 (2 years before PA adopted in 1982) to 2016 (2 years after NC adopted in 2014). SG is a firm's sales growth rate from year $t-1$ to year t. MSG_SIC is SG minus the industry median SG for the same year (with each industry being defined as a 4-digit SIC code). MSG_FF is computed in the same way as MSG_SIC but with each industry being defined as one of the Fama–French 49 industries. IDD is the indicator for whether a firm's headquarter state recognizes the inevitable disclosure doctrine in a given year. LN_ASSET is the log of total assets. MTB is market-to-book (assets) ratio. CASH is total cash holdings scaled by total assets. LEV is total debt scaled by total assets. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP.

	Variable					
	No. of Obs.	Mean	Std. Dev.	25th Percentile	50th Percentile	75th Percentile
Panel A. Main Dependent Variables						
SG	108,747	0.183	0.778	−0.056	0.071	0.226
MSG_SIC	108,747	0.086	0.761	−0.138	−0.009	0.116
MSG_FF	108,747	0.091	0.769	−0.138	−0.013	0.126
Panel B. Main Independent Variables						
IDD	108,747	0.318	0.458	0.000	0.000	1.000
Panel C. Firm-Level Control Variables						
LN_ASSET	108,747	4.570	2.361	2.915	4.476	6.163
MTB	108,747	2.736	5.464	1.096	1.518	2.486
CASH	108,747	0.193	0.224	0.028	0.098	0.281
LEV	108,747	0.272	0.430	0.031	0.190	0.366
Panel D. State-Level Control Variables						
LN_STATEGDP	108,747	12.452	1.040	11.798	12.468	13.196
STATEGDP_GROWTH	108,747	0.061	0.031	0.044	0.061	0.079
LN_STATEGDP_CAP	108,747	10.145	0.444	9.835	10.176	10.492

measures.[8] This leads to the baseline sample of 108,747 firm-year observations. To minimize the impact of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

Table 1 presents the descriptive statistics. The median sales growth (SG) among our sample firms is 7.1% per year. The market share growth measures (MSG_SIC and MSG_FF) have below zero medians (−0.9% and −1.3%) and positive means (8.6% and 9.1%). These statistics are consistent with Billett et al. (2017) and reflect the fact that, although most firms in a given industry grow their revenue over time, the majority of them are laggards and lose market shares to some fast-growing competitors. The mean value of the IDD indicator of 0.318 suggests that on average 31.8% of firm-years are headquartered in IDD-adopting states during our sample period. In total, there are 10,198 unique firms in our sample, of which 5,153 firms are treated at some point in their life, and 5,045 firms are never treated.

IV. Impact of IDD on Product Market Outcomes

A. Baseline Analysis

We use a difference-in-differences (DiD) regression framework to examine how the adoption of the IDD by a state court impacts the product market outcomes of firms in the same state:

[8]For example, if the minimum number of firms is not a requirement, the PMO measures can experience large variations simply because of new listings and delistings in certain 4-digit SIC codes.

$$\text{(1)} \qquad \text{PMO}_{i,t} = \alpha + \beta \text{IDD}_{s,t} + \gamma \mathbf{F}_{i,t-1} + \delta \mathbf{S}_{s,t-1} + \omega_i + \theta_{j,t} + \varepsilon_{i,t},$$

where $\text{PMO}_{i,t}$ is one of the three proxies for product market outcomes of firm i in year t: SG, MSG_SIC, or MSG_FF. $\text{IDD}_{s,t}$ is the indicator variable for whether the state court has adopted the IDD in the headquarter state s of firm i by year t. The coefficient β captures the average incremental changes in PMO of firms headquartered in an IDD-adopting state (treated firms) relative to the contemporaneous changes in PMO of firms headquartered in unaffected states (control firms). The terms ω_i and $\theta_{j,t}$ indicate firm fixed effects, which control for time-invariant firm characteristics, and industry-year fixed effects, which control for time-varying industry-level determinants of PMO, such as demand shocks and technological breakthroughs (Klasa et al. (2018)). Given that MSG_SIC (or MSG_FF) already adjusts a firm's sales growth against its specific industry peers, $\theta_{j,t}$ is defined at a broader industry level, using the 2-digit SIC code of each firm. To address concerns about auto-correlation, we cluster standard errors at the headquarter state level given that the key independent variable of interest, $\text{IDD}_{s,t}$, is measured at the state level.

$\mathbf{F}_{i,t-1}$ and $\mathbf{S}_{s,t-1}$ are two vectors of time-varying firm-level and state-level control variables. These variables are lagged by 1 year relative to the selected PMO measure. Similar to those used in Billett et al. (2017), our firm-level controls include i) LN_ASSET, which is the natural logarithm of total assets, ii) MTB, which is the ratio of market value to book value of total assets, iii) CASH, which is cash plus short-term investments, scaled by total assets, iv) LEV, which is total debt scaled by total assets, and v) and the lag term $\text{PMO}_{i,t-1}$. Smaller firms are likely to be new entrants with naturally more rooms to grow. Higher market-to-book ratio indicates shareholders' expectations for more growth opportunities. Larger cash reserves may provide the firm with more resources to finance its competitive strategies which help win over its rivals (Fresard (2010)). Controlling for leverage is necessary given its documented impact on PMO (Campello (2003), (2006)), as well as the possibility that IDD events may also influence firms' leverage decisions Klasa et al. (2018). Finally, the inclusion of $\text{PMO}_{i,t-1}$ follows the same approach of other studies in this area such as Fresard (2010) and Billett et al. (2017). Fresard ((2010), p. 1103) specifically suggests that "controlling for lagged sales growth … captures the influence of other firm characteristics that may have driven competitive performance in the recent past, such as a change in store location or distribution network."[9] With regard to state-level control variables, we follow Qiu and Wang (2018) and incorporate the following three broad measures that capture economic conditions in a firm's headquarter state: LN_STATEGDP, which is the natural logarithm of the state's income (collected from the U.S. Census Bureau and Bureau of Economic Analysis); STATEGDP_GROWTH, which is the percentage change in the state's income; LN_STATEGDP_CAP, which is the natural logarithm of per

[9]However, including both the lagged dependent variable and fixed effects into a regression model may create a bias in regression coefficient estimates, as pointed out by Angrist and Pischke (2008), although the extent of the bias reduces with sample size. To show that our results are not driven by this issue, some specifications and robustness tests will not include the lagged PMO variable as a regressor.

TABLE 2

Baseline Regression Results

The sample period in Table 2 is from 1980 (2 years before PA adopted the IDD in 1982) to 2016 (2 years after NC adopted the IDD in 2014). SG is a firm's sales growth rate from year $t-1$ to year t. MSG_SIC is SG minus the industry median SG for the same year (with each industry being defined as a 4-digit SIC code). MSG_FF is computed in the same way as MSG_SIC but with each industry being defined as one of the Fama–French 49 industries. IDD is the indicator for whether a firm's headquarter state recognizes the inevitable disclosure doctrine in a given year. LN_ASSET is the log of total assets. MTB is the market-to-book (assets) ratio. CASH is total cash holdings scaled by total assets. LEV is total debt scaled by total assets. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP. The *t*-statistics (in parentheses) are computed using standard errors clustered at the headquarter state level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SG		MSG_SIC		MSG_FF	
	1	2	3	4	5	6
IDD	0.025**	0.023**	0.023**	0.021*	0.024**	0.022*
	(2.66)	(2.04)	(2.59)	(1.87)	(2.57)	(1.95)
LN_ASSET_{t-1}		−0.156***		−0.152***		−0.155***
		(27.17)		(26.65)		(27.07)
MTB_{t-1}		0.009***		0.009***		0.009***
		(5.94)		(5.93)		(5.91)
$CASH_{t-1}$		0.646***		0.638***		0.644***
		(17.70)		(17.79)		(17.60)
LEV_{t-1}		−0.048**		−0.046**		−0.047**
		(2.84)		(2.73)		(2.80)
$LN\_STATEGDP_{t-1}$		−0.065		−0.045		−0.055
		(1.17)		(0.82)		(1.03)
$STATEGDP\_GROWTH_{t-1}$		−0.042		0.007		−0.032
		(0.22)		(0.03)		(0.17)
$LN\_STATEGDP\_CAP_{t-1}$		0.063		0.074		0.067
		(0.56)		(0.72)		(0.61)
SG_{t-1}		−0.055***				
		(7.87)				
MSG_SIC_{t-1}				−0.054***		
				(7.64)		
MSG_FF_{t-1}						−0.054***
						(7.76)
No. of obs.	108,747	108,747	108,747	108,747	108,747	108,747
Adj. R^2	0.093	0.130	0.077	0.114	0.079	0.117
Industry × year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes

capita state income. Firms located in states with better economies are likely to benefit from strong local demands which boost their sales growth relative to rivals located in other states.

Table 2 presents the estimation results of model 1. Similar to Klasa et al. (2018), we run regressions both with and without the full list of control variables. Across all of the models estimated on the three alternative PMO measures, the coefficients on the variable of interest, IDD, are positive and statistically significant at the conventional levels. The magnitude of the impact is economically meaningful. For example, the estimated coefficient on IDD in column 2 implies that, after an IDD adoption, a treated firm increases its annual sales growth by 2.3 percentage points more than a control firm, which translates into a 32.4% change (= 0.023/0.071) relative to the median SG. In column 4 (with MSG_SIC being the dependent variable), the estimated coefficient on IDD suggests that a treated firm gains *market share* faster than a control firm: the rate at which the treated firm grows revenue relative to its direct (4-digit SIC) industry rivals exceeds that of the control firm (selected from the same 2-digit SIC industry) by 2.1 percentage points. Note that these percentages are the annual compounding growth rates of sales and market shares for all years subsequent to the IDD adoption. For illustration, a firm in an IDD-adopting state with 2.3% growth rate could increase its sales by 25.5% $\left(=(1+0.023)^{10}-1\right)$ 10 years after the IDD adoption relative to a control rival in a non-IDD state. In sum, the baseline results in Table 2 lend strong support to the hypothesis that enhancing protection of a firm's proprietary knowledge makes the firm more competitive in its product markets.

We note that the estimates involving the firm-level controls generally exhibit the expected signs. For example, the negative coefficients on LN_ASSET suggest that smaller firms tend to generate greater market share gains. The positive coefficients on MTB and CASH suggest that firms with more growth opportunities and internal cash reserves also tend to have good product market outcomes. The negative coefficient on LEV reveals that excessive debt financing may limit market share gains.

We carefully check to ensure that the above results are not sensitive to model specifications. In Supplementary Table A2, we include four more time-varying control variables that may affect product market outcomes: acquisition intensity (Fresard (2010)), return on assets, R&D scaled by assets, and capital expenditure scaled by assets. In Panels A and B of Supplementary Table A3, we impose alternative fixed effects structures on the baseline regression model. In Panel C, we vary the industry definition that forms the industry-by-year fixed effects. This ensures that control firms are selected from a narrower set of peer firms, but at the expense of not including firms in closely related industries. In Panel A of Supplementary Table A4, we remove the lagged measure $\text{PMO}_{i,t-1}$ from the estimation to ensure that our results are not driven by the bias associated with including both the lags of the dependent variable and fixed effects in the same regression. In Panel B of Supplementary Table A4, we also examine a longer 3-year sales growth window. These tests produce qualitatively similar results to those obtained from Table 2.

B. Effect Heterogeneity: New Versus Established Firms

We now turn to the important economic question of which firm type, new entrants or established firms, benefits from stronger PKP. We rerun the baseline model separately for small and large firms (split by the median asset size in a given year) and for young and mature firms (split by the median firm age in a given year).[10] The results reported in Panel A (Panel B) of Table 3 clearly demonstrate a larger positive effect of IDD recognition on sales growth and market share growth of small firms relative to large firms (young firms relative to mature firms). For example, the coefficients on IDD in columns 3 and 4 of Panel A (on MSG_SIC) reveal that an IDD adoption helps small-treated firms increase their sales growth relative to their 4-digit SIC code peers by 4.5 percentage points faster than other small control firms. In comparison, this advantage is merely 1.8 percentage points for large treated firms. The IDD effect among small firms (4.5%) is comparable

[10]Firm age is defined as the difference between the current year and the year of first appearance in Compustat database. In a sensitivity check, we use an alternative definition of firm age which is the difference between the current year and the IPO year, and obtain smaller sample but consistent results.

TABLE 3

Heterogeneous Effects Across Subsamples of Firms Split by Firm Size and Age

The sample period in Table 3 is from 1980 (2 years before PA adopted the IDD in 1982) to 2016 (2 years after NC adopted the IDD in 2014). SG is a firm's sales growth rate from year $t-1$ to year t. MSG_SIC is SG minus the industry median SG for the same year (with each industry being defined as a 4-digit SIC code). MSG_FF is computed in the same way as MSG_SIC but with each industry being defined as one of the Fama–French 49 industries. IDD is the indicator for whether a firm's headquarter state recognizes the inevitable disclosure doctrine in a given year. The other control variables (measured with 2-year lag) are as follows: LN_ASSET is the log of total assets. MTB is market-to-book (assets) ratio. CASH is total cash holdings scaled by total assets. LEV is total debt scaled by total assets. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP. In Panels A and B, sample firms are split according to firm size (total assets) and firm age (number of years since the first appearance in the Compustat database), respectively. The t-statistics (in parentheses) are computed using standard errors clustered at the state level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SG		MSG_SIC		MSG_FF	
	1	2	3	4	5	6
Panel A. Results Based on Subsample Split by Firm Size						
	Small Firms	Large Firms	Small Firms	Large Firms	Small Firms	Large Firms
IDD	0.044**	0.021***	0.045**	0.018**	0.044**	0.020***
	(2.34)	(2.83)	(2.30)	(2.47)	(2.26)	(2.73)
No. of obs.	53,695	53,949	53,695	53,949	53,695	53,949
Adj. R^2	0.111	0.191	0.102	0.145	0.104	0.150
Panel B. Results Based on Subsample Split by Firm Age						
	Young Firms	Old Firms	Young Firms	Old Firms	Young Firms	Old Firms
IDD	0.037*	0.007	0.036*	0.006	0.036*	0.006
	(1.82)	(0.82)	(1.78)	(0.71)	(1.79)	(0.74)
No. of obs.	54,701	53,421	54,701	53,421	54,701	53,421
Adj. R^2	0.131	0.117	0.119	0.095	0.121	0.098
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes

to the impact of reduction in information asymmetry due to brokerage house mergers/closures (3.9%) as documented in Billett et al. (2017), and larger than the impact of 1-standard-deviation increase in the level of cash holdings (2.9%) as shown in Fresard (2010).

Likewise, the coefficients on IDD in columns 3 and 4 of Panel B show that, among young firms, the difference in market share gain following an IDD adoption between the treated and control groups is equivalent to a 3.6 percentage point growth in sales. This advantage again drops to a merely 0.6 percentage point and becomes statistically insignificant for mature firm subsample. It is also important to note that, while the tests in Table 3 are conducted on separate subsamples so that we can clearly show the magnitudes of the IDD effect for different firm types, we obtain qualitatively similar results by interacting IDD with an indicator variable for small firms (or for young firms), as reported in Supplementary Table A5. In summary, given that most of the new entries are small and/or young firms while incumbents tend to be large and/or mature firms in an industry, our results suggest that the new entrants enjoy disproportionately larger benefits offered by the IDD adoption. Thus, PKP is likely to promote rather than to stymie competition.

C. IDD Rejection and Dynamic DiD Models

Our next tests aim to strengthen the causal interpretation of our baseline results. The DiD framework requires that treatment and control firms follow parallel trends in the outcome variable before the treatment. A particular concern is that the adoption of the IDD in one state influences IDD court decisions in other states, potentially invalidating the parallel trends assumption.

To alleviate this concern, we now pay close attention to IDD rejection events, which are arguably more exogenous (less expected). We replace the original IDD indicator with two new variables (IDD_ADOPT and IDD_REJECT), which separately indicate the periods after an IDD adoption event and an IDD rejection event for each state. The same approach is also used by Klasa et al. (2018). Another commonly used test to validate the parallel trends assumption involves incorporating lead and lag terms in dynamic DiD regressions (Klasa et al. (2018), Li et al. (2018)). To do this, we create a new set of indicator variables: IDD_ADOPT_{-3}, IDD_ADOPT_{-2}, IDD_ADOPT_{-1}, IDD_ADOPT_{0}, IDD_ADOPT_{+1}, and IDD_ADOPT_{2+}. The variables with negative subscripts indicate whether a focal firm's headquarter state will adopt the IDD in 3 years, 2 years, and 1 year, respectively. The remaining three variables indicate an IDD adoption event in the current year, 1 year ago, and 2 or more years ago, respectively. These adoption timing indicators fully absorb the variable IDD_ADOPT used in the previous test, and we retain IDD_REJECT to indicate IDD rejection events. In both of the tests described here, our primary focus is on the differences in the coefficients on the various IDD indicators. To alleviate the potential "endogenous controls" issue associated with the leads and lags of the outcome variable, we do not include the control variables in these dynamic DiD regression models.

Columns 1, 3, and 5 in Table 4 show that the effect of IDD_ADOPT remains positive and statistically significant. Importantly, despite having only a few rejection events, the coefficient estimate for IDD_REJECT switches signs to negative, and is statistically significant, with the exception of the regression on MSG_SIC. This finding suggests that the removal of the IDD curtails a treated firm's product market performance. In columns 2, 4, and 6 of Table 4, we find that the coefficients on IDD_ADOPT_{-3}, IDD_ADOPT_{-2}, and IDD_ADOPT_{-1} are close to zero, while the coefficients on IDD_ADOPT_{0}, IDD_ADOPT_{+1}, and IDD_ADOPT_{2+} are positive and their magnitudes are similar to those of the main IDD variable obtained in the baseline results. Further, in columns 2, 4, and 6 the coefficients on IDD_ADOPT_{2+} are statistically significant. Thus, firms in IDD-adopting states appear to improve their PMO only after the actual adoption of the IDD, but not before. These results strengthen our interpretation that the product market effect of the IDD is likely causal.[11]

[11] An endogeneity concern can also arise because both IDD-related events and PMO are correlated with some unobservable local economic/political conditions. Qiu and Wang (2018) find that the timing and decision of the state IDD changes do not appear to be affected by the local economic/political conditions, however. To further alleviate this concern, we conduct a "placebo" treatment test. Specifically, we assume that the (real) control firms headquartered in states that are contiguous to an IDD-adopting state were also affected by the treatment ("placebo-treated" firms). We then compare their PMOs to those of the rest of the control firms. If unobserved local dynamics indeed drive both the IDD events and firms' PMO, then the PMO measures of the placebo-treated firms should rise in a similar fashion to those of real treated firms, and we would observe a similar "treatment" effect in these "placebo" tests as what we observed in the baseline results. Supplementary Table A6 shows that the coefficients on the placebo treatment indicator IDD_PLACEBO are insignificant and in fact switch to negative in some specifications.

TABLE 4

Validation of Parallel Trend Assumption

The sample period in Table 4 is from 1980 (2 years before PA adopted the IDD in 1982) to 2016 (2 years after NC adopted the IDD in 2014). SG is a firm's sales growth rate from year $t-1$ to year t. MSG_SIC is SG minus the industry median SG for the same year (with each industry being defined as a 4-digit SIC code). MSG_FF is computed in the same way as MSG_SIC but with each industry being defined as one of the Fama–French 49 industries. IDD_ADOPT is the indicator for all the years after a firm's headquarter state adopts the inevitable disclosure doctrine. The variable IDD_ADOPT with a subscript in the set of −3, −2, −1, 0, +1 indicate each of the years from 3 years before to 1 year after each IDD adoption event (year 0), and the subscript 2+ indicates all the remaining years after this event. IDD_REJECT is the indicator for all the years after a firm's headquarter state rejects the IDD. The following control variables are not reported. LN_ASSET is the log of total assets. MTB is the market-to-book (assets) ratio. CASH is total cash holdings scaled by total assets. LEV is total debt scaled by total assets. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP. The above control variables are measured with 1-year lag. The *t*-statistics (in parentheses) are computed using standard errors clustered at the state level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SG		MSG_SIC		MSG_FF	
	1	2	3	4	5	6
IDD_ADOPT	0.025**		0.024**		0.024**	
	(2.15)		(2.20)		(2.10)	
IDD_ADOPT_{-3}		−0.007		−0.008		−0.007
		(0.24)		(0.29)		(0.24)
IDD_ADOPT_{-2}		−0.006		−0.001		−0.006
		(0.45)		(0.11)		(0.47)
IDD_ADOPT_{-1}		0.005		0.007		0.004
		(0.30)		(0.38)		(0.24)
IDD_ADOPT_{0}		0.025		0.023		0.023
		(1.42)		(1.23)		(1.29)
IDD_ADOPT_{+1}		0.030		0.033*		0.030
		(1.61)		(1.68)		(1.55)
IDD_ADOPT_{2+}		0.022*		0.022*		0.021*
		(1.86)		(1.91)		(1.81)
IDD_REJECT	−0.017**	−0.017**	−0.011	−0.011	−0.015*	−0.015*
	(2.21)	(2.23)	(1.23)	(1.36)	(1.84)	(1.91)
No. of obs.	108,747	108,747	108,747	108,747	108,747	108,747
Adj. R^2	0.093	0.093	0.077	0.077	0.079	0.079
Control variables	No	No	No	No	No	No
Industry × year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes

D. IDD and Value of Proprietary Knowledge

We next address the possibility that the observed changes following an IDD adoption may reflect other implications unrelated to PKP. In particular, the IDD may restrict general labor mobility or may reflect changes in a state court's judicial stance on employee–employer disputes. We conduct a series of tests to examine how our baseline results vary with certain measures for the extent of proprietary knowledge and the competition for such knowledge. Our hypothesis will be strengthened if the benefits of IDD adoption are more pronounced for firms that specifically rely on PKP to stay competitive.

On the extent of proprietary knowledge, the first measure is based on the fraction of high-skill workers required in a particular industry, as constructed by Belo, Li, Lin, and Zhao (2017).[12] The second measure reflects the percentage of workers in a firm's (3-digit-SIC) industry that are in managerial/executive occupations, constructed using the data from the Bureau of Labor Statistics (BLS). The third

[12]We thank Frederico Belo for making these data publicly available.

measure captures a firm's own assessment of the risk of losing skilled labor, constructed by Qiu and Wang (2021) as the number of sentences in Item 1A (Risk Factors), Item 1 (Business), and Item 7 (Management's Discussion and Analysis) of a 10-K filing that mention keywords associated with such risk.[13] Combined together, these three measures speak to the fact that high-skill (and manager-level) workers are both the knowledge generators and the custodians of a firm's trade secrets; and are thus considered in the literature to be a primary channel through which such secrets are leaked to competitors (Jaffe et al. (1993), Matusik and Hill (1998), and Almeida and Kogut (1999)). The fourth and fifth measures are based on R&D expenditure and SG&A expenses, both scaled by total revenue. They reflect the extent to which a firm invests in new knowledge and the human capital of its workers (Eisfeldt and Papanikolaou (2013), Qiu and Wang (2018)).

We create the indicator variables, IND_SKILLS, MGT_OCC, SKILL_RISK, RD, and SGA, to indicate whether each of the above five measures is greater than its cross-sectional median in a given year, and interact each indicator variable with IDD. Given that our focus here is on the heterogeneity of the IDD effect (the interaction term), we add another specification that includes state $\times$ year fixed effects to control for all unobservable time-varying state-level factors that are potentially correlated with firm-level PMO. The results are reported in Panels A–E of Table 5. We find that the coefficients on the interaction terms of interest are positive and statistically significant in most cases (29 out of 30 specifications). Thus, consistent with our expectations, firms that actively produce crucial proprietary knowledge indeed benefit more from having their proprietary knowledge protected by the IDD.

Another source of heterogeneity that we consider is the competition environment. In a highly competitive product market, proprietary knowledge becomes an even more important source of competitive advantage. It is critical to protect such knowledge from being appropriated by rivals. We, therefore, conjecture that an IDD adoption will be even more valuable for firms that face intense competition. We employ two well-known measures of firm-level competition based on textual analysis of 10-K disclosures, including i) product market fluidity (Hoberg et al. (2014)), and ii) total product similarity (Hoberg and Phillips (2016)).[14] The former metric captures how quickly rival firms change their products relative to a focal firm and the latter metric captures how similar the descriptions of a firm's products are to those of rival firms. For both metrics, a higher value indicates greater product-level rivalry. Moreover, a more active local labor market increases the likelihood of employee job hopping to nearby rivals, so we also examine the state-level labor turnover rate, calculated as the annual average of (number of hires in quarter t + number of separations in quarter $t+1$)/(the full-quarter employment) in a state-year using the data from the U.S. Census Bureau.

Corresponding to the three measures described above, we create the variables, PROD_FLUID, PROD_SIM, and STATE_LABOR, to indicate the above-median values of each measure in a given year. These indicators then interacted with the

[13]We thank Yue Qiu for making these data publicly available.

[14]We thank Gerard Hoberg and Gordon Phillips for making the product market fluidity and total similarity data publicly available.

TABLE 5

Product Market Effect of IDD and Value of Proprietary Knowledge

In Table 5, SG is a firm's sales growth rate from year $t-1$ to year t. MSG_SIC is SG minus the industry (4-digit SIC code) median SG for the same year. MSG_FF is computed in the same way as MSG_SIC but based on the Fama–French 49 industries. IDD is the indicator for whether a firm's headquarter state recognizes the inevitable disclosure doctrine in a given year. In each Panel below, IDD is interacted with the indicator variable representing one of the following measures (indicating whether the measure for a given firm is above the cross-sectional median in the same year). IND_SKILLS represents the index of employees' skills required by a particular industry, constructed by Belo et al. (2017). MGT_OCC represents the industry-level (3-digit-SIC) percentage of workers in manager/executive occupations (obtained from the BLS). SKILLS _RISK represents the skill labor risk index computed as the number of sentences discussing such risk in a firm's 10-K filing. RD represents research and development expenditures scaled by total sales. SGA represents the ratio of selling, general, and administrative expenses (SG&A) to total sales. PROD_FLUID is the indicator variable for whether a firm has a higher Hoberg et al. (2014) fluidity score than its (4-digit SIC) industry-year median. PROD_SIM is calculated the same way, but using the total similarity score (Hoberg and Phillips (2016)). For both of these scores, a higher value indicates that the firm faces more intense competition. STATE_LABOR represents the state-level labor turnover rate in a given year (obtained using data from the U.S. Census Bureau). The other control variables (measured with 1-year lag) are as follows: LN_ASSET is the log of total assets. MTB is market-to-book (assets) ratio. CASH is total cash holdings scaled by total assets. LEV is total debt scaled by total assets. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP. For brevity, the regression coefficients of all the variables above are not reported, except those of the interaction terms. The *t*-statistics (in parentheses) are computed using standard errors clustered at the state level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SG		MSG_SIC		MSG_FF	
	1	2	3	4	5	6
Panel A. High Versus Low Skill Dependent Industries						
IDD × IND_SKILLS	0.027***	0.025***	0.027***	0.026***	0.024**	0.022**
	(3.25)	(2.96)	(3.44)	(4.43)	(2.87)	(2.81)
No. of obs.	75,383	75,313	75,383	75,313	75,383	75,313
Panel B. High Versus Low Prevalence of Managerial Occupations						
IDD × MGT_OCC	0.025	0.031*	0.026*	0.032*	0.030*	0.037**
	(1.44)	(1.72)	(1.68)	(1.97)	(1.74)	(2.01)
No. of obs.	54,800	54,760	54,800	54,760	54,800	54,760
Panel C. High Versus Low Firm-Level Skill Labor Risk						
IDD × SKILL_RISK	0.026*	0.034**	0.027*	0.036**	0.027*	0.035**
	(1.73)	(2.39)	(1.72)	(2.39)	(1.79)	(2.44)
No. of obs.	59,093	59,053	59,093	59,053	59,093	59,053
Panel D. High Versus Low R&D Intensity						
IDD × RD	0.067*	0.072**	0.064*	0.068*	0.067*	0.072**
	(1.93)	(2.05)	(1.84)	(1.93)	(1.92)	(2.03)
No. of obs.	54,121	53,928	54,121	53,928	54,121	53,928
Panel E. High Versus Low SG&A Intensity						
IDD × SGA	0.034*	0.034*	0.034*	0.034*	0.035**	0.034*
	(1.95)	(1.89)	(1.96)	(1.92)	(2.02)	(1.94)
No. of obs.	97,676	97,582	97,676	97,582	97,676	97,582
Panel F. High Versus Low Hoberg et al. (2014) Fluidity Index						
IDD × PROD_FLUID	0.021*	0.022***	0.020**	0.021***	0.020*	0.021***
	(1.97)	(4.15)	(2.08)	(4.04)	(1.86)	(3.76)
No. of obs.	47,822	47,769	47,822	47,769	47,822	47,769
Panel G. High Versus Low Hoberg and Phillips (2016) Similarity Index						
IDD × PROD_SIM	0.037*	0.038*	0.036*	0.037*	0.036*	0.038*
	(1.79)	(1.74)	(1.81)	(1.74)	(1.78)	(1.74)
No. of obs.	51,952	51,899	51,952	51,899	51,952	51,899
Panel H. High Versus Low State-Level Labor Market Activeness						
IDD × STATE_LABOR	0.034**		0.033**		0.036**	
	(2.11)		(2.08)		(2.29)	
No. of obs.	53,901		53,901		53,901	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
State × year FEs	No	Yes	No	Yes	No	Yes

IDD indicator, as reported in Panels F–H of Table 5. We find positive and statistically significant coefficients on the interaction terms of interest. Thus, consistent with our conjecture, firms facing more intense competition and a greater risk of losing employees to nearby rivals appear to benefit more from increased PKP created by an IDD adoption.

E. Does IDD Adoption Alleviate External Financing Barriers?

A key element of our hypothesis is that PKP helps firms achieve better product market outcomes by alleviating (rather than exacerbating) financing frictions. We argue that PKP can alleviate the problem raised in the Bolton and Scharfstein (1990) theory: strict profit requirements imposed by a staged financing arrangement can prevent a "shallow-pocket" firm from entering a product market due to the predatory behavior of "deep-pocket" incumbents. More precisely, PKP can help lengthen the useful life of proprietary knowledge, improving the entrant firm's ability to pledge interim profits (even under incumbents' predatory actions) to meet external financiers' requirements. If this logic holds, we should observe that the impact of an IDD adoption is concentrated among treated firms that are financially weaker and threatened by financially superior rivals. We should also observe that such treated firms benefit in terms of their ability to raise new profit-contingent financing on an ongoing basis.

To show the first observation, we follow Valta (2012) and Klasa et al. (2018) to use credit ratings to identify the relative financial strength of rival firms. In particular, we concentrate on the subsample of unrated firms (i.e., those with very limited access to debt markets) and interact IDD with the average long-term and short-term credit ratings of the firm's rated 4-digit-SIC rivals in a given year (RIVAL_LCR and RIVAL_SCR). The results reported in Panels A and B of Table 6 show that the estimated coefficients on the interaction terms of interest are always positive and are statistically significant in most regressions, indicating that an IDD adoption has a significantly stronger impact on the PMO measures of financially weak firms when they face financially strong industry rivals.[15]

To investigate the second point on financing ability (PKP can improve firms' ability to raise ongoing profit-contingent financing), we focus on their equity issuance activities. This reflects the fact that equity (rather than debt) is the type of financing that is highly dependent on future cash flows and thus closely reflects the setting of the Bolton and Scharfstein (1990) theory. We follow Lewis and Tan (2016) to construct the measure of additional equity financing, EQ_ISSUES, which is computed as the net amount of cash from issuing and repurchasing equities scaled by lagged assets. To capture the impact of the IDD on equity issues, in the long run, we measure these financing activities during 1 year, 2 years, and 3 years after the current year (represented by the 1Y, 2Y, and 3Y suffices on the variable). The estimation results reported in Panel A of Table 7 show that IDD has a positive and

[15] In Supplementary Table A7, we rerun the same regression models on rated firms, which have better access to external financing than unrated firms. We expect that, for rated firms, the predatory threats of "deep pocket" rivals are less relevant. The results indeed indicate that the effects of rival firms' financial strengths on rated firms are generally weaker (the coefficients on the interaction terms IDD × RIVAL_LCR and IDD × RIVAL_SCR are smaller or less significant than those in Table 6).

TABLE 6

Product Market Effect of IDD and Relative Financing Strength

Panel A (B) of Table 6 only includes firms without a long-term (short-term) S&P credit rating. The alternative dependent variables are: SG is a firm's sales growth rate from year $t-1$ to year t. MSG_SIC is SG minus the industry (4-digit SIC code) median SG for the same year. MSG_FF is computed in the same way as MSG_SIC but based on the Fama–French 49 industries. IDD is the indicator for whether a firm's headquarter state recognizes the inevitable disclosure doctrine in a given year. In each Panel below, IDD is interacted with one of the following measures. RIVAL_LCR is the average long-term credit ratings of the firm's rated rivals in the same 4-digit SIC industry. RIVAL_SCR is the average short-term credit ratings of the firm's rated rivals in the same 4-digit SIC industry. The other control variables (measured with 1-year lag) are as follows: LN_ASSET is the log of total assets. MTB is market-to-book (assets) ratio. CASH is total cash holdings scaled by total assets. LEV is total debt scaled by total assets. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP. For brevity, the regression coefficients of all the variables above are not reported, except those of the interaction terms. The t-statistics (in parentheses) are computed using standard errors clustered at the state level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SG		MSG_SIC		MSG_FF	
	1	2	3	4	5	6
Panel A. IDD Effect Interacted with Long-Term S&P Credit Rating of Rival Firms						
IDD × RIVAL_LCR	0.060*	0.063*	0.048	0.051	0.059*	0.062*
	(1.69)	(1.73)	(1.35)	(1.40)	(1.69)	(1.74)
No. of obs.	89,706	89,618	89,706	89,618	89,706	89,618
Panel B. IDD Effect Interacted with Short-Term S&P Credit Rating of Rival Firms						
IDD × RIVAL_SCR	0.124***	0.130***	0.112***	0.118***	0.120***	0.126***
	(3.21)	(3.26)	(2.91)	(2.94)	(3.15)	(3.18)
No. of obs.	103,227	103,167	103,227	103,167	103,227	103,167
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
State × year FEs	No	Yes	No	Yes	No	Yes

statistically significant effect on the 2- and 3-year equity issuance measures. This finding indicates that treated firms indeed intensify their equity-raising activities in comparison to control firms, especially over a longer horizon.

In Panel B of Table 7, we split the sample into large and small firms, similar to the extension of our baseline analysis in Table 3. Again, we find that the effect of an IDD adoption on ongoing equity issues appears to be concentrated among small firms. In Panel C, we further split the sample into young and mature firms. We find that the IDD coefficients, albeit statistically insignificant, are larger for young firms than for mature firms. These findings are generally consistent with the implication from the Bolton and Scharfstein (1990) theory.

Taken together, the results in Tables 6 and 7 provide support for the hypothesized role of financing barriers in facilitating the positive impact of the IDD on PMO. It is the knowledge protection function of the IDD that helps "shallow-pocket" new entrants to better access external financing and overcome the predatory threats posed by "deep-pocket" incumbents.

V. Other Measures of Product Market Entries

Our results thus far on sales and market shares growth rates, especially in relation to small/young firms, imply that an improvement in PKP establishes conditions for successful product market entries. In this section, we seek to strengthen this interpretation by showing more clearly how firms undertake specific entry strategies

TABLE 7

Effect of IDD on Access to Equity Financing

The alternative dependent variables in Table 7 are EQ_ISSUES_1Y, EQ_ISSUES_2Y, EQ_ISSUES_3Y, which are the total amount of net equity issued during 1 year, 2 years, and 3 years following the current year, scaled by total assets. IDD is the indicator for whether a firm's headquarter state recognizes the inevitable disclosure doctrine in a given year. The following control variables are not reported. LN_ASSET is the log of total assets. MTB is market-to-book (assets) ratio. CASH is total cash holdings scaled by total assets. LEV is total debt scaled by total assets. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP. In Panels B and C, sample firms are split according to firm size (total assets) and firm age (number of years since the first appearance in Compustat database), respectively. The *t*-statistics (in parentheses) are computed using standard errors clustered at the state level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	EQ_ISSUES_1Y		EQ_ISSUES_2Y		EQ_ISSUES_3Y	
	1	2	3	4	5	6
Panel A. Results Based on the Full Sample						
IDD	0.007	0.006	0.008*	0.007*	0.009**	0.008**
	(1.39)	(1.16)	(1.95)	(1.84)	(2.14)	(2.15)
No. of obs.	99,179	99,179	102,375	102,375	103,824	103,824
Adj. R^2	0.240	0.266	0.369	0.393	0.459	0.479
Control variables	No	Yes	No	Yes	No	Yes
Panel B. Results Based on Subsamples Split by Firm Size						
	Small Firms	Large Firms	Small Firms	Large Firms	Small Firms	Large Firms
IDD	0.017	0.000	0.022**	−0.001	0.023***	−0.001
	(1.57)	(0.21)	(2.37)	(0.55)	(2.71)	(0.93)
No. of obs.	49,011	49,271	50,758	50,723	51,482	51,451
Adj. R^2	0.246	0.203	0.379	0.314	0.466	0.419
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Panel C. Results Based on Subsamples Split by Firm Age						
	Young Firms	Old Firms	Young Firms	Old Firms	Young Firms	Old Firms
IDD	0.011	−0.002	0.014	0.002	0.013	0.003
	(0.93)	(0.53)	(1.30)	(0.46)	(1.32)	(0.50)
No. of obs.	48,969	49,635	50,467	50,777	51,355	51,366
Adj. R^2	0.260	0.256	0.416	0.355	0.537	0.432
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes

to exploit their improved protection. To do this, we examine firms' internal development of new products and decisions to go public.

A. Internal Development of New Products

We predict that firms headquartered in IDD-adopting states more intensively engage in internal new products development. This competition strategy is likely to emerge after a firm enjoys better PKP, because without it, new products can be both costly to develop and at risk of being adopted by rivals. To measure the development of new products, we follow Mukherjee, Singh, and Zaldokas (2017) and rely on new product announcements sourced from LexisNexis News database. In particular, the authors analyze company press releases that are tagged under the subject "New Products" and where their headlines include keywords (with the roots of words) such as "Launch," "Product," "Introduce," "Begin," "Unveil" in order to identify new product launches. They then calculate cumulative abnormal returns (CARs) over a 3-day period (1,1) around the announcement and construct two

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TABLE 8

Effect of IDD on New Product Development

In Table 8, PROD_CAR_1Y, PROD_CAR_2Y, and PROD_CAR_3Y are the total CARs of the positive announcement returns over the period of 1 year, 2 years, and 3 years following a focal year. PROD_COUNT_1Y, PROD_COUNT_2Y, and PROD_COUNT_3Y are the total number of announcement returns in the top quartile (of all announcements) counted for the periods of 1 year, 2 years, and 3 years following a focal year. IDD is the indicator for whether a firm's headquarter state recognizes the inevitable disclosure doctrine in a given year. The following control variables are not reported. LN_ASSET is the log of total assets. MTB is market-to-book (assets) ratio. CASH is total cash holdings scaled by total assets. LEV is total debt scaled by total assets. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP. The *t*-statistics (in parentheses) are computed using standard errors clustered at the state level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
Panel A. CARs Around Successful Product Launches						
	PROD_CAR_1Y		PROD_CAR_2Y		PROD_CAR_3Y	
IDD	0.009	0.008	0.018**	0.022	0.025***	0.035**
	(1.29)	(0.95)	(2.51)	(1.58)	(3.00)	(2.19)
No. of obs.	8,132	7,231	12,881	10,855	15,610	12,925
Adj. R^2	0.400	0.418	0.498	0.510	0.545	0.549
Control variables	No	Yes	No	Yes	No	Yes
Industry × year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. Number of Highly Successful Product Launches						
	PROD_COUNT_1Y		PROD_COUNT_2Y		PROD_COUNT_3Y	
IDD	0.153	0.159	0.265**	0.349	0.353***	0.515**
	(1.38)	(1.09)	(2.21)	(1.53)	(2.88)	(2.07)
No. of obs.	8,132	7,231	12,881	10,855	15,610	12,925
Adj. R^2	0.478	0.479	0.532	0.532	0.560	0.556
Control variables	No	Yes	No	Yes	No	Yes
Industry × year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes

distinct measures: i) sum all positive CARs around product announcements made by firms over the year, or ii) count the number of announcements with CARs above the 75th percentile in the respective calendar year. The first metric captures the total incremental value of all new product introductions by a firm during the year. The second metric is meant to distill major new innovations introduced by the firm.

Consistent with Mukherjee et al. (2017), we use both of the above measures, labeled PROD_CAR and PROD_COUNT, respectively.[16] To account for the possibility that the development of new products is a long-term process, we aggregate each measure over three alternative forward-looking windows of 1, 2, and 3 years after the current year (denoted by the 1Y, 2Y, and 3Y suffices on the two variables). We then rerun the baseline DiD model with the dependent variable being replaced by one of these new product announcement variables and report the estimation results in Panels A and B of Table 8, respectively. The coefficients on IDD are positive in all regression models and statistically significant for the next 2 or 3 years, indicating that firms in IDD-adopting states not only launch more new products but also experience greater value increases upon these new product launches. The results in Table 8 provide support for our prediction that improved PKP provides firms with the certainty required to internally develop new products, which in turn help them gain market shares from competitors.

[16]We thank Abhiroop Mukherjee for making the new product introductions data publicly available.

B. Initial Public Offerings

Our evidence thus far points toward small/young firms (i.e., new entrants) as the primary beneficiaries of IDD adoption benefits, consistent with our conjecture that these firms heavily rely on PKP to survive predation and grow. To provide further evidence on whether small firms benefit more from the adoption of the IDD, we examine the effect of the IDD on IPO activity. IPOs provide us with another setting to closely analyze *new firms'* product market success. We argue that, if firms are encouraged to enter the product markets because their proprietary knowledge is better protected, then this should be reflected in IPO activities across states and over time.

To test our prediction, we count the average annual number of IPO firms headquartered in each state in the next year (IPO_1Y), next 2 years (IPO_2Y), and next 3 years (IPO_3Y) using data sourced from Thomson Reuters SDC Platinum database. We then run DiD regressions at the state level to examine the effect of a state's recognition of the IDD on IPO activity within that state. The regression results, documented in Table 9, support our prediction. In particular, the positive and statistically significant coefficients on the IDD indicator in five out of six models confirm that IDD-adopting states indeed experience an increase in the annual number of IPOs relative to nonadopting states. The effect remains robust after we control for time-varying local economic conditions as well as state- and year-fixed effects.

Thus, an important and broad economic implication of IDD adoption appears to be improvements in new firms' competitiveness, as evidenced through IPO activities in the adopting state. Our finding also sheds new light on the debate on whether PKP harms entrepreneurial activity (e.g., Qiu and Wang (2018), Jeffers (2019), and Carlino (2021)) and suggests that PKP may actually encourage such activity.

TABLE 9

The Effect of Adopting the IDD on State-Level IPO Activity

In Table 9, IPO_1Y, IPO_2Y, and IPO_3Y are the average annual numbers of IPOs by firms headquartered in a given state for the periods of 1 year, 2 years, and 3 years following a focal year. IDD is the indicator for whether the state recognizes the inevitable disclosure doctrine in the same year. LN_STATEGDP is the natural logarithm of headquarter state GDP. STATEGDP_GROWTH is headquarter state GDP growth rate. LN_STATEGDP_CAP is the natural logarithm of per capita state GDP. The *t*-statistics (in parentheses) are computed using standard errors clustered at the state level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	IPO_1Y		IPO_2Y		IPO_3Y	
	1	2	3	4	5	6
IDD	1.425*	1.789**	1.242*	1.449**	0.783	1.025*
	(1.76)	(2.13)	(1.92)	(2.17)	(1.33)	(1.70)
LN_STATEGDP		5.724**		3.250**		1.004
		(2.51)		(2.09)		(0.76)
STATEGDP_GROWTH		18.191		−1.967		0.598
		(1.15)		(0.16)		(0.06)
LN_STATEGDP_CAP		−12.638*		−7.052		−9.297**
		(1.91)		(1.51)		(2.55)
No. of obs.	1,116	1,116	1,227	1,227	1,260	1,260
Adj. R^2	0.747	0.748	0.794	0.795	0.828	0.828
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

VI. Additional Analyses

As the last step, we conduct a number of auxiliary tests (reported in the Supplementary Material) that consolidate the evidence documented in our study. The first is a robustness check on the IDD measure. We construct this measure in the same way as Qiu and Wang (2018), who identify 34 IDD-related court rulings spanning from 1960 to 2014. As an alternative construction, we follow Klasa et al. (2018), who identify 21 precedent-setting cases in which state courts adopt the IDD, and three cases in which state courts later reject it, spanning from 1919 to 2006. The results using this alternative IDD variable, as reported in Panel A of Supplementary Table A8, show that the coefficients for IDD remain positive and statistically significant. Another point of contention is the special treatments of California and North Carolina in Qiu and Wang (2018). They assign IDD a value of 0.5 for these two states following their first IDD precedent-setting cases, reflecting the fact that the IDD was not fully adopted. To ensure that our findings are not driven by these special treatments, we exclude firms headquartered in these two states from our sample and reestimate the baseline results. Panel B of Supplementary Table A8 shows that the results after the exclusion are very similar to those reported in Table 2.

Second, we consider the possibility that the headquarter locations of firms change during our sample period and may therefore confound our IDD indicator construction. Given the long sample period from 1980 to 2016, we do not have a consistent source of information to define a firm's headquarter location in a given year. As a robustness check, we rely on two alternative sources: Bai, Fairhurst, and Serfling (2019), who compile historical headquarter location information for a subsample of firms from 1980 to 2003, and Loughran and McDonald (2016), who provide this information for firms from 1994 to 2016. These sources indicate that headquarter relocation is a rare event, accounting for only about 1.6% (2.1%) of their firm-year observations during the 1980–2003 (1994–2016) period. In Supplementary Table A9, we reestimate our baseline regression using these two alternative subsamples, with IDD defined using a firm's historical headquarter location. Our baseline results remain unchanged.

Finally, we explore the expansion strategies that may contribute to the sales growth observed after the adoption of the IDD by a firm's headquarter state. Does a firm experiencing better PKP take on new geographic markets or new business activities? Geographic expansion is a plausible outcome following an IDD adoption because without some forms of knowledge protection, the returns on new market expansions can be highly uncertain. Critical employees may easily move to rival firms, carrying with them knowledge about the new markets and the expansion technologies/strategies. To test this conjecture, we regress a firm's average numbers of geographic segments reported in the next 1, 2, and 3 years on the IDD variable. The results reported in Panel A of Supplementary Table A10 show a consistent pattern indicating that after the IDD recognition, treated firms indeed expand their geographic segments faster than control firms. This is corroborated by additional evidence that the IDD even encourages firms to expand into *foreign* markets. In Panel B of Supplementary Table A10, we show that IDD has a positive and significant relationship with a firm's fraction of total revenue derived from foreign sources. We then check if the observed sales growth partially reflects firms' expansion into new business activities. In Panel C of Supplementary Table A10, we find no evidence to suggest that this is the case: the relationship between IDD and a firm's number of business segments is statistically insignificant. In summary, treated firms appear to take advantage of the IDD-induced knowledge protection to pursue the strategy of geographically expanding their core businesses rather than further diversifying across different business lines.

VII. Conclusion

This study demonstrates that improvements in PKP strengthen firms' abilities to compete in their product market space, leading to their higher sales growth relative to rivals. In the existing literature, this PKP-PMO link remains an assumption rather than an established empirical fact, as it is unclear whether firms with proprietary knowledge can exploit it to improve their competitive positions if doing so is associated with significant financing frictions and predation risk (Bolton and Scharfstein (1990)).

Utilizing the setting involving the staggered adoptions (and rejections) of the IDD across U.S. states and over time, we show that an exogenous increase in knowledge protection, imposed by this legal doctrine, leads to market share gains for affected firms relative to their rivals. The effect is partly driven by the relative external financing strengths of firms and their rivals, implying that the protection actually alleviates (rather than exacerbates) financing frictions associated with knowledge asset investment and new product market entries.

Our study provides several significant economic implications. First, we show that legal decisions on intellectual property protection have far-reaching implications on firms' abilities to compete and the competition strategies they employ. Second, the protection appears to be particularly important for new entrants (i.e., small firms and young firms), and can therefore improve the competitive environment of the knowledge-based economy and promote economic growth and consumer welfare. Other policies aimed at alleviating the difficulty of financing investments in long-term intangible assets can perhaps lead to similar desirable outcomes.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001247.

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