Firing Costs and the Decoupling of Technological Invention and Post-Invention Investments

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Abstract
We document the decoupling of invention and post-invention investment in the US. Decoupling began in the 1970s as states adopted employment protection laws that increased firing costs and played a significant role in jobless growth and the vertical and geographical fragmentation of firm activities. Technological inventions lead to significant job creation, but employment protection laws almost fully moderate this positive effect, especially in fast-changing and high-offshore industries and for radical inventions. Firms responded to the increased firing costs by pursuing less-novel inventions, factor substitution toward capital, and offshoring through international acquisitions and JVs with manufacturing partners. Our findings suggest that decoupling serves as a critical context under which these drivers of jobless growth emerged in the 1990s and that firms aggressively manage complementary in upstream-downstream resources by adjusting geographical and vertical boundaries of the firm.

1. Introduction

Presenting one of the most fundamental economic challenges of today, declining employment and jobless growth have had serious social consequences in the United States, including falling marriage rates, increased incidences of drug abuse and suicide, and political polarization (Dorn and Hanson, 2019; Pierce and Schott, 2020; Autor et al., 2020). Technological innovation has been proposed as a key solution to reversing this trend, which has led to various policy proposals to expand R&D subsidies. Most recently, in his "Made-in-All-of-America" campaign, President Joe Biden proposed a "New $300 Billion Investment in Research and Development (R&D) and Breakthrough Technologies" in the first four years of his presidency.[1] However, even while maintaining their R&D activities locally, US firms have increasingly outsourced their production, often to places with lower wages and lax labor laws.[2] This point is perhaps best illustrated in the familiar fine print, "Designed by Apple in California. Assembled in China." The disjoining of R&D from more labor-intensive downstream investments calls into question the strategy of R&D as a national industrial policy to preserve and bring back jobs.

Commercializing and profiting from technological inventions, often embodied in patents that contain valuable yet early-stage ideas, is a learning process that requires many rounds of trial and error at various stages of the downstream production processes (Teece, 1986; Zhang and Tong, 2020).[3,4] Even as firms aggressively outsourced and offshored routine activities (e.g., call centers) and the production of mature products, this adjustment requirement prioritized close coordination over access to cheaper resources and kept the investments necessary to commercialize new technologies vertically integrated and in close geographical proximity to the location of the invention, especially prior to the 1990s (Amour and Teece, 1980; Delgado, 2020; Fort et al., 2020). We examine how the loss of flexibility in adjusting the production process, specifically the pace and efficiency with which firms can dismiss workers, reduced the coordination benefits of collocation and decoupled invention and the investments needed to commercialize (or more simply, post-invention investments) in

[1] http://joebiden.com/madeinamerica/

[2] Fuchs, Combemale, Whitefoot, and Glennon (2020) estimate that manufacturing represents 66 percent of industrial R&D in the US but only 14 percent of the value add and attribute this low share to the offshoring of manufacturing assets by multinational firms.

[3] Beyond production (or manufacturing), post-invention commercialization spans design, marketing, distribution, and after-sales services activities.

[4] In addition to the research on complementary assets, the distinction between invention and commercialization is central to research on public vs. private and basic vs. applied R&D (Mansfield, 1988; Azoulay et al., 2019), technology licensing (Arora and Ceccagnoli, 2006), patent reforms (Sichelman, 2010), and the new product development process (Wagner and Wakeman, 2016).

the US. We then link the decoupling to (1) the decline in employment and the phenomenon of jobless growth; (2) the vertical and geographical disintegration in firm activities through foreign acquisitions and joint ventures; and (3) underinvestment relative to Tobin's Q.

It is intuitive that firms would try to bypass high firing costs by decoupling invention and post-invention investment. Commercializing technological inventions is internally disruptive and requires significant adjustments to existing resources (Aghion and Howitt, 1994), including dismissing obsolete workers and hiring new workers with complementary skills. However, documenting the effects of high firing costs on post-invention investment has been complicated by their effect on upstream R&D activities: high firing costs also affect *ex-ante* incentives for R&D and bias them toward incremental technologies that rely more heavily on existing resources. As a result, even if increased firing costs reduce employment growth, it is unclear whether the negative effect stems from constraining inventions or the decoupling of invention and post-invention investments. Disentangling these two channels, while seemingly minor, is critical to assessing the causes of jobless growth and formulating effective solutions. The former makes a renewed case for R&D subsidies. The latter calls for labor market reforms.

To hold the technological characteristics of inventions as constant as possible and isolate how firing costs affect post-invention investment, our research design takes advantage of two unique features of our empirical context. First, we follow Autor et al. (2006) and use the staggered adoption of the implied contract exception laws (or IC) by the state supreme courts as a judicial shock that increased the cost of employee dismissal between 1972 and 1992. Second, we leverage the two- to three-year lags between the patent application and its grant. The gap provides three categories of patents: (i) patents that are both applied for and granted prior to IC adoption ("*pre*"-patents), (ii) patents that are applied for prior to but granted post-IC adoption ("*interim*"-patents), and (iii) patents that are both applied for and granted post-IC adoption ("*post*"-patents). The key assumption is that because of the "test of enablement" at the US patent office, which requires the patent application to disclose all major components of the invention (further detailed in Section 2.3), applicant firms are largely finished with inventing by the time of application but have not yet started on investments to commercialize. As a result, IC impedes the commercialization of *interim*-patents without affecting their technological characteristics while affecting neither the development nor commercialization of *pre*-patents. We compare *pre*- and *interim*- patents on their market value as well as their effects on firm employment, capital investment, profit growth, and firm preferences for direct or indirect commercialization through JVs and acquisitions. The difference-in-differences estimation takes advantage of the staggered adoptions of IC at different stages of the patent review process. It effectively rules out confounding national and sectoral trends, such as increasing productivity of the foreign workforce, the sophistication of communication technology, and falling trade barriers.[5]

At the patent level, we first establish that IC indeed decreases disruptive inventions, decreasing the originality (Hall et al., 2001) and novelty (Eggers and Kaul, 2018) of *post*-patents relative to *pre*-patents by 2-7 percent as well as their market value by 3.9 percent. For *interim*-patents, IC does not affect their technological characteristics or the number of citations received but still decreases their market value relative to *pre*-patents by 3.7 percent, as measured in the three-day abnormal returns in response to news of their grant by the US Patent Office (Kogan et al., 2017). The null effects on interim-patents' the technological characteristics and the negative effect on their market value validate the key assumption of our research design and provide patent-level evidence that increased firing costs constrain a firm's ability to commercialize and profit from technological invention. These effects are robust to controlling for firm, technology class-by-year, and technology class-by-firm fixed effects.

Next, at the firm-level, we adopt a similar research design and conduct a difference-in-differences estimation that compares the *pre*-IC period to narrow windows of the *post*-IC period. In our baseline specification, a 10 percent increase in a firm's patent application leads to a 4.1 percent increase in employment, but the positive effect decreases by 85.2 percent after IC adoption. The decline is concentrated in technologically fast-changing sectors, industries that are more exposed to offshoring (Blinder and Krueger, 2013), and radical patents whose commercialization requires more drastic adjustments to firms' existing workforce. We also find that firms aggressively adopt measures to bypass the increased firing costs. In addition to developing less-novel inventions, firms substitute labor with capital and increase international acquisitions and JVs with foreign manufacturing partners. Lastly, we show that IC contributes to lower employment growth relative to Tobin's Q. These effects are robust to industry-by-year and state-by-year fixed effects as well as a series of sensitivity checks on patent-investment relations.

Demonstrating the decoupling between invention and post-invention investment informs multiple streams of research. First, this study relates to a recent body of research that

[5] Fort (2017) and Steinwender (2018) show that the adoption of communication technology facilitates offshoring and trade by reducing the coordination costs of remote production.

links innovation and firm growth dynamics (e.g., Kogan et al., 2017; Acemoglu, Akcigit, and Bloom, 2018; Farre-Mansa, Hegde, and Ljungqvist, 2020). We show that the increased rigidity in the US labor market weakened the relationship between invention and post-invention investment, and that there is much risk to taking for granted that technological inventions lead to employment growth. The extent of the decoupling is highly heterogeneous and varies based on the pace of technological change, offshorability, and the disruptive nature of inventions. Second, this study complements research on the causes of declining US employment. Our findings verify the importance of capital-substitution, outsourcing, and offshoring but highlight commercialization of technological invention as a discrete and critical instance in which firms employ these actions to engage in regulatory arbitrage of employment laws (Holmes, 1998). One key implication is that the negative (domestic) employment effect of technological advances was shaped in significant part by changes to the labor market originating from state supreme courts and need not have been as strong (Cabarello and Hammour, 1997).

Third, our findings inform the corporate strategy research on firm boundaries. According to Teece (1986), whether firms directly commercialize or license inventions should depend on intellectual property protection and the asset positioning of other market participants. We add to the discussion that labor market flexibility, by affecting the comparative cost of internal commercialization, is another critical determinant of firm boundaries. Beyond licensing, we find that firms rely on external and foreign partners through JVs and acquisitions to commercialize and profit from invention, leading to the geographical and vertical disintegration in a firm's value chain. The emphasis on flexibility in labor adjustment provides a natural link to strategic management research on dynamic capabilities (e.g., Helfat and Raubitschek, 2000; Helfat et al., 2007). While prior studies emphasize control over an existing set of complementary assets, the disruptive nature of technological invention requires a firm to dynamically adjust and "co-evolve" the assets in order to profit from innovation. We discuss the implications for research on employment protection laws and public policy in the conclusion section.

2. Related Literature and Empirical Strategy

2.1 Technological invention and post-invention investment

In the seminal study "Profiting from technological innovation," Teece (1986) notes that the relationship between innovation and firm profits is highly variable. In understanding how innovation drives firm investment and growth, he emphasizes the importance of decomposing innovation into its constituent parts and looking separately at R&D and downstream production activities.[6] Because of competitive imitation and supplier bargaining power, being the first to discover and patent a technology ('invention') is often insufficient to appropriate value (e.g., Cohen et al., 2000; Furman, Porter, Stern, 2002); firms must also control the downstream resources necessary to embed the technology into products, produce them physically in scale, and bring them to market ('commercialization').

Whether firms choose to control these downstream activities directly through investment and acquisitions, indirectly through JVs and more temporary arrangements with external partners, or simply license or sell inventions in the markets for technology has critical implications for the geographical and vertical organization of firm activities.[7] Earlier research considers the coordination benefits and the contractual hazards to keep invention and production activities vertically integrated and in close geographical proximity. However, firms have increasingly outsourced and offshored production activities to low-cost countries even while retaining R&D activities at home (Belderbos, Leten, and Suzuki, 2013). As a case in point, today's configuration of Apple's value chain would have been unimaginable before the 2000s. Apple employs 43,000 people in the United States and 20,000 overseas; 700,000 people work for Apple's contract manufacturers, including Taiwan's Foxconn, which assembles the latest models of iPhones in China.[8]

An influential and growing body of research focuses on technological advances and falling trade barriers as driving the decline in US manufacturing employment, jobless growth (Autor, Dorn, and Hansen, 2015), and the emergence of "factoryless goods producing firms" (Bernard and Fort, 2015). We point to the increasing rigidity of the US labor market and the consequent decoupling of invention and post-invention investment. Furthermore, we show that the decoupling began as early as the 1970s and served as the critical context under which other drivers of jobless growth subsequently emerged in the 1990s.

2.2 Firing costs and firm investment

A long-standing body of research examines how labor market rigidity affects employment and firm innovation (e.g., Lazear, 1990; Kugler and Saint-Paul, 2004; Cingano et al., 2010; Griffith and Macartney, 2014). Following Autor et al. (2006), our research design exploits staggered adoptions of employment protection laws across US states as an exogenous judicial

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[6] See Levin, Klevorick, Nelson, and Winter (1987) for a related discussion in the context of the patent system and intellectual property rights.

[7] Rothaermel (2001) examine how firms access complementary assets through alliances, and Arora and Ceccagnoli (2006) show that firms are more likely to license patents in markets for technology when they lack the complementary manufacturing assets required to commercialize new technologies.

[8] https://www.nytimes.com/2012/01/22/business/apple-america-and-a-squeezed-middle-class.html?_r=1&hp=&pagewanted=all.

shock that increases firing costs and, in turn, the cost of adjusting the production processes necessary to commercialize technological inventions. Historically, the United States had maintained an "employment-at-will" doctrine, which allowed employers to dismiss their employees without any restriction or advance notice. From the early 1970s through the 1990s, however, state supreme courts adopted common law exceptions to an employer's ability to fire at will. These "exceptions" are commonly referred to as wrongful discharge laws (or WDLs).

Prior research takes advantage of the staggered adoptions of WDLs across states over time and compares investment by firms located in adopting states to non-adopting states in the following difference-in-differences OLS specification:

$$Investment_{it+1} = \beta_1 WDL_{st} + \boldsymbol{X}_{ist} + \varepsilon_{ist}, \qquad (1)$$

where i indexes firm, s indexes state of firm's primary operation that governs labor contracts, and t indexes year. *WDL* is a binary variable set to one if a specific wrongful discharge law is adopted in state s by year t. The increased firing costs from WDLs reduce the speed and efficiency with which firms laid off obsolete workers and have wide-ranging consequences at various parts of a firm's value chain, including both upstream (R&D) and downstream activities. They make firms more reluctant to hire (Oyer and Schaefer, 2002), decrease state-level employment by 0.8 to 1.7 percent (Autor et al. 2006), increase outsourcing (Autor 2003), reduce acquisitions (John, Knyazeva, and Knyazeva, 2015; Dessaint, Golubov, and Volpin, 2017), lower firm productivity (Autor et al., 2007; Bird & Knopf, 2009), generate negative abnormal stock returns (Serfling, 2016), and lower sales growth and investment sensitivity to Tobin's Q (Bai, Fairhurst, and Serfling, 2019).[9]

Rather than examining the overall effects of WDLs on firm investments, we need to isolate how they affect firm investments to commercialize a given invention and not the invention itself. How WDLs affect the quantity of technological inventions remains less clear with mixed results, but there is strong evidence that they reduce radical inventions whose commercialization requires reconfiguring a broader set of existing resources (Griffith and Macartney, 2014).[10] Our research design centers on overcoming the endogenous relations between employment protection laws and the direction of firm R&D activities. Compared to general investments, we expect the increased firing costs to have a much stronger negative

[9] Autor et al. (2006) do not detect a significant effect on wages. In theory, IC can affect wages through multiple channels, including worker productivity, workers' bargaining power, demand for labor, and lower compensation for unemployment risk.
[10] The related research is too vast to be reviewed in sufficient depth here, and we refer the reader to Griffith and Macartney (2014). Bradley, Kim, and Tian (2017) provide an excellent review of the competing effects of increasing employment protection in the context of unionization.

effect on investments to commercialize technological inventions, in particular radical inventions, because they require more drastic adjustments to a firm's existing workforce (Aghion and Howitt, 1994).

Of the different types of WDLs, we focus on the implied contract exception (IC), which has been adopted by forty-three states (Autor et al., 2006). We also check for robustness to other exceptions, particularly the good faith exception (GF), which has been adopted by thirteen states (Autor et al., 2007; Acharya et al., 2014; Bai, Fairhurst, and Serfling, 2019). An implied contract exception becomes effective when an employer promises not to terminate a worker without "good cause." The good faith exception prohibits employers from dismissing workers for "bad cause," especially if the cause is to deprive them of earned benefits. Aside from its broader coverage, IC is better suited to our research design because it does not directly affect the average rate of firm invention while affecting firm demand for labor as well as outsourcing (Autor, 2003).[11] In contrast, GF affects both invention and employment but not outsourcing, and Autor et al. (2007) find significant pre-trends in their adoption decisions in some specifications. We also detect pre-trends for GF in similar specifications (further detailed in Appendix C).

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2.3 Decoupling of invention and post-invention investment

Technological invention, employment protection laws, and employment do not show a clear relation in the aggregate data. Figures 1A and 1B show the number of manufacturing jobs in the US plotted against the total number of patents and the number of states that adopted IC between 1970 and 2000. The number of patent applications shows a steady increase with little relation to the large swings in manufacturing employment. The adoption of IC by fifteen states between 1979 and 1983 coincides with the sharp decline in US manufacturing employment from its peak of 19.4 to 17.0 million but does not show a clear relation in other periods. These pictures likely mask a diverse set of interdependent and co-evolutionary channels, such as capital-labor substitution, advances in automation, computerization, and communication technologies, and the falling costs of remote production (Brynjolfsson et al., 1994; Autor, Dorn, and Hanson, 2015; Fort, 2017) that both influence and are influenced by technological invention and labor market flexibility (Cabarello and Hammour, 1997).

[11] Acharya et al. (2014) find a positive effect on the rate of firm innovation from the good faith exception because it encourages risk-taking and reduces the holdup problem. Keum (2020) finds a null average effect of IC but a negative effect on poorly performing firms that are in need of greater resource adjustment and risk-taking. The two studies differ in the specific WDLs that drive their findings (IC vs. GF) and their focus on R&D or production activities as an underlying mechanism.

We differ from prior studies in that, rather than looking for the average effect, we focus on the commercialization of technological invention as a discrete instance where IC affects firm investment. The increased firing costs should not affect firm investments uniformly at all times but primarily when firms need to aggressively and rapidly adjust their existing workforce, for example, in response to negative macroeconomic shocks (Bentolila and Bertola, 1990; Blanchard and Portugal, 2001), low firm performance (Keum, 2020), or in our case, when firms need to commercialize disruptive technological inventions quickly.

To test whether IC indeed decouples invention and post-invention investment, we augment equation (1) with patent-based proxies of a firm's technological inventions and its interaction with IC and estimate the following two equations:

$$Investment_{it+1} = \beta_1 IC_{st} + \beta_2 Invention_{it} + \beta_3 IC_{st} \times Invention_{it} + \alpha_i + \alpha_t + X_{ist} + \varepsilon_{ist}, \quad (2)$$

$$Outsourcing_{it+1} = \beta_1 IC_{st} + \beta_2 Invention_{it} + \beta_3 IC_{st} \times Invention_{it} + \alpha_i + \alpha_t + X_{ist} + \varepsilon_{ist}, \quad (3)$$

In equation (2), β_2 estimates the extent to which technological invention increases firm investment. Our main variable of interest is the coefficient for the interaction between IC and invention (β_3), which estimates whether the increase in firing costs from IC decreases or increases post-invention investment. While we expect β_3 to be unequivocally negative for employment growth, whether β_3 should be negative or positive with respect to capital investment is less clear (Cingano et al., 2010). By increasing the relative cost of labor, IC should encourage a factor substitution toward capital. However, IC could raise the threshold for commercializing technological inventions, decreasing the overall number of inventions in which firms invest to commercialize.[12] IC could also induce firms to outsource post-invention investments (Autor 2003), decreasing direct investment but with an ambiguous effect on aggregate investment.[13] We examine as an empirical question whether IC positively or negatively affects post-invention capital investment. It is important to note that there need not be a one-to-one mapping between a patent and a product (or any of its features). A patent may constitute a small part of the family of patents that support a product (or a "patent thicket") (Shapiro, 2000; Hall and Ziedonis, 2001; Somaya, 2003). The analysis applies as long as a technological invention contained in a patent improves demand for a new or existing products in a firm's portfolio, and in turn, increase demand for input resources.[14] In this regard, labor-saving process inventions represent an important exception that exerts

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[12] Sichelman (2010) estimates that less than half of patented inventions in the United States are commercialized.

[13] Past empirical studies on how the stringency of employment protection affects capital investment have found varied effects ranging from null to negative (Cingano et al., 2010) and positive (Autor et al., 2007).

[14] Refer to Wagner and Wakeman (2016) for a detailed analysis that links individual patents to new product developments in the pharmaceutical industry.

downward bias in our estimation of β_3 and β_3.

Even when IC adoption decisions are exogenous, β_3 from equations (2) and (3) above suffers from an important bias in assessing whether increased firing costs indeed decouple invention and post-invention investments. This is because after its adoption, IC likely biases the direction of firm R&D activities toward incremental inventions that minimize firing costs (i.e., $IC_{t+0} \rightarrow Invention_{t+n}$). As a result, even when β_3 is negative and reduces the positive effect on employment growth from invention, it is unclear whether this is because IC decreases the investment in post-invention commercialization activities or because of its effect on the direction of technological invention. The *inter*-dependent nature of invention and commercializing activities, in particular how downstream activities both encourage and constrain upstream R&D activities, relates to Teece's (1986) discussion of co-specialized complementary assets and has received growing academic and media attention.[15,16] For example, in a *Wall Street Journal* article, Kota and Mahoney (2019) lament that offshoring "destroyed …our capacity to develop new products and processes."

To hold the characteristics of inventions as constant as possible and isolate the effect of firing costs on post-invention investment, we leverage the lag between the timing of IC adoption and its effect on firm invention. R&D activities consist of slow-to-adjust, irreversible investments (Bloom, 2007; Peters and Taylor, 2017), such as wages of R&D personnel, making it highly costly to cancel or modify projects that are already underway. Prior empirical studies on WDLs as well as other legislative or judicial shocks on firm incentives to innovate find their effects to appear with lags, typically ranging between two to four years.[17] In contrast, IC affects firing and hiring decisions immediately (Bai, Fairhurst, and Serfling, 2019). The key identifying assumption is that there is a short yet substantive window after adopting IC, where IC affects a firm's post-invention commercialization activities without yet affecting the quantity, quality, and technological characteristics of the

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[15] The complementarity across vertical activities has been examined extensively (Kremer, 1993); in the context of innovation, Pisano and Shish (2012) and Naghavi and Ottaviano (2009) show that outsourcing or offshoring production activities has negative spillover to firm R&D activities. Helfat (1997) documents that oil companies with greater coal reserves invest more in synthetic fuels derived from coal. Reitzig and Wagner (2010) show that the converse also holds. Seru (2014) shows that a diversification through acquisition decreases (novel) innovation, and Zhang and Tong (2020) show that vertical integration increases systemic innovation that requires greater intra-organizational coordination.

[16] Research on the Bayh-Dole Act examines a closely related issue. This law intended to increase the commercialization of scientific inventions by granting full patent ownership to inventors even when the invention was supported with federal funding. One concerns was that the law biased the direction of university research away from basic science to more applied commercial ends (Mowery et al., 1980).

[17] Acharya et al. (2014) and Keum (2020) find that GF and IC affect the number of firm patent counts with two and three year lags, respectively. The two-to-four year lags on affecting technological inventions extend beyond WDLs to other shocks on firm incentives to innovate. For example, Cerqueiro et al. (2017) find that bankruptcy laws that restrict financing starts to affect firm patent counts in two years and peaks in three years.

inventions. We detail our research design based on the institutional features of the patent application process below.

3. Research Design and Empirical Approach

In our empirical analysis, we rely on patents and their citation patterns as proxies for the technological inventions and their characteristics. Firms invest in R&D activities and file a patent application with the United States Patent and Trademark Office (USPTO) when they discover new and non-obvious knowledge. The application must provide sufficient detail so that "all of the methods needed to practice the invention [are] well known," but it does not require the applicant to build a prototype.[18] As a result, firms have largely completed the technological aspects of the invention when they first file for a patent but have not started on investments to commercialize them. This system has been criticized as "reward[ing] the best *inventor*, but not necessarily the best *commercializer* (Sichelman, 2010:344)." The application is then examined by the patent examiner on a first-come, first-served basis.[19] The Patent Office on average takes about one to two years to work through its backlog of patent applications before an application is examined. The initial application is typically rejected, and the firm responds with an amended application that addresses the examiner's objections. The back-and-forth with the patent examiner largely centers on adjusting the patent's scope and takes one to two years.

When we overlay the inventive activity with the administrative process of obtaining a patent, patents can be divided into three categories based on the time of IC adoption: (i) patents that are both applied for and granted prior to IC adoption ("*pre*"-patents); (ii) patents that are applied for prior to but issued post-IC adoption ("*interim*"-patents); and (iii) patents that are both applied for and granted post-IC adoption ("*post*"-patents). IC affects neither the invention nor commercialization of *pre*-patents, while affecting just the commercialization of *interim*-patents and the invention and commercialization of *post*-patents. By comparing *interim*- and *pre*-patents, we can isolate how the increased firing cost affects post-invention investments.[20] Figure 2 provides a graphical representation of our empirical design that compares the three categories of patents.[21]

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[18] https://www.uspto.gov/web/offices/pac/mpep/s2164.html

[19] USPTO introduced prioritized examination for an additional $4,000 fee after the America Invents Act in 2012.

[20] The research design draws some resemblance to Chondrakis, Serrano, and Ziedonis (2020) who leverage the American Inventors Protection Act (AIPA) and look at how mandating disclosure after 18 months has varying effects across technological classes with long and short application-grant lags.

[21] By relying on patents that are already submitted for review, the research design also addresses other potential concerns. For example, the slowed pace of commercialization from IC may affect firm propensity to patent (Cohen et al., 2000; Arora et al., 2001). Employment protection laws may also affect the productivity and turnover of inventors (Acharya et al., 2014) or induce firms to focus on process-related improvements.

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We first examine how IC affects the direction of firm invention using the following pooled OLS regression:

$$Patent\ characteristics_{ipt} = \beta_1 IC_{it} + X_{ipt} + \varepsilon_{ipt}, \tag{4}$$

where p indexes a patent, t indexes the month of the patent application, and i indexes the applicant firm. IC is a binary variable set to one if the implied contract exception affects the applicant firm i by the filing month t. We expect the coefficient for IC (β_1) to be significant for *post*-patents but not for *pre*- and *interim*- patents.

To test how IC affects a firm's ability to commercialize and appropriate value from technological invention, we next take advantage of two distinctive, yet correlated, measures of the invention's value contained in the patent, as discussed in Kogan et al. (2017). As a proxy for its public scientific value, we use the number of citations accumulated during a patent's lifetime. As a proxy for its private economic value to the patent holder, we use the market value of the patent estimated using the three-day abnormal returns in response to news of its grant. We expect IC to impede commercialization and weaken their relation by reducing the market value of *interim*-patents to their holders but not their scientific value. To test this, we estimate the following equation:

$$Market\ value_{ipt} = \beta_1 Citation_p + \beta_2 IC_{it} + \beta_3 IC_{it} \times Citation_{pt} + X_{ipt} + \varepsilon_{ipt}. \tag{5}$$

We expect β_1 to be positive and β_2 and β_3 to be negative.

Our firm-level analysis takes a similar approach and varies the sample window after the IC adoption (or the post-period in a difference-in-differences estimation used to compare the differences in pre- and post-trends). The expectation is that, during the two- to three-year period immediately after the IC adoption, firms are focused on commercializing inventions that were developed previously (i.e., *interim*-patents) and are therefore little affected in their technological characteristics by IC. We compare the *pre*-IC period to "*interim*"-IC and "*post*"-IC periods and examine three questions: (i) how firing costs affect post-invention investment and profit growth, (ii) the adaptive measures taken by firms to bypass the increased firing costs, especially the substitution toward capital investment and outsourcing, and (iii) whether these effects increase or decline over time.

We also show below that our results are robust to a series of sensitivity checks to investments that do not fall neatly around the month of patent application. In all of our analyses, standard errors are double clustered at the technology class and state level for patent-level analysis and at the firm and state level for firm-level analysis.

4. Sample and Data

4.1. Patent-based proxies of technological inventions

As a proxy for technological invention (*Invention*), we obtain patent data from Kogan et al. (2017), who conduct a textual analysis of all patent applications filed at the US Patent Office and provide information on their application date, grant date, (3-digit) technology class, and applicant firm identity. They also provide the estimated market value of patents based on the three-day abnormal returns in response to news of their grant at the USPTO. We rely on the NBER patent database from Hall et al. (2001) for other patent characteristics, including the number of citations received, originality, and generality. Originality captures a patent's technological breadth, measured as one minus the Herfindahl index of the number of subclasses cited by the patent, and has been widely used as a proxy for the disruptive nature of the technology contained in the patent (e.g., Cerqueiro et al., 2017). We expect patents with higher originality scores to incur larger adjustment costs from IC. Generality measures how widely the patent has been cited by subsequent patents. As an alternative measure of the patent's disruptive nature, we obtain Eggers and Kaul's measure of patent novelty (2018). They consider a patent to contain a more novel technology if it combines technology classes that have not been combined before by other patents in the same USPTO's technology class in the past five years.

Patent counts and their market value are winsorized at the top 1%. All of the results are robust to using nominal values. Because of the large skew in their distribution, interpreting the magnitude of the effects from changes in patent counts or their market value requires some caution. The median value of the average number of patent applications per firm-year is zero, with a mean of 3.2 and a standard deviation of 11.7. The most frequent change is from zero to one patent application. We interpret the effect sizes based on a ten percent increase in the number of patents (log) and market value (log), and whenever available, compare them to other studies.

4.2. Firm investment, growth, and boundary choices

Firm-level data are obtained from the Compustat database. We examine employment growth, capital investment, and adjustments in vertical and geographical firm boundaries through acquisitions, JVs, and their locations. Employment growth is a year-to-year percentage change in the number of employees. The number of acquisitions and JVs is obtained from the SDC Platinum Database. SDC reports the nationality of acquisition targets and JV partners, allowing us to divide them into domestic and foreign deals. SDC also provides a description of the main activity for JVs, allowing us to categorize them into manufacturing and non-manufacturing partnerships. The database does not provide the primary purpose of acquisitions but does provide summary descriptions of the target firm's business activities. We consider an acquisition to be focused on manufacturing if manufacturing (or its close variations) is listed as the primary activity of the target firm (refer to Appendix A.5 for additional details). As an alternative proxy for offshoring, we use the income from foreign operations (*Foreign operation*) as disclosed in a firm's annual 10-k filing. Our baseline sample period covers 1970-2000 for both the patent and firm-level analyses but with the later starting years for some dependent variables due to data coverage. Variables definitions, data sources, and sample years are detailed in Appendix A.

4.3. Employment protection laws

We obtain the adoption month and year for the implied contract and good faith exceptions from Autor at al. (2006). Labor contracts are governed by state laws, and we follow prior studies and use the state of firm headquarters as governing the firm's overall employment contracts (e.g., Bird & Knopf, 2009; Acharya et al., 2014; Bai, Fairhurst, and Serfling, 2019). Appendix B provides the adoption schedule for each state.

A causal interpretation of our results requires that IC adoption decisions are exogenous. The judicial nature of the adoption decisions based on common law better insulates them against potential influence from state economic and political conditions when compared to legislative and policy decisions (Walsh and Schwarz, 1999). Prior studies using WDLs also conduct a battery of tests showing that their adoption decisions are not a function of a state's economic and political conditions. We review them in Appendix C along with our own test results showing that IC adoption decisions are uncorrelated with state-level inventive activities as well as in-state firms' investment and patenting activities.

4.4. Control variables

For the patent-level analysis, we control for firm fixed effects as well as grant year-by-(3 digit) technology class fixed effects. We check for robustness to additionally controlling for firm-by-technology class fixed effects.

For the firm-level analysis, we control for factors related to a firm's incentives to invest in technological inventions, including Tobin's Q, industry revenue growth rates, and firm size based on log of sales and total assets. Because we include patent counts as the independent variable, we use a traditional measure of Tobin's Q based on physical capital, calculated as the market value of a company divided by its assets' replacement cost, but we check for robustness to using Peters and Taylor's new measure of Tobin's Q (2017) that accounts for R&D investment and other intangible capital. Prior research emphasizes financial constraint as a critical impediment to technological inventions and employment.

Matsa (2010) and Serfling (2016) show that increased firing costs act as a de-facto increase in operational leverage and decrease financial leverage. We include four different measures of a firm's financial resources: distance from bankruptcy based on Altman's Z-score (1983), financial leverage based on its debt ratio, and financial slack measured with the current ratio (current assets divided by current liabilities) and working capital to sales ratio. To control for industry concentration, we include the Herfindahl-Hirschman Index (HHI) and its square term based on the revenue of Compustat firms. All industry-level controls are constructed at the 4-digit SIC code level. In addition, we control for industry-level trends using industry-by-year fixed effects and local economic conditions using state-by-year fixed effects. Table 1 reports sample statistics.

--------------------------------------- Insert Table 1 Here ---------------------------------------

On average, it takes 26 months for a patent to be approved from its initial application with a standard deviation of 14 months. These values closely align with Chondrakis, Serrano, and Ziedonis (2019).

5. Patent-level Results

5.1. Firing costs and the direction of technological inventions

In Table 2, we examine whether IC affects a patent's technological characteristics: originality, novelty, generality, and the number of citations received. The first sample compares *pre*-patents to both *interim*- and *post*- patents; the second sample compares *pre*- to *interim*- patents; and the third sample compares *pre*- to *post*- patents. In constructing the *post*-patents to compare to *pre*- and *interim*- patents, we restrict the post-period to 60 months after the IC adoption (or approximately two standard deviations from the average application-grant window) in our baseline sample. The length of the post-period is set to balance the competing needs to secure sufficient post-IC observations to power the test and the risk of introducing unrelated confounding shocks. All specifications include firm and grant year-by-technology class fixed effects.

IC reduces originality (column 3), novelty (column 6), and generality (column 9) of *post*-patents relative to *pre*-patents by 2.1 percent, 7.3 percent, and 3.2 percent, respectively.[22] In contrast, IC does not affect the technological characteristics of *interim*-patents relative to *pre*-patents (columns 2, 5, 8). As an exception, IC does not have a significant effect on the number of citations received for both *interim*- and *post*-patents in columns 10-12. These results provide granular, project-level evidence that IC biases the

[22] The mean value for novelty is calculated as its absolute mean.

direction of firm R&D activities toward less disruptive inventions and align well with Griffith and Macartney (2014), who find that multinational firms conduct more radical R&D activities in low employment protection countries. The null effects of IC on *interim*-patents and the significant effects on *post*- patents validate our research design.

--------------------------------------- Insert Table 2 Here --

5.2. Decoupling in scientific and market value of invention

In Table 3, we examine whether increased firing costs weaken the relation between a patent's public scientific value and private market value to the patent holder. In columns 1-3, we first verify that the number of citations received positively correlates with a patent's market value. The positive relation is significant in columns 1 and 2 that control for firm and grant year-by-technology class fixed effects, respectively, but weakens significantly once we control for both simultaneously. The overall pattern closely mirrors Kogan et al. (2017). Looking across columns 5 and 6, IC reduces the market value of *interim*- and *post*-patents relative to *pre*-patents by 3.67 percent ($p<0.10$) and 5.61 percent ($p<0.05$), respectively. It is crucial to note that the coefficient for *IC* is negative even for *interim*-patents that are little affected by IC in their technological characteristics (Table 2). In columns 7-9, we repeat the analysis but include the interaction term *Citation×IC*. *IC* is no longer independently significant, but the coefficient for the interaction term is negative ($p<0.05$) and sufficient in magnitude to fully negate the positive relation between the scientific and market value of patents. The coefficient for *Citation×IC* is again negative ($p<0.05$) even for *interim*-patents. These findings verify that the flexibility to adjust downstream production processes is a critical complementary capability to profit from invention.

In Appendix D, we show that the results from Table 2 and Table 3 are robust to additionally controlling for firm-by-technology class fixed effects and adjusting the pre- and post- periods around IC adoption, for example, limiting the pre-IC period to five years or increasing the post-IC period to eight years. Kogan et al. (2017) note that the relationship between the scientific and market value of patents is log-linear except for patents that receive very few citations. Excluding patents with zero or one citation yields consistent and slightly sharper results.

--------------------------------------- Insert Table 3 Here --

6. Firm-level Results

The patent-level analyses provide evidence that IC affects the direction of a firm's technological invention and decreases its ability to profit from invention. These analyses also establish the validity and the importance of our empirical design using the application-grant lag. We next shift the level of analysis to the firm. In a panel analysis (*vs.* the earlier pooled OLS), we examine how IC affects post-invention investments and firm growth, including employment, capital investment, firm revenue and profit growth, and vertical and geographical firm boundaries through JVs, acquisitions, and offshoring. The overall empirical approach is analogous to the earlier analyses, but the post-IC period is tracked in years, rather than months, due to the annual corporate reporting cycle.

6.1. IC and firm resource adjustment

In Table 4, we first show that IC indeed increases firing costs and decreases the performance sensitivity of firing and hiring decisions. As economic shocks that require firms to fire and hire workers, we use negative and positive firm performance based on returns on assets (ROA) relative to the industry performance benchmark. The benchmark is defined as the median ROA at the four-digit SIC level. *Positive Performance*$_{it}$ takes the value of firm performance, if firm performance is above the benchmark, and is set to zero otherwise, and *Negative Performance*$_{it}$ takes the value of firm performance, if firm performance is below the benchmark, and is set to zero otherwise. *Negative Performance*$_{it}$ takes a negative value by construction, and we take its absolute value for the ease of interpretation.

In column 1, we find an expected pattern where firms increase (decrease) their workforce by 0.98 (0.80) percent in response to over- (under-) performing the industry benchmark by ten percentage points ($p<0.01$). IC does not independently affect employment growth in column 2, consistent with Blanchard and Portugal (2001) who suggest that employment protection laws most directly affect employment flow and turnover while only having a secondary effect on the overall employment level. In column 3, IC decreases firing in response to low performance by 25.4 percent ($p<0.05$). IC also reduces hiring by 13.2 percent, but the effect lacks statistical significance ($p=0.40$). We find a consistent pattern with respect to capital investment in columns 4-6 where firms actively increase and decrease capital investment based on firm performance ($p<0.01$), but IC decreases the extent of adjustment ($p<0.05$).

-- Insert Table 4 Here --

6.2. Post-invention growth in employment

We next examine how increased firing costs affect employment growth from invention. In Table 4, we sequentially introduce technological invention, IC, and their interaction. Panel A uses patent counts (log), and Panel B uses the patents' market value (log) as a proxy for invention. The dependent variable is the percent growth in firm employment multiplied by 100, and the coefficient is interpreted as a percent change in firm employment associated with a percent increase in invention.

In columns 1-4, we do not impose any restrictions on the post-IC period and use the full firm history. In Panel A, technological invention has a positive but insignificant effect on employment growth (0.186, p=0.203). This null average effect obscures the heterogeneity in post-invention investment based on firing costs. In column 2, *IC* has a small insignificant effect. Including *Invention* and *IC* simultaneously in column 3 makes little difference to their coefficients. However, once we include the interaction term *Invention*×*IC* in column 4, there is a drastic increase in their coefficients; a ten percent increase in patent counts increases employment by 4.05 percent (p<0.01), but this positive effect is moderated by 85.1 percent after IC adoption (p<0.01). Additionally controlling for state-by-year fixed effects in column 5 yields consistent results.[23]

In columns 1-4 of Panel B, we observe a consistent but sharper pattern. This is not surprising given that the market value of patents provides a much more precise estimate for the value of a firm's technological inventions compared to the simple patent counts. Even without controlling for IC, technological invention is already highly significant in column 1 (p<0.01). A ten percent increase in patent market value increases employment by 8.18 percent, which is almost twice as large compared to patent counts in Panel A. The coefficient for the interaction term *Invention*×*IC* is negative (p<0.01) but moderates the positive employment effect of technological invention only by 25.6 percent. The magnitude is significantly smaller than that based on patent counts in Panel A. We expect that this is because the patent's market value already incorporates IC's negative impact on a firm's ability to commercialize and profit from technological invention (Table 3).

In columns 6-10, we incrementally decrease the post-IC period from five to one year. We expect IC's negative effect on employment growth to be the largest immediately after IC adoption, when firms have not yet been able to put in adaptive measures, such as relocating their production plants. In column 11, we remove the three years immediately after IC adoption; the sample estimates IC's effect in the mid-to-long term and allows us to compare it to IC's short-term effect in columns 8-10. Across both Panel A and B, the negative coefficient for *Invention*×*IC* is indeed the largest one year after IC adoption and gradually declines as we expand the post-IC period. The effect size declines by approximately half over time but retains its economic and statistical significance and persists in the mid-to-long term

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[23] Farre-Mansa, Hegde, and Ljungqvist (2020) find a much larger employment effect for startups. Startups that are serendipitously assigned a lenient examiner and awarded a patent experience 55% higher employment growth five years later.

(columns 4 and 11).

These results are robust to a battery of robustness checks. Autor et al. (2007) point to the possibility that IC's effect wanes over time, not because firms adapt, but because the legal uncertainty around the scope of IC is resolved; however, we show below that IC's effect increases over time with respect to capital and other investments. In Appendix E, we obtain consistent and sharper results using patent citations as an alternative proxy for invention. We prefer using patent counts and their market value because the number of citations received may be influenced by IC and firm investments in commercialization. In Appendix F, we limit the pre-IC period to five years and obtain a consistent pattern across various lengths of post-IC periods. Appendix G provides results from a dynamic specification that simultaneously include multiple lags of *Invention*, *IC*, and *Invention*×*IC*. We do not detect a significant pre-trend. In Appendix H, we verify that the results are also robust to simultaneously controlling for GF and its interaction with technological invention.

-------------------------------------- Insert Table 5 Here --------------------------------------

These results provide robust evidence that firing costs decouple invention and post-invention employment growth. They also indicate that firing costs reduce the employment growth from technological invention, but the conclusion requires some qualification: even as IC suppresses direct within-firm job creation, its aggregate effect could be much smaller because jobs are created outside firm boundaries instead (as explored in Section 6.6). However, we also find strong evidence of substitution toward capital below.

6.3. Post-invention investment in capital equipment

In Panel A and B of Table 6, we repeat the earlier analysis but use capital investment (log) (CAPEX) as the dependent variable. In column 4, a ten percent increase in patent counts increases CAPEX by 2.8 percent in Panel A, and a ten percent increase in market value increases CAPEX by 5.8 percent in Panel B. In direct contrast to the negative result on employment growth, *Invention*×*IC* has a positive significant coefficient ($p<0.01$) and increases CAPEX by an additional 4.2 percentage points or 150 percent in marginal terms in Panel A and by 2.7 percentage points or 46.6 percent in marginal terms in Panel B. Additionally controlling for state-by-year fixed effects in column 5 makes little difference. Columns 6-11 incrementally decrease the post-IC period, and we observe a pattern opposite to that observed for employment growth in Table 5. The positive coefficient for *Invention*×*IC* is actually the smallest immediately after IC adoption (column 10) and gradually increases as we expand the post-IC period. The temporal pattern provides nuanced and robust support that IC increases capital-labor substitution in commercializing technological inventions.

------------------------------------- Insert Table 6 Here -------------------------------------

The results in Table 5 and 6 show that technological inventions augment the demand for both labor and capital, but the positive employment effect is almost entirely contingent on a flexible labor market, in part through factor substitution towards capital. As a growing share of US firm investment and productivity growth derives from technological advances (Peters and Taylor, 2017), the substitution will likely play an increasing role in shaping labor market dynamics.

6.4 Timing of patent citation and firm investment

The end of an invention and the start of post-invention commercialization likely do not fall exactly on the date that a patent application is filed. The fuzzy separation should bias our findings towards zero, but to link technological invention and IC more clearly to the observed effect on post-invention investments, we next examine when a patent is cited by other patents. The intuition is that, albeit with much noise, patents should lead to post-invention investment when they are being actively used for scientific and commercial purposes, proxied by when they accumulate citations. We divide received citations into short-term citations (1-2 years after grant) and mid-term citations (3-5 years after grant). We then repeat the earlier analysis on employment growth and capital investment but explore a longer investment horizon with a forward lag of one, two, and three years.

With respect to employment growth in columns 1-3, mid-term citations have a limited immediate effect (column 1) but increase employment growth with a lag of two years (column 2). Analogously, the coefficient for *Citation*×*IC* is negative for employment growth at year 1 for short-term citations, and at year 2 for mid-term citations. We do not find any significant effect at year 3. With respect to capital investment in columns 4-6, short term citations drive capital investment at year 1 and 2 but not year 3, and mid-term citations drive capital investment at year 3 but not before. The positive investment effect from IC appears more immediately at year 1 but do not affect investment at year 2 and 3.

------------------------------------- Insert Table 7 Here -------------------------------------

6.5. Heterogeneity based on adjustment requirements

If IC's negative effect on post-invention investment is driven by increasing the cost and time to adjust production processes and taking away the coordination benefits of collocation, we then expect its effect to vary across industries and patents based on the adjustment requirements of the commercialization process. In Table 8, we use patent counts in Panel A and their market value in Panel B as a proxy for technological invention.

In columns 1-6, we first divide each 3-digit SIC code into technologically fast- or slow-moving industries based on the mean speed at which patents accumulate citations (Fabrizio and Tsolmon, 2014). This measure captures the speed at which new technology is adopted and closely corresponds to the notion of a half-life in natural sciences. We expect the slowed pace of commercialization from IC to take a greater toll in fast-moving industries that require rapid commercialization. The negative coefficient for *Invention×IC* on employment is indeed driven by fast-changing industries in columns 1-3 and absent in slow-changing industries in columns 4-6.

In columns 7-12, we next divide 2-digit NAICS codes into high and low offshorability industries using the survey-based measure of offshorability from Blinder and Krueger (2013).[24] We interpret related results more tentatively because of the significant decrease in the sample size and coverage. IC reduces post-invention investment in both subsamples but with important differences. The positive coefficient for *Invention* is close to six-times larger for the low offshorability sample in column 8 relative to the high offshorability sample in column 11 (0.268 *vs*. 1.555, $p<0.01$) in Panel A; the negative coefficient for *Invention×IC* is also two times larger in low offshorability industries (-1.067 *vs*. -2.017, $p=0.11$). The overall pattern suggests that both the employment growth from inventions and its constraint from IC are greater in low offshorability industries where firms cannot readily relocate post-invention investments.

--------------------------------------- Insert Table 8 Here ---------------------------------------

In Table 9, we next divide patents into incremental and radical patents based on the median value of patent originality (Hall et al., 2001). Commercializing high-originality patents, which draw from multiple technology classes, should require reconfiguring a broader set of existing resources, and in turn, suffer more from the increase in firing costs. Because firms quickly adjust the technological characteristics of their R&D investments (Table 2), we also expect IC's effect on employment growth to be stronger shortly after IC adoption and to decrease over time. We find support for both. With respect to employment growth, the coefficient for *Radical×IC* is negative (-1.249, $p<0.05$), whereas the coefficient for *Incremental×IC* is actually positive (0.749, $p<0.10$) in column 2. Both effects are short-lived and disappear after three years in column 3. With respect to capital investment in columns 4-6, we observe an opposite pattern that is in line with the earlier result on labor-capital substitution (Table 6). The coefficient for *Radical×IC* is positive and strengthens over time, achieving economic and statistical significance after three years in column 6 but not before.

[24] We use externally coded values from Table 3, as recommended by the authors.

-------------------------------------- Insert Table 9 Here ---------------------------------------

6.6. Adjustments in firm boundaries and offshoring

We have shown that firms adapt the direction of R&D (Table 2) and substitute labor with capital (Table 6) in order to bypass the increased firing costs. We next estimate equation (3) and examine whether firms outsource and offshore the commercialization of invention more after IC adoption.[25]

In Table 10, we first examine the number of acquisitions (log) announced in the next two years as the dependent variable.[26] As a proxy for offshoring, we divide acquisitions into domestic and foreign acquisitions. As before, we vary the post-period and use the full sample in columns 1-3, restrict the post-period to three years in columns 4-6, and remove the first three years after IC adoption in columns 7-9. In column 1, IC reduces acquisition counts by 3.7 percent, consistent with the earlier finding by Dessaint, Golubov, and Volpin (2017) that stringent employment protection suppresses acquisitions by reducing the potential cost-synergies from laying off redundant workers. However, this pattern reverses when a firm needs to commercialize inventions; a ten percent increase in patents increases the number of acquisitions by 0.57 percent after IC adoption. Looking across columns 2 and 3, we find that the acquisitions of foreign targets drive the increase with an effect size more than three times larger relative to domestic targets. Looking across columns 4-6 and 7-9, the propensity to use foreign acquisitions for commercializing inventions increases more than two-fold over time. The pattern suggests that the increased firing costs likely accelerated offshoring between 1970-2000. We obtain a consistent pattern using a Poisson quasi-maximum likelihood estimation, reported in Appendix I. We also obtain a consistent pattern when using sales contribution from acquisitions reported in a firm's 10-k filings in Appendix J; a ten percent increase in patent counts increases revenue contribution from acquisitions by 0.43 percent after IC adoption.

To further investigate increased offshoring, we next examine the first incidence of firms reporting foreign income as the proxy for foreign operation in a linear probability model in column 10. *Foreign income* is a binary variable set to one when a firm first reports its foreign income. The coefficient for *Invention* is negative, but its interaction with IC is

[25] How invention and trade affect each other and jointly drive the geographical and vertical fragmentation of firms' value chain has received much attention. Bøler, Moxnes, and Ulltveit-Moe (2015) show that R&D and international sourcing are complementary activities; a reduction in R&D costs increases the imports of intermediate inputs. Also refer to Atkeson and Burstein (2010), Bloom et al. (2014), and Wu and Wan (2017).

[26] Seru (2014) documents that a horizontal diversification through M&A decreases internal innovation and increases external knowledge acquisition through JVs and alliances.

positive and highly significant. A ten percent increase in patent counts increases the likelihood of starting an operation in a non-domestic location by 0.95 percent ($p<0.01$).[27]

--------------------------------------- Insert Table 10 Here ---------------------------------------

To probe the relocation of production activities as driving the short-term increase in foreign acquisitions, we next examine the acquisitions of target firms that list manufacturing as their primary business activity in Table 11. In column 1, we find that a ten percent increase in patents increases the number of manufacturing acquisitions by 0.41 percent after IC adoption. This represents 71.9 percent of the overall increase in acquisition counts from column 1 of Table 10 while manufacturing acquisitions represent only 25.9 percent of all acquisitions in our sample period. Looking across columns 2 and 3, the increase is again driven by foreign manufacturing acquisitions. We observe a consistent pattern in the short-term in columns 4-6 and the mid-to-long term in columns 7-9.

--------------------------------------- Insert Table 11 Here ---------------------------------------

In Table 12, we repeat the analysis from Table 10 and 11 but examine whether technological invention and IC affect firm propensity to engage in domestic, foreign, and manufacturing JVs. The dependent variable is the number of JVs (log) announced in the next two years. In column 1, the coefficient for IC is negative, indicating that firms on average reduce external collaborations in response to the increased firing costs. However, the pattern reverses when IC makes it more difficult to commercialize inventions internally; the coefficient for *Invention×IC* is positive, and a ten percent increase in patents increases the number of JVs by 0.39 percent in states adopting IC. When we divide the increase into domestic and foreign JVs based on the nationality of partner firms, the increase is driven almost entirely by foreign JVs. Looking at the short-term effect in columns 4-6 and the mid-to-long term effect in columns 7-9, we observe a similar increase across domestic and foreign JVs in the short-term, but the mid-to-long term increase persists only for foreign JVs.

We next divide the short-term increase in JVs from columns 4-6 into manufacturing and non-manufacturing JVs in columns 10-12.[28] We find that 32.3 percent and 64.4 percent of the domestic and foreign JVs report manufacturing as their primary activities, respectively.[29] We obtain a consistent panel using a Poisson quasi-maximum likelihood estimation, reported in Appendix K.

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[27] We obtain a similar result using foreign tax expense as an alternative proxy.
[28] We do not observe any significant effects of *IC* and *Invention×IC* for the mid-to-long term sample.
[29] During our sample period of 1985-2000, manufacturing services is the largest category of JVs (29.5 percent). The second largest category is marketing services (14.9 percent).

-------------------------------------- Insert Table 12 Here ---------------------------------------

Taken together, these results show that firms actively manage the strength of complementarity in upstream-downstream resources by reorganizing their vertical and geographical boundaries. In commercializing inventions, firms bypass increased firing costs by offshoring manufacturing activities through foreign acquisitions and joint ventures. The findings also highlight a broader array of corporate strategic activities as an alternative to licensing (Teece, 1986; Arora et al., 2001), in part by incorporating the geographical scope of downstream activities. Our firm-level approach to identifying offshoring is admittedly obtuse but enables us to track external investments through acquisitions and JVs in non-US regions that are not covered in previous studies using more granular plant-level census data (e.g., Fort, 2017; Bai, Fairhurst, and Serfling, 2019).

Pisano and Shish (2012) and Naghavi and Ottaviano (2009) find that offshoring negatively affects innovation. Our findings complement these studies by pointing to converse temporal dynamics: technological invention leads to increased offshoring in the presence of stringent employment protection laws. There are additional channels that we do not examine here that allow firms to bypass the increased firing costs. In particular, the increased cost of direct commercialization likely increases incentives for technological licensing (Arora and Ceccagnoli, 2006). While the precise estimates on their relative importance as a means to commercialize invention are difficult to obtain, Arora, Fosfuri, and Gambardella (2004) suggest that they are comparatively minor but have rapidly grown in its size since the 1990s. We speculate that the increased rigidity of the US labor market and the incentives for decoupling played an important role in the growth of markets for technology.

6.7. Investment sensitivity to Tobin's Q

Jobless growth and underinvestment relative to Tobin's Q have raised important concerns and led to extensive research exploring their causes (e.g., Gutiérrez and Philippon, 2017). In Table 13, we relate the decoupling between invention and post-invention investment can to the underinvestment. We use a measure of Tobin's Q from Peters and Taylor (2017) (or *Total Q*) that also includes intangible capital, including past R&D investment.[30]

We find that *Total Q* is positively related to employment growth at t+1, but the coefficient for *Invention*×*IC* is negative (p<0.05) and reduces the positive relation by 64.7 percent in column 3. When we divide our sample into fast- or slow-moving industries in columns 4 and 5, the underinvestment from IC is driven entirely by fast-changing industries.

[30] We obtain consistent results using the standard Tobin's Q.

When we divide our sample into high and low offshorability industries in columns 6 and 7, the positive employment growth from *Total Q* (0.193 *vs.* 0.338, $p<0.10$) and its constraint from IC (-0.172 *vs.* -0.350, $p<0.05$) are both significantly larger in low offshorability industries. The pattern closely mirrors the earlier results on employment growth (Table 5) and indicates the decoupling from increased firing costs as one of the drivers of underinvestment relative to the Tobin's Q. At the same time, our findings on foreign and manufacturing acquisitions and JVs (Table 10-12) also raise an important measurement concern. As firms increasingly outsource and offshore more labor and capital intensive downstream processes, looking solely at a firm's direct and domestic investments will significantly underestimate the actual amount of firm investment.

--------------------------------------- Insert Table 13 Here ---------------------------------------

6.8. Revenue and profit growth

Lastly, in Panel A and B of Table 14, we examine whether IC constrains firm revenue and profit growth. A ten percent increase in patent counts and market value is associated with a 0.13 and 0.24 percent increase in revenue and a 0.21 and 0.39 percent increase in profits, respectively. Unlike IC's significant effect on post-invention investments, the coefficient for the interaction term *Invention×IC* is generally negative but fails to reject the null (with the single exception of Panel A column 5). Using longer lags of revenue and profit growth yields consistent results. We interpret these null results with much caution, because specific financial arrangements determine whether revenues and profits from newly acquired firms or JVs are reported to the parent firm and because they contrast with the significant negative effect on the market value of patents (Table 3). More generally, we suspect that the null results reflect the inherently noisy relation between technological invention and profits (Teece, 1986) and that the adaptive actions undertaken by firms, including the pursuit of less novel inventions, factor substitution, JVs, and acquisitions, allow firms to at least partially bypass the constraint from IC.

In columns 7-12, we next examine revenue and profits per employee. We expect the outsourcing of downstream processes to reduce labor intensity of firm operations. The coefficient for *Invention* does not show a consistent pattern and generally fails to reject the null. The pattern is expected as technological invention increases both revenue and employment. In contrast, the coefficient for the interaction term *Invention×IC* is consistently positive for both revenue and profits per employee, and its economic and statistical significance increases over time, especially in Panel B. The temporal pattern is in line with the gradual increase in offshoring observed in Tables 10-12.

--------------------------------------- Insert Table 14 Here ---------------------------------------

7. Conclusion

In *Science, The Endless Frontier* (1945), Vannevar Bush reported to President Truman, "Scientific progress is one essential key to our security as a nation, to our better health, to more jobs, to a higher standard of living, and to our cultural progress." This foundational premise continues to shape American industrial policy, but its relevance requires reassessment that reflects the US labor market's changing conditions. Using a research design that combines the staggered adoptions of employment protection laws and institutional features of the patent review process, we present evidence of decoupling: technological invention, while continuing to contribute to firm profit and revenue growth, has significantly weakened in its ability to create jobs locally.

Establishing the decoupling provides critical theoretical implications. First, it suggests that firms aggressively manage the strength of complementarity (or coupling) between upstream and downstream resources, in part by reorganizing their vertical and geographical boundaries. Second, for the research on firm investment, the decoupling separates invention and post-invention investment as two interdependent yet distinct determinants of firm investment and growth and inserts innovation into the discussions of jobless and investmentless growth. In particular, it extends the discussion beyond certain technologies (e.g., automation, communication technologies) and explains why technological invention in general has lost its ability to create (local) jobs even while continuing to contribute to firm profit growth. Third, to the research on offshoring and outsourcing, the decoupling suggests that these measures center on efforts to commercialize technological invention and occur in a discrete and punctuated process, rather than a smooth and continuous one.

With respect to labor policy, highlighting the decoupling provides a more precise assessment of the causes behind the jobless growth and explicates the critical tradeoffs that complicate devising an effective national response. Efforts to ensure fair employment practices came at significant costs to technological invention and job creation. Alarmingly, US multinational firms are increasingly offshoring even R&D activities to be closer to their production sites, particularly radical inventions (Griffith and Macartney, 2014; Bernard et al., 2017), and firms in emerging countries have leveraged their production capabilities to climb upward in the value chain and challenge American technological leadership (Wan and Wu, 2017). In response, policy debates have focused on R&D investments and boosts to worker productivity, for example, through R&D subsidies, tax credits, and education (Goldin and

Katz, 2008; PricewaterhouseCoopers, 2012; McKinsey Global Institute, 2013). However, increased R&D spending, in the absence of a flexible labor market policy that supports post-invention investments in commercialization, is unlikely to revive US employment, especially in technologically dynamic sectors and disruptive technologies that have been the current national focus. Technological inventions are also unlikely to bring back ‘‘good’’ jobs, which provide a high level of employment security.

We suspect that the US labor market's increasing rigidity accelerated and reinforced other causes of the US employment sag: declining market dynamism and technological leadership, automation, and offshoring. The bias against novel and radical technological inventions likely played a key role in decreasing new firm entries and market dynamism and contributed to the increased market power of a few incumbent firms (Autor et al., 2006; Gutiérrez and Philippon, 2017). The substitution toward capital from technological invention is contingent on the adoption of employment protection laws, and the negative domestic employment effects of technology need not have been negative or at least not so strongly negative. These effects were likely exacerbated in more recent decades by the advances in automation, computerization, and communication technologies. Recoupling invention and post-invention investment is critical to both reviving US manufacturing jobs and technological competitiveness. Restoring labor market flexibility is critical to this goal, but any substantive reforms will require a legislative response, which will prove to be far more challenging to achieve than a policy response.

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Figure 1. US Manufacturing Employment, IC, and Inventive Activities

Figure 1A. Patent Outputs and Manufacturing Employment

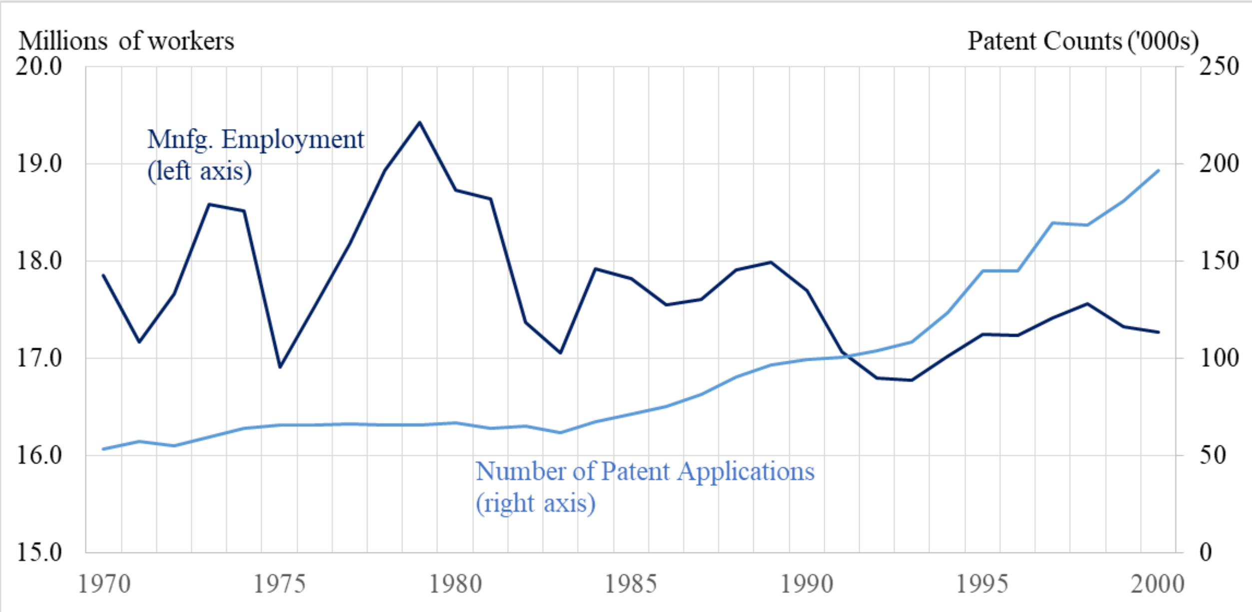

Figure 1B. Implied contract exceptions and Manufacturing Employment

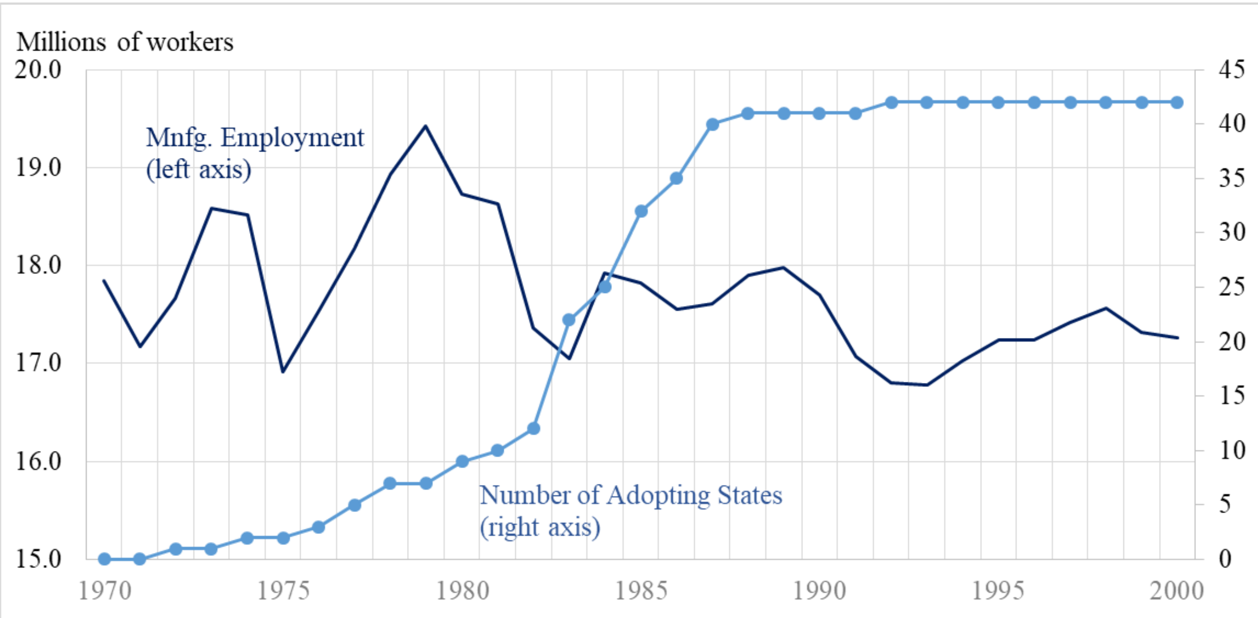

Figure 2. Patent Review Process and Research Design

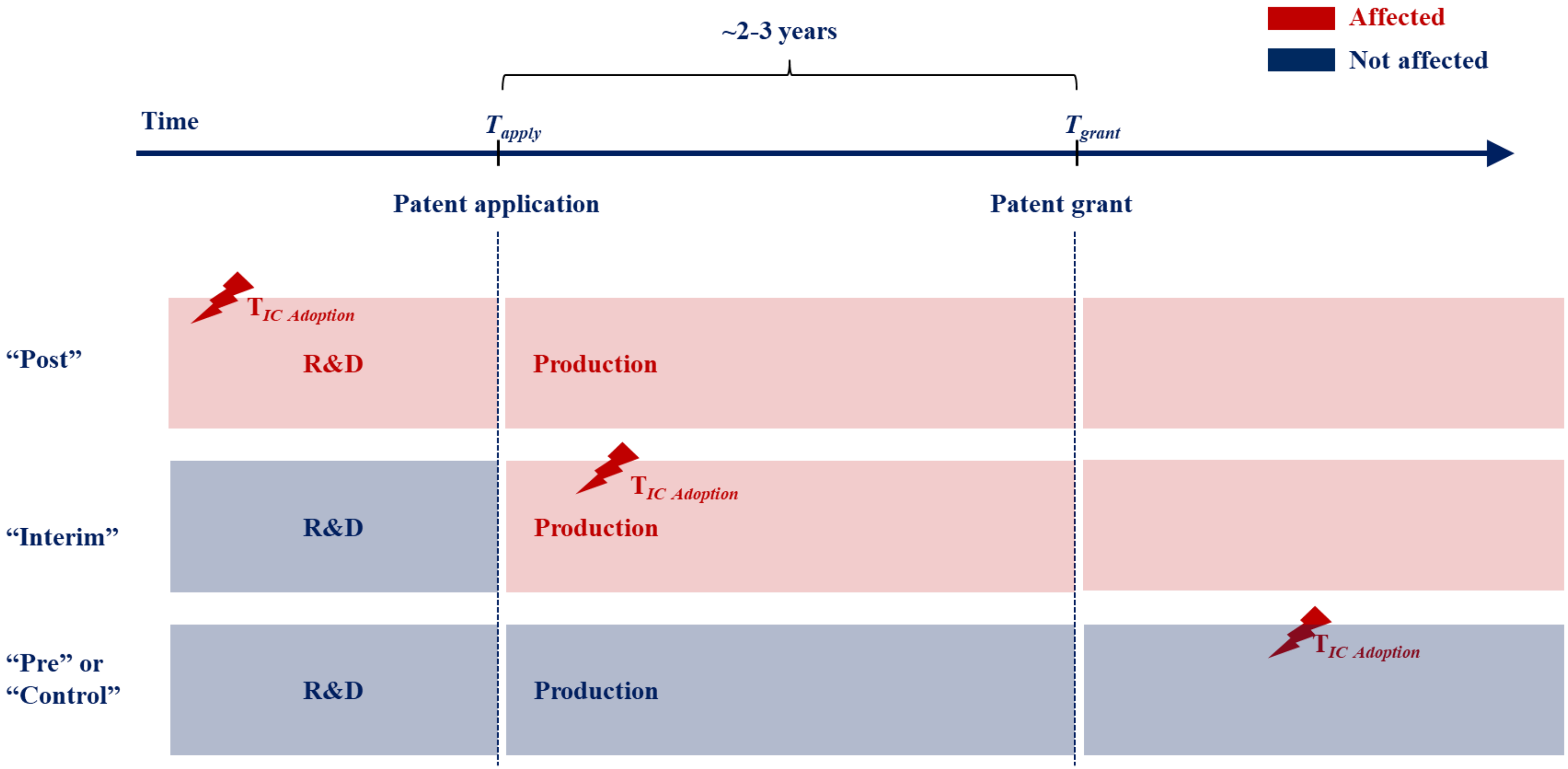

Table 1. Sample Statistics

Variables	N	Mean	SD	Min	Max
Panel A. Patent-level variables					
1. Citations (log)	230,241	2.20	1.05	0.00	6.89
2. Market value (log)	342,122	2.12	1.03	0.00	6.89
3. Originality	144,502	0.52	0.37	0.00	1.00
4. Novelty	131,442	-0.04	0.25	-0.68	0.71
5. Generality	195,945	0.58	0.31	0.00	1.00
6. Implied contract (=1)	230,241	0.30	0.46	0.00	1.00
7. Application-grant lag (month)	696,798	25.63	14.14	1.00	364.00
Panel B. Firm-level variables					
1. Employee growth$_{t+1}$	100,177	1.96	10.60	-32.72	44.63
2. Capital investment$_{t+1}$	103,273	1.99	1.75	0.00	7.85
3. Patent count (log)$_t$	100,177	0.48	0.98	0.00	4.33
4. Patent market value (log)$_t$	100,177	0.58	1.41	0.00	6.34
5. Implied contract (=1)$_t$	100,177	0.59	0.49	0.00	1.00
6. Tobin's Q$_t$	100,177	1.90	3.47	0.08	315.07
7. Total Q$_t$	99,731	1.39	8.49	-17.99	1935.00
8. Industry adjusted ROA$_t$	100,177	-0.03	0.27	-5.98	2.92
9. Industry revenue growth$_t$	100,177	0.13	0.15	-1.96	3.59
10. Debt ratio$_t$	100,177	0.26	0.35	0.00	41.82
11. Current ratio$_t$	100,177	2.97	10.60	0.00	1719.25
12. Working capital to sales ratio$_t$	100,177	1.48	62.39	-2554.50	13450.00
13. Distance to bankruptcy$_t$	100,177	5.06	26.81	-2776.37	3679.15
14. Total asset$_t$ (log)	100,177	4.34	1.97	0.01	12.04
15. Total revenue$_t$ (log)	100,177	4.32	2.25	-6.91	11.70
16. Industry concentration$_t$	100,177	0.24	0.18	0.02	1.00
17. JV$_{t+1,2}$	56,726	0.18	1.12	0.00	53.00
18. Alliance$_{t+1,2}$	56,726	0.52	3.62	0.00	276.00
19. Revenue from acquisition (log)$_{t+1}$	83,106	0.35	1.15	-5.30	10.69
20. Foreign operation (=1)$_{t+1}$	69,429	0.04	0.20	0.00	1.00

This table presents summary statistics for the main variables used in the study. The baseline sample for patent-level analysis includes all patents in the NBER patent database between 1970 and 2000. The baseline sample for the firm-level analysis includes all Compustat firms between 1970 and 2000 and their patent portfolio. *Patent market value* is from Kogan et al. (2017). For patent counts and their market value, we transform them by taking the natural log of one plus their nominal values. The adoption month and years for the implied contract exception are obtained from Autor et al. (2006) and Serfling (2016). Total Q is from Peters and Taylor (2017). Refer to Appendix A for a detailed description of how each variable is constructed.

Table 2. Employment Protection and the Direction of Technological Invention

DV:	Originality × 100			Novelty × 100			Generality × 100			Citation × 100		
	All	*pre* - vs. *Interim*	*pre* - vs. *Post*	All	*pre* - vs. *Interim*	*pre* - vs. *Post*	All	*pre* - vs. *Interim*	*pre* - vs. *Post*	All	*pre* - vs. *Interim*	*pre* - vs. *Post*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$IC(=1)_t$	-0.654*	-0.093	-1.071***	-1.194***	-0.447	-1.575***	-0.757**	-0.509	-0.997***	1.554	1.961	0.568
	[0.328]	[0.399]	[0.344]	[0.383]	[0.389]	[0.503]	[0.305]	[0.380]	[0.269]	[1.186]	[1.563]	[1.276]
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Grant year × T. Class FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.21	0.22	0.21	0.09	0.11	0.10	0.24	0.25	0.24	0.27	0.27	0.25
N	144,502	111,192	127,090	131,442	96,013	111,455	195,945	156,396	201,955	230,241	185,273	312,856

Notes. This table reports OLS estimations of equation (4). Standard errors are clustered at the technology class and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. IC and the Weakening Relationship between Scientific and Market Value of Technological Invention

DV:	Patent market value ×100 $(\log)_t$								
	All	All	All	All	*pre* - vs. *Interim*	*pre* - vs. *Post*	All	*pre* - vs. *Interim*	*pre* - vs. *Post*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Citation $(\log)_t$	2.509**	2.014**	0.048	0.051	0.09	0.026	0.345*	0.198	0.297*
	[1.032]	[0.784]	[0.166]	[0.163]	[0.151]	[0.155]	[0.175]	[0.147]	[0.168]
$IC(=1)_t$				-3.865*	-3.660*	-5.610**	-0.945	-1.207	-1.705
				[2.098]	[2.118]	[2.277]	[1.852]	[2.005]	[2.026]
Citation $(\log)_t \times IC_t$							-1.318**	-1.100**	-1.763**
							[0.494]	[0.539]	[0.664]
Firm FE	*no*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Grant year × T. Cla	*yes*	*no*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.34	0.55	0.76	0.76	0.76	0.76	0.75	0.76	0.75
N	342,670	343,512	342,122	342,122	342,122	295,399	314,611	295,399	314,611

Notes. This table reports OLS estimations of equation (5). Standard errors are clustered at the technology class and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. IC and Constraint on Firm Resource Adjustment

DV:	ΔEmp × 100_{t+1}			CAPEX $(\log)_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Positive ROA_t	9.842***		10.919***	0.716***		0.975***
	[1.050]		[1.251]	[0.063]		[0.099]
Negative ROA_t	-8.871***		-10.946***	-0.278***		-0.348***
	[0.605]		[1.038]	[0.037]		[0.046]
IC_t		0.049	-0.066		0.000	0.000
		[0.152]	[0.150]		[0.015]	[0.015]
IC_t ×Positive ROA_t			-1.448			-0.357***
			[1.705]			[0.107]
IC_t ×Negative ROA_t			2.786**			0.093**
			[1.142]			[0.046]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.29	0.32	0.33	0.94	0.94	0.94
N	163,192	100,262	98,515	175,678	103,375	101,411

Notes. This table reports OLS estimations of equation (3) but replaces *Invention* with firm performance. *Overperformance* (*Underperformance*) takes the nominal value of industry adjusted firm performance (ROA) if firm performance is positive (negative), and zero otherwise. *Underperformance* takes a negative value by construction, and we take its negative value for the ease of interpretation. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. IC and Post-Invention Employment Growth

	DV: ΔEmp × 100_{t+1}										
Post period:	All					5 yrs	4 yrs	3 yrs	2yr	1yr	Exclude *post* 3 yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Patent count (log)											
Invention_t	0.186		0.186	0.405***	0.444***	0.231**	0.291***	0.268**	0.227**	0.281**	0.416***
	[0.144]		[0.144]	[0.130]	[0.127]	[0.111]	[0.108]	[0.102]	[0.110]	[0.115]	[0.145]
IC_t		0.037	0.039	0.236		0.311*	0.341*	0.400*	0.499**	0.381	0.316
		[0.150]	[0.152]	[0.160]		[0.172]	[0.201]	[0.214]	[0.228]	[0.276]	[0.264]
$\text{Invention}_t \times \text{IC}_t$				-0.345***	-0.377***	-0.445***	-0.432***	-0.485***	-0.623***	-0.691**	-0.320***
				[0.110]	[0.113]	[0.133]	[0.131]	[0.152]	[0.229]	[0.332]	[0.109]
Adj. R2	0.32	0.32	0.32	0.32	0.33	0.36	0.37	0.37	0.38	0.39	0.33
Obs.	100,177	100,177	100,177	100,177	100,145	55,013	51,346	48,454	45,479	42,554	91,298
Panel B: Patent market value (log)											
Invention_t	0.818***		0.818***	1.010***	1.024***	0.922***	0.987***	0.981***	0.959***	1.007***	1.000***
	[0.087]		[0.087]	[0.080]	[0.080]	[0.096]	[0.107]	[0.098]	[0.111]	[0.117]	[0.083]
IC_t		0.037	0.048	0.228		0.280*	0.310	0.375*	0.479**	0.380	0.323
		[0.150]	[0.158]	[0.156]		[0.166]	[0.190]	[0.203]	[0.217]	[0.258]	[0.259]
$\text{Invention}_t \times \text{IC}_t$				-0.259***	-0.257***	-0.324***	-0.316***	-0.368***	-0.492***	-0.580**	-0.252***
				[0.076]	[0.081]	[0.097]	[0.094]	[0.113]	[0.173]	[0.286]	[0.075]
Adj. R2	0.32	0.32	0.32	0.32	0.33	0.36	0.37	0.37	0.38	0.39	0.33
Obs.	100,177	100,177	100,177	100,177	100,145	55,013	51,346	48,454	45,479	42,554	91,298
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×State FE	*no*	*no*	*no*	*no*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*

Notes. This table reports OLS estimations of equation (3). Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. IC and Post-Invention Capital Investment

	DV: CAPEX $(\log)_{t+1}$										
Post period:	All					5 yrs	4 yrs	3 yrs	2yr	1yr	Exclude *post* 3 yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Patent count (log)											
Invention_t	0.055***		0.055***	0.028***	0.030***	0.027**	0.030**	0.034***	0.035***	0.037***	0.026***
	[0.008]		[0.008]	[0.009]	[0.009]	[0.011]	[0.012]	[0.012]	[0.011]	[0.011]	[0.009]
IC_t		0.000	0.000	-0.023		-0.031*	-0.032*	-0.031*	-0.021	-0.009	-0.012
		[0.014]	[0.015]	[0.017]		[0.017]	[0.017]	[0.017]	[0.015]	[0.015]	[0.026]
$\text{Invention}_t \times \text{IC}_t$				0.042***	0.041***	0.038***	0.038***	0.035***	0.029***	0.024***	0.043***
				[0.008]	[0.008]	[0.005]	[0.006]	[0.006]	[0.005]	[0.008]	[0.010]
Adj. R2	0.94	0.94	0.94	0.94	0.94	0.95	0.95	0.95	0.95	0.95	0.94
Obs.	103,273	103,273	103,273	103,273	103,236	56,961	53,185	50,195	47,139	44,119	94,091
Panel B: Patent market value (log)											
Invention_t	0.078***		0.078***	0.058***	0.058***	0.059***	0.063***	0.065***	0.064***	0.064***	0.056***
	[0.006]		[0.006]	[0.005]	[0.005]	[0.008]	[0.009]	[0.009]	[0.009]	[0.009]	[0.005]
IC_t		0.000	0.001	-0.017		-0.026	-0.027	-0.027*	-0.015	-0.004	-0.006
		[0.014]	[0.015]	[0.016]		[0.016]	[0.016]	[0.016]	[0.014]	[0.015]	[0.026]
$\text{Invention}_t \times \text{IC}_t$				0.027***	0.027***	0.025***	0.025***	0.024***	0.018***	0.014*	0.026***
				[0.007]	[0.007]	[0.004]	[0.005]	[0.005]	[0.005]	[0.007]	[0.008]
Adj. R2	0.94	0.94	0.94	0.94	0.94	0.95	0.95	0.95	0.95	0.95	0.94
Obs.	103,273	103,273	103,273	103,273	103,236	56,961	53,185	50,195	47,139	44,119	94,091
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×State FE	*no*	*no*	*no*	*no*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*

Notes. This table reports OLS estimations of equation (3). Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Patent Citation Timing and Firm Investment

DV:	ΔEmp × 100_{t+n}			CAPEX $(\log)_{t+n}$		
Post period:	All			All		
	$n=1$	$n=2$	$n=3$	$n=1$	$n=2$	$n=3$
	(1)	(2)	(3)	(4)	(5)	(6)
Citation $(\log)_t$: 1-2 yr	0.184	-0.466**	-0.235	0.027**	0.024*	-0.006
	[0.180]	[0.195]	[0.288]	[0.011]	[0.013]	[0.012]
Citation $(\log)_t$: 3-5 yr	0.177	0.707***	0.180	-0.003	0.010	0.042***
	[0.209]	[0.199]	[0.301]	[0.011]	[0.016]	[0.013]
IC_t	0.234	0.400*	0.343	-0.013	-0.016	-0.001
	[0.155]	[0.239]	[0.222]	[0.016]	[0.020]	[0.023]
Citation $(\log)_t$: 1-2 yr × IC	-0.561**	0.377	-0.361	-0.007	-0.007	0.005
	[0.254]	[0.324]	[0.298]	[0.014]	[0.018]	[0.020]
Citation $(\log)_t$: 3-5 yr × IC	0.290	-0.606*	0.266	0.028*	0.027	0.010
	[0.276]	[0.325]	[0.317]	[0.015]	[0.021]	[0.022]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.32	0.31	0.30	0.94	0.93	0.93
N	100,177	94,037	88,127	103,273	96,723	90,439

Notes. This table reports OLS estimations of equation (3). Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Heterogeneous Effects of IC across Industries

DV:	Emp × 100_{t+1}											
Sumsample:	Pace of tech. change						Offshorability					
	Fast			Slow			High			Low		
Post period:	All	3 yrs	Exclude *post* 3yrs	All	3 yrs	Exclude *post* 3yrs	All	3 yrs	Exclude *post* 3yrs	All	3 yrs	Exclude *post* 3yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Patent count (log)												
Invention_t	0.404**	0.319	0.534***	0.403**	0.203	0.373**	0.665**	0.268	0.167	1.799***	1.555**	0.094
	[0.168]	[0.219]	[0.166]	[0.152]	[0.142]	[0.159]	[0.277]	[0.337]	[0.144]	[0.641]	[0.732]	[0.125]
IC_t	0.449**	0.749***	0.467	0.011	0.041	0.173	0.311	0.764*	0.272	0.014	-0.142	-0.246
	[0.214]	[0.255]	[0.345]	[0.257]	[0.362]	[0.360]	[0.333]	[0.388]	[0.427]	[0.602]	[0.617]	[0.835]
$\text{Invention}_t \times \text{IC}_t$	-0.597***	-0.737***	-0.452***	-0.017	-0.222	-0.082	-1.055***	-1.067**	-0.781***	-1.956	-2.017***	-0.729
	[0.129]	[0.145]	[0.133]	[0.152]	[0.294]	[0.132]	[0.300]	[0.465]	[0.209]	[1.281]	[0.703]	[1.308]
Adj. R2	0.35	0.41	0.36	0.31	0.37	0.35	0.31	0.32	0.33	0.33	0.37	0.33
Obs.	49,809	21,435	67,978	50,041	26,608	73,079	16,412	6,968	43,252	12,963	6,418	40,364
Panel B: Patent market value (log)												
Invention_t	0.860***	0.642***	0.812***	1.218***	1.193***	1.267***	0.906***	0.679**	0.862***	1.161***	1.116***	1.040***
	[0.106]	[0.144]	[0.106]	[0.116]	[0.139]	[0.114]	[0.179]	[0.291]	[0.182]	[0.386]	[0.371]	[0.370]
IC_t	0.351	0.718***	0.387	0.115	0.063	0.224	0.339	0.786*	0.548	0.079	-0.085	-0.227
	[0.222]	[0.262]	[0.326]	[0.246]	[0.324]	[0.334]	[0.342]	[0.457]	[0.513]	[0.616]	[0.661]	[0.815]
$\text{Invention}_t \times \text{IC}_t$	-0.317***	-0.542***	-0.280***	-0.133	-0.194	-0.157	-0.556***	-0.778***	-0.562***	-1.237**	-1.693***	-1.183*
	[0.068]	[0.099]	[0.073]	[0.123]	[0.211]	[0.119]	[0.122]	[0.215]	[0.128]	[0.545]	[0.401]	[0.627]
Adj. R2	0.36	0.41	0.37	0.31	0.37	0.32	0.35	0.39	0.37	0.36	0.42	0.38
Obs.	49,809	21,435	45,538	50,041	26,608	45,408	16,266	6,783	14,957	12,756	6,205	11,634
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×State FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*

Notes. This table repeats earlier analysis from Table 5 but divides the sample based on the pace of technological change and offshorability. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Heterogeneous Effects of IC across Incremental and Radical Patents

DV:	ΔEmp × 100_{t+1}			CAPEX $(\log)_{t+1}$		
Post period:	All	Post 3yrs	Exclude *post* 3yrs	All	Post 3yrs	Exclude *post* 3yrs
	(1)	(2)	(3)	(4)	(5)	(6)
Incremental $(\log)_t$	-0.049	-0.549*	-0.157	0.096***	0.048	0.051***
	[0.292]	[0.273]	[0.285]	[0.016]	[0.031]	[0.014]
Radical $(\log)_t$	0.173	0.192	0.208	0.037**	0.013	0.013
	[0.336]	[0.488]	[0.372]	[0.014]	[0.015]	[0.012]
IC_t	-0.306	-0.203	-0.117	-0.023	-0.018	0.005
	[0.208]	[0.352]	[0.417]	[0.021]	[0.027]	[0.033]
Incremental $(\log)_t \times IC_t$	0.240	0.749*	0.282	-0.007	0.015	-0.008
	[0.308]	[0.442]	[0.327]	[0.017]	[0.029]	[0.017]
Radical $(\log)_t \times IC_t$	-0.173	-1.249**	-0.115	0.064***	0.005	0.040***
	[0.346]	[0.539]	[0.370]	[0.014]	[0.030]	[0.013]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.35	0.47	0.36	0.94	0.95	0.95
N	68,902	20,416	61,855	70,889	21,167	63,615

Notes. This table repeats earlier analysis from Table 5 and 6 but divides patents into incremental and radical patents based on their originality score. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10. Invention, IC, and Foreign Acquisitions

DV:	Acquisition count (log)$_{t+1,2}$									Foreign income (=1)$_{t+1}$
Post period:	All			*post* 3 yrs			Exclude *post* 3yrs			All
Sample:	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Patent count (log)$_t$	-0.021	0.005	-0.058***	-0.001	0.006	-0.008	-0.026*	0.004	-0.070***	-0.045***
	[0.014]	[0.013]	[0.016]	[0.011]	[0.010]	[0.007]	[0.013]	[0.013]	[0.018]	[0.008]
IC$_t$	-0.037***	-0.019	-0.044***	-0.019	-0.014	-0.013**	-0.040**	-0.017	-0.056***	-0.035***
	[0.011]	[0.012]	[0.008]	[0.016]	[0.015]	[0.006]	[0.018]	[0.020]	[0.012]	[0.010]
Patent count (log)$_t$ ×IC$_t$	0.057***	0.024*	0.079***	0.029**	0.009	0.038**	0.061***	0.020	0.094***	0.095***
	[0.014]	[0.012]	[0.016]	[0.013]	[0.007]	[0.018]	[0.015]	[0.015]	[0.018]	[0.011]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adj. R2	0.67	0.63	0.60	0.74	0.72	0.69	0.68	0.64	0.62	0.76
Obs.	63,638	63,638	63,638	14,835	14,835	14,835	57,520	57,520	57,520	69,429

Notes. This table reports OLS estimations of equation (4). Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11. Invention, IC, and Manufacturing Acquisitions

DV:	Manufacturing acquisition count (log)$_{t+1,2}$								
Post period:	All			*post* 3 yrs			Exclude *post* 3yrs		
Sample:	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent count (log)$_t$	-0.017	-0.003	-0.029***	0.015*	0.016**	0.001	-0.020*	-0.006	-0.033***
	[0.010]	[0.008]	[0.010]	[0.008]	[0.008]	[0.007]	[0.012]	[0.010]	[0.010]
IC$_t$	-0.036***	-0.024**	-0.027***	-0.016	-0.014	-0.005	-0.035***	-0.020	-0.032***
	[0.009]	[0.009]	[0.006]	[0.014]	[0.013]	[0.005]	[0.012]	[0.012]	[0.009]
Patent count (log)$_t$ ×IC$_t$	0.041***	0.020**	0.044***	0.018*	-0.003	0.029**	0.045***	0.023*	0.050***
	[0.010]	[0.009]	[0.011]	[0.010]	[0.007]	[0.014]	[0.012]	[0.011]	[0.010]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adj. R2	0.65	0.59	0.55	0.74	0.70	0.67	0.66	0.61	0.57
Obs.	63,638	63,638	63,638	14,835	14,835	14,835	57,520	57,520	57,520

Notes. This table reports OLS estimations of equation (4). Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12. Invention, IC, and Joint Ventures with Foreign Partners

DV:	JV count (log)$_{t+1,2}$											
Post period:	All			*post* 3 yrs			Exclude *post* 3yrs			*post* 3 yrs: Mnfg JVs		
Sample:	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Patent count (log)$_t$	-0.026	-0.008	-0.031	-0.004	-0.003	-0.001	-0.023	-0.005	-0.030	0.007**	0.003	0.005
	[0.020]	[0.009]	[0.020]	[0.005]	[0.006]	[0.004]	[0.020]	[0.010]	[0.020]	[0.003]	[0.003]	[0.003]
IC$_t$	-0.024**	-0.011**	-0.023**	-0.036*	-0.021**	-0.022	-0.028**	-0.011*	-0.027**	-0.014**	-0.002	-0.013*
	[0.011]	[0.005]	[0.011]	[0.018]	[0.008]	[0.017]	[0.011]	[0.006]	[0.010]	[0.006]	[0.003]	[0.007]
Patent count (log)$_t$ ×IC$_t$	0.039*	0.013	0.044**	0.071***	0.034***	0.059**	0.034	0.009	0.043**	0.040***	0.011***	0.038***
	[0.021]	[0.011]	[0.020]	[0.015]	[0.010]	[0.025]	[0.021]	[0.011]	[0.020]	[0.010]	[0.002]	[0.013]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adj. R2	0.64	0.55	0.61	0.75	0.65	0.74	0.66	0.56	0.63	0.79	0.65	0.79
Obs.	56,726	56,726	56,726	10,750	10,750	10,750	52,752	52,752	52,752	10,750	10,750	10,750

Notes. This table reports OLS estimations of equation (4). Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13. IC and Underinvestment Relative to Tobin's Q

DV:	ΔEmp_{t+1}						
	All			Tech. Change		Offshorability	
				Fast	Slow	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total Q_t	0.036**	0.036**	0.088***	0.076**	0.155***	0.193***	0.338***
	[0.015]	[0.015]	[0.024]	[0.029]	[0.037]	[0.067]	[0.082]
IC_t		0.061	0.120	0.209	-0.007	0.177	0.410
		[0.159]	[0.159]	[0.226]	[0.240]	[0.352]	[0.640]
Total Q×IC_t			-0.057**	-0.054*	0.023	-0.172**	-0.350***
			[0.024]	[0.027]	[0.041]	[0.068]	[0.088]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.31	0.31	0.31	0.35	0.31	0.35	0.34
N	102,187	102,187	102,187	49,605	49,786	16,583	13,048

Notes. This table reports OLS estimations of equation (3) but replaces *Invention* with Tobin's Q (or Total Q) from Peters and Taylor (2017). Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 14. IC, Invention, and Firm Growth

DV:	ΔRevenue × 100_{t+1}			ΔProfit × 100_{t+1}			Rev / EMP_{t+1}			Profit / EMP_{t+1}		
Post period:	All	3 yrs	Exclude *post* 3yrs	All	3 yrs	Exclude *post* 3yrs	All	3 yrs	Exclude *post* 3yrs	All	3 yrs	Exclude *post* 3yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Patent count (log)												
$Invention_t$	1.305***	0.903**	1.516***	2.115***	0.936	2.880***	-3.307	0.681	-3.790*	-1.138	0.153	-1.261*
	[0.383]	[0.365]	[0.393]	[0.571]	[0.980]	[0.583]	[2.040]	[1.109]	[2.239]	[0.679]	[0.305]	[0.652]
IC_t	0.434	-0.771	1.599**	1.119	0.342	1.664	-1.444	0.495	-0.891	-3.619***	-3.497**	-1.938**
	[0.643]	[0.716]	[0.777]	[1.147]	[1.611]	[1.174]	[3.245]	[1.996]	[4.259]	[1.266]	[1.686]	[0.772]
$Invention_t \times IC_t$	0.106	0.534	-0.257	-0.021	1.412*	-0.659	4.740***	0.301	5.838***	3.155***	2.500**	3.123***
	[0.324]	[0.396]	[0.390]	[0.470]	[0.792]	[0.636]	[1.598]	[1.318]	[2.030]	[0.629]	[1.167]	[0.582]
Adj. R2	0.43	0.50	0.43	0.25	0.30	0.26	0.75	0.80	0.76	0.54	0.55	0.56
Obs.	106,232	51,294	96,885	73,615	38,674	67,327	101,066	48,927	92,144	100,928	48,805	92,015
Panel B: Patent market value (log)												
$Invention_t$	2.350***	2.007***	2.500***	3.856***	3.911***	4.168***	-1.670	1.033	-2.068	0.551	0.801**	0.469
	[0.212]	[0.307]	[0.217]	[0.430]	[0.776]	[0.403]	[1.668]	[1.224]	[1.783]	[0.522]	[0.304]	[0.466]
IC_t	0.536	-0.503	1.583**	1.182	0.838	1.452	-1.760	0.436	-1.256	-3.784***	-3.232**	-2.278***
	[0.649]	[0.674]	[0.764]	[1.188]	[1.511]	[1.191]	[3.119]	[1.946]	[4.113]	[1.212]	[1.584]	[0.758]
$Invention_t \times IC_t$	-0.071	0.299	-0.296	-0.079	0.787	-0.482	4.386***	0.373	5.066***	2.869***	1.778**	2.901***
	[0.247]	[0.232]	[0.283]	[0.415]	[0.482]	[0.540]	[1.167]	[1.093]	[1.460]	[0.502]	[0.832]	[0.510]
Adj. R2	0.43	0.50	0.43	0.25	0.30	0.26	0.75	0.80	0.76	0.54	0.55	0.56
Obs.	106,232	51,294	96,885	73,615	38,674	67,327	101,066	48,927	92,144	100,928	48,805	92,015
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*

Notes. This table reports OLS estimations of equation (3) with year-to-year firm revenue and profit (ebit) growth as the dependent variable. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A. Variable Definitions and Data Sources

A.1. Patent related variables

From Kogan et al. (2017): accessible at https://kelley.iu.edu/nstoffma/

1. Patent market value (log): total market value of patents filed for each calendar year (1970-2000)

From Hall et al. (2001): accessible at
https://sites.google.com/site/patentdataproject/Home/downloads?authuser=0

1. Patent counts (log): number of patent applications for each calendar year (1970-2000)
2. Patent citations (log): total number of citations received for each calendar year (1970-2000)
3. Patent originality (1976-2000)
4. Patent generality (1976-2000)

From Eggers and Kaul (2018): accessible at
https://sites.google.com/stern.nyu.edu/jpeggers/data

1. Patent novelty (1981-2000)

A.2. Other dependent variables

1. Employment growth (log): year-to-year change in the number of employees (Compustat variable *emp*), calculated as a log difference and winsorized at the top and bottom one percent (1970-2000)
2. Capital investment (log): capital investment (Compustat variable *capx*), winsorized at the top and bottom one percent (1970-2000)
3. Acquisitions (log): the total number of announced acquisitions documented in SDC platinum database for each calendar year (1983-2000)
4. Joint ventures (log): the total number of announced joint ventures documented in SDC platinum database for each calendar year. Manufacturing joint ventures are those that report "Manufacturing" as the main activity (1985-2000)
5. Revenue and profit growth: year-to-year change in revenue (Compustat variable *rev*) and profit (Compustat variable *ebit*), calculated as a log difference and winsorized at the top and bottom one percent (1970-2000)

A.3. Wrongful discharge laws: refer to Appendix B.

A.4. Control variables (1970-2000)

1. Tobin's Q: [market value of equity (*mve*) + total assets (*at*) - book value of equity (*ceq*) – deferred taxes (*txdb*)] / total assets (*at*)
2. Total Q: from Peters and Taylor (2017); accessible at WRDS.
3. Firm size: natural logarithm of total assets (*at*)
4. Industry growth: industry mean value of ln(revenue ($revt_t$)) – ln(lagged sales ($revt_{t-1}$)) at the 4-digit SIC level
5. Book leverage: long-term debt (*dlc*) plus debt in current liabilities (*dltt*) divided by total assets (*at*)
6. Altman's Z: 1.2 × working capital (*wcap*) / total assets (*at*) +1.4×retained earnings (*re*) / total assets (*at*) + 3.3 × operating income before depreciation (*ebit*) / total assets (*at*) + 0.6 × (market value of equity (*mve*) / total liabilities (*lt*)) + 1.0 × (revenue (*revt*) /

total assets (*at*))

7. Working capital ratio: working capital (*wcap*) divided by revenue (*revt*)
8. Current ratio: current total assets (*act*) divided by curret total liabilities (*lct*)
9. Herfindahl-Hirschman Index (HHI): calculated at the 4-digit SIC code level based on the revenue of Compustat firms

A.5. Categorizing acquisitions into manufacturing and non-manufacturing targets

We categorize acquisitions based on the business description of the target firm provided by the SDC. Firms whose description starts with manufacturing or Mnfr are considered manufacturing targets.

Date Announce	Target Firm Nation	Acquirer Business Description	Target Business Description
1/1/1980	United States	Bank (foreign)	Bank holding company
1/8/1980	United States	Pvd railroad transport svcs	Railroad
1/21/1980	United States	**Manufactures**,wholesales pharmaceuticals	**Mnfr** defilbrillators
2/26/1980	United States	Own,op dept stores	Own,operate restaurants
2/28/1980	United States	**Mnfr** motor vehicle parts	Hydraulic pumps and valves
3/10/1980	United States	Oil and gas exploration	Oil & gas
3/13/1980	United States	**Manufacture** dyestuffs	Produce seasonings, spices
3/14/1980	United States	Operate grocery, dept stores	Operate retail grocery stores
3/26/1980	United States	**Manufacture** oil drilling tools	**Mnfr,** whl energy equipment
3/27/1980	United States	Grocery	Convenience store/gas stations
4/3/1980	United States	**Mnfr** optical instruments	Office machines
4/11/1980	United States	Operate luggage,leather prod	Operate bars; produce liquor
4/13/1980	United States	Own,op retirement ctr	Nursing homes
4/14/1980	United States	Cafeterias, vending machines	Vending machine operators
4/14/1980	United States	Prod liquor,beer;own,op pubs	**Mnfr**,whl cigarettes,tobacco
4/23/1980	United States	**Mnfr** motor vehicle parts	Savings & loan holding co
4/30/1980	United States	Savings and loan	S&l
5/9/1980	United States	Construct, operate buildings	Develop shopping centers
5/15/1980	United States	Operate railroads, pipelines	Own,op railroad lines
5/30/1980	United States	**Mnfr** industrial mach	**Mnfr** drilling,steel equipment
5/30/1980	United States	Bank holding company	Bank holding company

Appendix B. Adoption Schedule for Wrongful Discharge Laws

	Adoption Year		
State	Implied Contract Exception	Good Faith Exception	Public Policy Exception
Alabama	7/1987		
Alaska	5/1983	5/1983	2/1986
Arizona	6/1/1983 (rev. 4/1984)	6/1985	6/1985
Arkansas	6/1984		3/1980
California	3/1972	10/1980	9/1959
Colorado	10/1983		9/1985
Connecticut	10/1985	6/1980	1/1980
Delaware		4/1992	3/1992
Florida			
Georgia			
Hawaii	8/1986		10/1982
Idaho	4/1977	8/1989	4/1977
Illinois	12/1974		12/1978
Indiana	8/1987		5/1973
Iowa	11/1987		7/1985
Kansas	8/1984		6/1981
Kentucky	8/1983		11/1983
Louisiana		1/1998	
Maine	11/1977		
Maryland	1/1985		7/1981
Massachusetts	5/1988	7/1977	5/1980
Michigan	6/1980		6/1976
Minnesota	4/1983		11/1986
Mississippi	6/1992		7/1987
Missouri	1/1/1983 (rev. 2/1988)		11/1985
Montana	6/1987	1/1982	1/1980
Nebraska	11/1983		11/1987
Nevada	8/1983	2/1987	1/1984
New Hampshire	8/1988	2/1/1974 (rev. 5/1980)	2/1974
New Jersey	5/1985		7/1980
New Mexico	2/1980		7/1983
New York	11/1982		
North Caroliina			5/1985
North Dakota	2/1984		11/1987
Ohio	4/1982		3/1990
Oklahoma	12/1976	5/1/1985 (rev. 2/1989)	2/1989
Oregon	3/1978		6/1975
Pennsylvania			3/1974
Rhode Island			
South Caroline	6/1987		11/1985
South Dakota	4/1983		12/1988
Tennessee	11/1981		8/1984
Texas	4/1985		6/1984
Utah	5/1986	3/1/1989*	3/1989
Vermont	8/1985		9/1986
Virginia	9/1983		6/1985
Washington	8/1977		7/1984
West Virginia	4/1986		7/1978
Wisconsin	6/1985		1/1980
Wyoming	8/1985	1/1994	7/1989

* From Serfling (2016); Autor et al. (2006) does not recognize Utah as adopting the good faith exception whereas Serfling (2016) and Walsh and Schwarz (1996) do.

Appendix C. Exogeneity of IC Adoption Decisions

Wrongful discharge laws have been used by a number of prior studies. Studies closely related to ours include Autor (2003), Autor et al. (2006), Autor et al (2007), Acharya et al. (2014), Serfling (2016), and Bai, Fairhurst, and Serfling (2019). These studies conduct a battery of tests to show that WDL adoption decisions are not a function of states' economic, political, and other observable conditions. We here test whether the state or firm's inventive activities predict IC's adoption. We follow Acharya et al. (2014) and estimate in Table C.1 a Weibull hazard model where the failure event is the adoption of IC in forty-three US states. States are dropped from the sample once they adopt the implied contract exception. The adoption takes place at the state-level, and the appropriate unit of analysis is at the state-year level, but we also check whether they are related to firm-level investments in Table C2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.1 State level

DV:	IC adoption				
	(1)	(2)	(3)	(4)	(5)
Number of patents $_{s,t-1}$ *(log)*	-0.039				
	[0.092]				
Number of citations $_{s,t-1}$ *(log)*		-0.011			
		[0.079]			
Market value of patents $_{s,t-1}$ *(log)*			-0.046		
			[0.058]		
State firm R&D Spending $_{s,t-1}$ *(log)*				-0.068	
				[0.066]	
New firm entrying $_{s,t-1}$ *(log)*					-0.074
					[0.125]
N	730	730	730	729	730

Table C.2 Firm level

DV:	IC adoption					
	(1)	(2)	(3)	(4)	(5)	(6)
Number of patent (log) $_{firm,t-1}$	0.005					
	[0.054]					
Number of citations (log) $_{firm,t-1}$		0.01				
		[0.028]				
Market value of patents (log) $_{firm,t-1}$			-0.006			
			[0.037]			
R&D spending (log) $_{firm,t-1}$				0.019		
				[0.050]		
Employment growth (log) $_{firm,t-1}$					-0.504	
					[0.450]	
Capital investment (log) $_{firm,t-1}$						0.012
						[0.028]
N	66,009	66,009	66,009	66,009	50,881	60,878

Appendix D. Robustness Tests on Patent-level Results

We show that our patent-level results in Table 2 and Table 3 are robust to additionally controlling for firm-by-technology class fixed effects and varying the pre- and post-IC windows. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.1 Table 2 with firm-by-technology class fixed effects

DV:	Originality × 100			Novelty × 100			Generality × 100			Citation × 100		
Post period:	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IC(=1)$_t$	-0.641**	-0.071	-1.166***	-1.060**	-0.249	-1.350**	-0.577*	-0.214	-0.861***	1.539	1.305	-0.135
	[0.278]	[0.305]	[0.411]	[0.418]	[0.442]	[0.521]	[0.300]	[0.285]	[0.313]	[1.004]	[1.402]	[1.438]
Firm × T. Class FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Grant year × T. Class FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.32	0.33	0.32	0.20	0.22	0.21	0.34	0.35	0.34	0.37	0.38	0.35
N	134,524	102,815	117,580	122,688	88,571	103,263	183,121	145,402	188,505	216,656	173,653	295,834

Table D.2 Table 3 with firm-by-technology class fixed effects

DV:	Patent market value ×100 (log)$_t$					
Post period:	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*
	(1)	(2)	(3)	(4)	(5)	(6)
Citation (log)$_t$	0.051	0.082	2.623**	0.277*	0.175	0.241
	[0.136]	[0.117]	[1.074]	[0.154]	[0.122]	[0.145]
IC(=1)$_t$	-3.898*	-3.338	9.599	-1.643	-1.166	-2.813
	[2.246]	[2.250]	[6.236]	[2.054]	[2.194]	[2.188]
Citation (log)$_t$ ×IC$_t$				-1.028**	-0.980*	-1.410**
				[0.499]	[0.584]	[0.628]
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Grant year × T. Class FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.76	0.76	0.76	0.75	0.76	0.75
N	342,122	342,122	295,399	314,611	295,399	314,611

Table D.3 Table 2 with post-IC period extended to 96 months (*vs.* 60 months)

DV:	Originality × 100			Novelty × 100			Generality × 100			Citation × 100		
Post period	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IC(=1)$_t$	-0.654*	-0.093	-1.071***	-1.194***	-0.447	-1.575***	-0.757**	-0.509	-0.997***	1.554	1.961	0.568
	[0.328]	[0.399]	[0.344]	[0.383]	[0.389]	[0.503]	[0.305]	[0.380]	[0.269]	[1.186]	[1.563]	[1.276]
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Grant year × T. Class FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.21	0.22	0.21	0.09	0.11	0.10	0.24	0.25	0.24	0.27	0.27	0.25
N	144,502	111,192	127,090	131,442	96,013	111,455	195,945	156,396	201,955	230,241	185,273	312,856

Table D.4 Table 2 with pre-IC period restricted to 60 months

DV:	Originality × 100			Novelty × 100			Generality × 100			Citation × 100		
Post period	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*	All	*pre* - vs. *interim*	*pre* - vs. *post*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IC(=1)$_t$	-0.614	-0.156	-1.071***	-1.230***	-0.518	-1.575***	-0.652**	-0.460	-0.997***	1.518	1.887	0.568
	[0.375]	[0.394]	[0.344]	[0.398]	[0.390]	[0.503]	[0.289]	[0.356]	[0.269]	[1.049]	[1.306]	[1.276]
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Grant year × T. Class FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.22	0.23	0.21	0.09	0.11	0.10	0.26	0.27	0.24	0.29	0.30	0.25
N	128,793	95,507	127,090	127,890	92,459	111,455	158,047	118,482	201,955	186,567	141,595	312,856

Appendix E. Citation Counts as an Alternative Proxy for Invention

We replicate key results from Table 5 and Table 6 but use citation counts, rather than patent counts or their market value, as a proxy for invention. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

DV:	ΔEmp × 100_{t+1}			CAPEX $(\log)_{t+1}$		
Post period:	All	3 yrs	Exclude *post* 3yrs	All	3 yrs	Exclude *post* 3yrs
	(1)	(2)	(3)	(4)	(5)	(6)
Citation count_t	0.405***	0.268**	0.416***	0.028***	0.034***	0.026***
	[0.130]	[0.102]	[0.145]	[0.009]	[0.012]	[0.009]
IC_t	0.236	0.400*	0.316	-0.023	-0.031*	-0.012
	[0.160]	[0.214]	[0.264]	[0.017]	[0.017]	[0.026]
Citation $\text{count}_t \times IC_t$	-0.345***	-0.485***	-0.320***	0.042***	0.035***	0.043***
	[0.110]	[0.152]	[0.109]	[0.008]	[0.006]	[0.010]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adj. R2	0.32	0.37	0.33	0.94	0.95	0.94
Obs.	100,177	48,454	91,298	103,273	50,195	94,091

Appendix F. Shorter pre-IC Period

We replicate the key results from Table 5 and Table 6 but limit the pre-IC period to five years. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

DV:	ΔEmp × 100_{t+1}					DV: CAPEX $(\log)_{t+1}$				
Pre period	5 yrs					5 yrs				
Post period:	5 yrs	4 yrs	3 yrs	2yr	1yr	5 yrs	4 yrs	3 yrs	2yr	1yr
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Patent count (log)										
Invention_t	0.202	0.282*	0.281*	0.271	0.349*	0.022*	0.025*	0.029**	0.032**	0.035**
	[0.138]	[0.156]	[0.153]	[0.165]	[0.175]	[0.012]	[0.013]	[0.013]	[0.013]	[0.014]
IC_t	0.071	0.100	0.190	0.314	0.229	-0.029*	-0.030*	-0.028*	-0.020	-0.003
	[0.143]	[0.179]	[0.210]	[0.232]	[0.261]	[0.017]	[0.017]	[0.017]	[0.014]	[0.015]
$\text{Invention}_t \times \text{IC}_t$	-0.280**	-0.257**	-0.318**	-0.453**	-0.520*	0.024***	0.024***	0.021***	0.015***	0.009
	[0.127]	[0.125]	[0.142]	[0.216]	[0.304]	[0.006]	[0.006]	[0.006]	[0.005]	[0.008]
Adj. R2	0.40	0.41	0.42	0.43	0.44	0.95	0.95	0.95	0.96	0.96
Obs.	42,829	39,156	36,245	33,288	30,333	44,372	40,587	37,579	34,528	31,490
Panel B: Patent market value (log)										
Invention_t	0.874***	0.947***	0.970***	1.000***	1.074***	0.058***	0.063***	0.066***	0.066***	0.065***
	[0.101]	[0.133]	[0.129]	[0.134]	[0.143]	[0.007]	[0.008]	[0.009]	[0.008]	[0.009]
IC_t	0.044	0.075	0.168	0.296	0.227	-0.026	-0.028	-0.026	-0.017	-0.002
	[0.137]	[0.170]	[0.204]	[0.227]	[0.252]	[0.017]	[0.017]	[0.016]	[0.014]	[0.014]
$\text{Invention}_t \times \text{IC}_t$	-0.201**	-0.186**	-0.241**	-0.358**	-0.440	0.016***	0.017***	0.015***	0.010*	0.005
	[0.088]	[0.086]	[0.103]	[0.164]	[0.270]	[0.005]	[0.005]	[0.005]	[0.005]	[0.007]
Adj. R2	0.40	0.41	0.42	0.43	0.45	0.95	0.95	0.95	0.96	0.96
Obs.	42,829	39,156	36,245	33,288	30,333	44,372	40,587	37,579	34,528	31,490
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*

Appendix G. Dynamic Specification

Here we examine the dynamic effects of the adoption of the implied contract exception and invention on post-invention employment growth and capital investment. We divide the adoption of IC laws into five separate time periods with indicator variables for each period: $IC^{2yrs\ before}$, $IC^{1year\ before}$, IC^{0yr}, $IC^{1yr\ after}$, *and* $IC^{2\geq yr\ after}$ (Bertrand and Mullainathan, 2003). IC's negative effect on post-invention investments does not show a significant pre-trend. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

DV:	ΔEmp_{t+1}			CAPEX $(log)_{t+1}$		
Post period:	All	All		All	All	
		Run simultaneously			Run simultaneously	
		n=0	*n=1*		*n=0*	*n=1*
	(1)	(2)		(3)	(4)	
Implied Contract $(IC)^{2yr\ before}$	-0.424 [0.355]	-0.111 [0.316]		-0.009 [0.020]	-0.009 [0.020]	
Implied Contract $(IC)^{1\ yr\ before}$	0.051 [0.309]	0.07 [0.299]		-0.024 [0.015]	-0.023 [0.015]	
Implied Contract $(IC)^{0\ yr}$	0.335 [0.264]	0.670** [0.272]		-0.008 [0.019]	-0.002 [0.018]	
Implied Contract $(IC)^{1yr\ afer}$	-0.200 [0.376]	0.169 [0.291]		-0.012 [0.024]	-0.012 [0.024]	
Implied Contract $(IC)^{2\geq yr\ after}$	0.223 [0.313]	0.546 [0.345]		-0.044 [0.027]	-0.044 [0.026]	
Patent $count_{t-n}$		0.458*** [0.113]	-0.027 [0.142]		0.029*** [0.006]	0.001 [0.008]
Patent $count_{t-n}$ × $IC^{2yr\ before}$		-0.534 [0.451]	-0.172 [0.483]		0.005 [0.026]	-0.002 [0.024]
Patent $count_{t-n}$ × $IC^{1yr\ before}$		0.181 [0.387]	-0.142 [0.431]		0.018 [0.021]	-0.004 [0.024]
Patent $count_{t-n}$ × IC^{0yr}		-0.495 [0.517]	-0.329 [0.512]		-0.007 [0.019]	0.037* [0.021]
Patent $count_{t-n}$ × $IC^{1yr\ after}$		-0.338 [0.707]	-0.443 [0.632]		0.015 [0.023]	0.003 [0.023]
Patent $count_{t-n}$ × $IC^{2\geq yr\ after}$		-0.247* [0.134]	-0.297* [0.157]		0.029*** [0.007]	0.025*** [0.007]
Controls	*yes*	*yes*		*yes*	*yes*	
Year×SIC3 FE	*yes*	*yes*		*yes*	*yes*	
Firm FE	*yes*	*yes*		*yes*	*yes*	
R-squared	0.32	0.32		0.94	0.94	
N	103,978	102,006		110,712	108,159	

Appendix H. Good-faith Exception

Here we show that our results are robust to (1) using the good faith exception or (2) simultaneously using the implied contract exception (IC) and the good faith exception (GF). The economic significance and the exogeneity of GF has found mixed support. With respect to employment patterns, Autor et al. (2006) find a significant effect of IC but a null effect of GF using Current Population Survey (CPS) monthly files and Current Employment Statistics (CES) data. Autor et al. (2007:207) find significant effects of GF using the Longitudinal Business Database (LBD) and the Annual Survey of Manufacturers (ASM), but the effects "commences a year prior to adoption and becomes puzzlingly large in subsequent years when state-specific trends are included." Autor (2003) find that only IC significantly increases outsourcing. Acharya et al. (2014) and Bai, Fairhurst, and Serfling (2019) examine a universe of public firms from Compustat and find that GF stimulates innovation but decreases firm sales growth and investment sensitivity to Tobin's Q. To check for the exogeneity of GF's adoption decisions, these studies estimate a hazard model where the failure event is the adoption of GF and find that GF adoption decisions are not a function of states' economic, political, and other observable conditions. Bai, Fairhurst, and Serfling (2019) use a triple-differences specification based on firm-level characteristics, such as financial slack or performance volatility, to further address any concerns.

In Table G1, with respect to employment growth, we find that using GF instead IC or including GF and IC simultaneously yields highly consistent results. With respect to capital investment, while the coefficients are positive, GF does not show a statistically significant effect. The positive effect from IC remains positive and significant.

In Table G2, we repeat the dynamic specification from Appendix E using GF. We find the presence of significant pre-trend. The coefficients for both $\textit{Patent count}^{t} \times GF^{2yr\ before}$ and $\textit{Patent count}^{t} \times GF^{1yr\ before}$ are statistically significant with respect to both employment growth, and $GF^{2yr\ before}$, $GF^{1yr\ before}$, and $\textit{Patent count}^{t} \times GF^{2yr\ before}$ are significant with respect to capital investment.

Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table H.1 Good faith as an alternative shock on firing costs

	DV: ΔEmp × 100_{t+1}						DV: CAPEX $(\log)_{t+1}$					
post_gf period:	All		3 yrs (GF)		Exclude post GF 3yrs		All		3 yrs (GF)		Exclude post GF 3yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Patent count (log)												
Invention_t	0.382***	0.535***	0.304**	0.470***	0.391***	0.539***	0.043***	0.022*	0.048***	0.029***	0.043***	0.022*
	[0.110]	[0.114]	[0.119]	[0.124]	[0.113]	[0.116]	[0.011]	[0.012]	[0.010]	[0.010]	[0.012]	[0.012]
GF_t	0.427	0.362	0.692*	0.652	0.440	0.360	-0.018	-0.009	-0.001	0.001	-0.023	-0.013
	[0.267]	[0.265]	[0.406]	[0.414]	[0.290]	[0.300]	[0.029]	[0.028]	[0.029]	[0.029]	[0.035]	[0.035]
IC_t		0.177		0.067		0.132		-0.020		-0.027		-0.023
		[0.149]		[0.175]		[0.151]		[0.018]		[0.020]		[0.018]
$\text{Invention}_t \times \text{GF}_t$	-0.733***	-0.656***	-0.883**	-0.884**	-0.735***	-0.653***	0.044**	0.033*	0.020	0.020	0.049***	0.037*
	[0.131]	[0.144]	[0.431]	[0.435]	[0.134]	[0.151]	[0.017]	[0.017]	[0.023]	[0.023]	[0.018]	[0.019]
$\text{Invention}_t \times \text{IC}_t$		-0.273**		-0.310**		-0.265**		0.038***		0.037***		0.038***
		[0.123]		[0.137]		[0.127]		[0.008]		[0.009]		[0.008]
Adj. R2	0.32	0.32	0.33	0.33	0.32	0.32	0.94	0.94	0.94	0.94	0.94	0.94
Obs.	100,177	100,177	83,051	83,051	98,639	98,639	103,273	103,273	85,627	85,627	101,679	101,679
Panel B: Patent market value (log)												
Invention_t	0.970***	1.112***	0.851***	1.013***	0.972***	1.112***	0.068***	0.052***	0.067***	0.054***	0.068***	0.052***
	[0.121]	[0.098]	[0.109]	[0.092]	[0.125]	[0.100]	[0.006]	[0.006]	[0.005]	[0.005]	[0.006]	[0.007]
GF_t	0.282	0.221	0.691*	0.651	0.258	0.180	-0.021	-0.013	0.000	0.001	-0.026	-0.019
	[0.272]	[0.261]	[0.400]	[0.403]	[0.291]	[0.292]	[0.028]	[0.028]	[0.028]	[0.029]	[0.035]	[0.035]
IC_t		0.174		0.067		0.129		-0.014		-0.021		-0.018
		[0.146]		[0.170]		[0.149]		[0.017]		[0.019]		[0.017]
$\text{Invention}_t \times \text{GF}_t$	-0.519***	-0.462***	-0.802***	-0.807***	-0.497***	-0.435***	0.033**	0.026**	0.013	0.013	0.037***	0.030**
	[0.096]	[0.108]	[0.283]	[0.284]	[0.100]	[0.116]	[0.013]	[0.013]	[0.019]	[0.018]	[0.013]	[0.014]
$\text{Invention}_t \times \text{IC}_t$		-0.214**		-0.254***		-0.212**		0.024***		0.021***		0.024***
		[0.092]		[0.094]		[0.093]		[0.007]		[0.007]		[0.007]
Adj. R2	0.32	0.32	0.33	0.33	0.32	0.32	0.94	0.94	0.94	0.94	0.94	0.94
Obs.	100,177	100,177	83,051	83,051	98,639	98,639	103,273	103,273	85,627	85,627	101,679	101,679
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year×State FE	*no*	*no*	*no*	*no*	*no*	*yes*	*no*	*no*	*no*	*no*	*no*	*yes*

Table H.2 Dynamic specification using good faith

DV:	ΔEmp_{t+1}			CAPEX (log)$_{t+1}$		
Post period:	All	All		All	All	
		Run simultaneously			Run simultaneously	
		n=0	*n=1*		*n=0*	*n=1*
	(1)	(2)		(3)	(4)	
Patent count$_{t-n}$		0.770** [0.319]	0.019 [0.230]		0.001 [0.022]	-0.020 [0.016]
Patent count$_{t-n}$ × GF$^{2yr\ before}$		1.597*** [0.458]	-1.673*** [0.449]		0.077** [0.037]	-0.046 [0.033]
Patent count$_{t-n}$ × GF$^{1yr\ before}$		-1.704*** [0.355]	2.403*** [0.404]		0.019 [0.024]	0.034* [0.017]
Patent count$_{t-n}$ × GF^{0yr}		-0.582 [0.695]	-0.148 [0.673]		0.080** [0.034]	-0.032 [0.032]
Patent count$_{t-n}$ × GF$^{1yr\ after}$		0.621 [0.888]	-1.229** [0.489]		0.083*** [0.027]	-0.047 [0.030]
Patent count$_{t-n}$ × GF$^{2\geq yr\ after}$		-0.530* [0.303]	-0.263 [0.238]		0.048* [0.024]	0.040** [0.018]
Good Faith (GF)$^{2yr\ before}$	0.350 [0.352]	0.515 [0.472]		-0.038 [0.024]	-0.057* [0.030]	
Good Faith (GF)$^{1\ yr\ before}$	-0.283 [0.282]	-0.553 [0.381]		-0.036* [0.020]	-0.074*** [0.019]	
Good Faith (GF)$^{0\ yr}$	-0.493 [0.479]	0.033 [0.494]		-0.039 [0.025]	-0.071** [0.029]	
Good Faith (GF)$^{1yr\ afer}$	-0.029 [0.573]	0.374 [0.611]		0.018 [0.018]	-0.015 [0.024]	
Good Faith (GF)$^{2\geq yr\ after}$	-0.173 [0.405]	0.484 [0.446]		-0.01 [0.033]	-0.070* [0.040]	
Controls	*yes*	*yes*		*yes*	*yes*	
Year×SIC3 FE	*yes*	*yes*		*yes*	*yes*	
Firm FE	*yes*	*yes*		*yes*	*yes*	
R-squared	0.32	0.32		0.94	0.94	
N	103,978	102,006		110,712	108,159	

Appendix I. Invention, IC, and Foreign Acquisitions

We repeat the analysis from Table 10 but use the raw count of acquisitions as the dependent variable in a Poisson quasi-maximum likelihood estimation. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

DV:	Acquisition count$_{t+1,2}$								
Post period:	All			*post* 3 yrs			Exclude *post* 3yrs		
Sample:	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent count (log)$_t$	-0.010	0.058	-0.168**	-0.026	0.002	-0.055	-0.006	0.066	-0.165*
	[0.043]	[0.043]	[0.084]	[0.056]	[0.054]	[0.133]	[0.048]	[0.047]	[0.088]
IC$_t$	-0.111	-0.017	-0.221	-0.059	-0.059	-0.109	-0.083	0.025	-0.244
	[0.074]	[0.080]	[0.237]	[0.127]	[0.121]	[0.486]	[0.104]	[0.119]	[0.256]
Patent count (log)$_t$ ×IC$_t$	0.064*	-0.008	0.207***	0.063	0.027	-0.515	0.045	-0.034	0.197***
	[0.036]	[0.038]	[0.070]	[0.041]	[0.027]	[0.321]	[0.048]	[0.052]	[0.074]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Log-likelihood	-46,504	-42,227	-11,326	-7,707	-7,128	-1,174	-42,997	-38,881	-10,748
Obs.	37,584	36,625	12,554	6,563	6,365	1,339	33,989	33,092	11,446

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Appendix J. Revenue Contribution from Acquisitions

We repeat the analysis from Table 10, but instead of the acquisition counts, use their contribution to the overall firm revenue.

DV:	Revenue from acquisition$_{t+1}$		
Post period:	All	*post* 3 yrs	Exclude *post* 3yrs
	(1)	(2)	(3)
Patent count (log)$_t$	0.027	0.030*	0.026
	[0.019]	[0.018]	[0.019]
IC$_t$	-0.021	-0.036	-0.011
	[0.021]	[0.026]	[0.032]
Patent count (log)$_t$ ×IC$_t$	0.043***	0.023	0.047***
	[0.014]	[0.023]	[0.017]
Controls	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*
Adj. R2	0.69	0.84	0.71
Obs.	56,726	10,750	52,752

Notes. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix K. Invention, IC, and JVs with Foreign Partners

We repeat the analysis from Table 11 but use the raw count of joint ventures as the dependent variable in a Poisson quasi-maximum likelihood estimation. We omit the Year×SIC3 FEs for the results to converge. Standard errors are clustered at the firm and state level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

DV:	JV count$_{t+1,2}$											
Post period:	All			*post* 3 yrs			Exclude *post* 3yrs			*post* 3 yrs: Mnfg JVs		
Sample:	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Patent count (log)$_t$	0.013	0.007	-0.015	-0.017	-0.045	-0.007	0.018	0.035	-0.022	0.134*	0.094	0.185***
	[0.045]	[0.063]	[0.063]	[0.075]	[0.143]	[0.078]	[0.049]	[0.074]	[0.063]	[0.078]	[0.193]	[0.051]
IC$_t$	0.431	0.434	0.396	0.386*	0.638***	0.013	0.504	0.560	0.387	0.463**	1.894***	-1.025*
	[0.399]	[0.452]	[0.412]	[0.201]	[0.245]	[0.276]	[0.375]	[0.439]	[0.386]	[0.232]	[0.495]	[0.616]
Patent count (log)$_t$ ×IC$_t$	-0.031	-0.067	0.028	0.147**	0.018	0.446***	-0.037	-0.090	0.039	0.226**	-0.298**	0.939***
	[0.033]	[0.047]	[0.050]	[0.058]	[0.071]	[0.100]	[0.035]	[0.057]	[0.051]	[0.088]	[0.134]	[0.209]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Log-likelihood	-8,057	-4,558	-5,275	-1,414	-837	-872	-7,639	-4,335	-5,003	-592	-276	-433
Obs.	14,075	8,949	9,807	2,473	1,703	1,536	13,040	8,344	9,051	1,044	586	772