PENALIZING THE UNDERDOGS?
EMPLOYMENT PROTECTION AND THE COMPETITIVE DYNAMICS OF FIRM INNOVATION

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This study examines how constraining a firm's ability to adjust resources affects innovation. In response to losing competitiveness, laggard firms must release obsolete resources and increase experimentation with new resources. Limiting the pace and efficiency at which they can do so impedes their ability to innovate and challenge leaders. I explore these ideas empirically by exploiting the staggered adoption of employment protection laws by U.S. state courts that were intended to protect employees but also had the effect of limiting the ability of laggards to reconfigure human resources. Increasing employment protection indeed results in fewer and less impactful patents by laggards, driven by a decrease in radical innovations that require significant resource adjustments. By distinguishing between firms that have the incentive to adjust resources *versus* those that do not, the study articulates the process and the black box between constraints on resource adjustment and innovation in a way that explains why the relationship is more complex than a simple average effect. More broadly, this study proposes a firm's competitive position as a critical yet neglected contingency, complementing the prior emphasis on industry- and task-level considerations.

Key words: innovation; resource adjustment; technology race; employment protection; performance feedback

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1. Introduction

Innovation is a competitive process that requires dynamic adjustments to firm resources (Penrose, 1959; Utterback and Abernathy, 1975; Helfat et al., 2007). In response to losing competitiveness, laggard firms adjust resources in part by imitating leader firms (Peteraf, 1993, Polidoro and Toh, 2011; Posen et al., 2013) but also by taking greater risks in experimenting with new resources (Cyert and March, 1963; Toh and Polidoro, 2013). A vast body of research since Schumpeter (1942) examines the dynamic creation and destruction of resources as both driving and resulting from technological innovation.

Contrary to the intuition, varied streams of research continue to disagree on whether constraining a firm's ability to adjust resource stifles firm innovation. In particular, research on employment protection highlights two competing effects from limiting a firm's ability to dismiss employees. First and perhaps more obviously, employment protection reduces the pace and flexibility with which firms can respond to changes in the competitive environment by releasing obsolete employees and hiring new employees with requisite skills, resulting in less innovation ("adjustment effects"). On the other hand, there are significant costs to maintaining flexibility and benefits to giving it up. Among others, increased job security motivates higher employee effort, thereby improving the productivity of existing resources and increasing the returns to investing in innovation ("resource effects"). In fact, current empirical evidence emphasizes the dominance of positive resource effects and advocates employment protection as stimulating firm innovation (Acharya et al., 2014; Griffith and Macartney, 2014). This tradeoff between flexible adjustment and the efficient use of existing resources represents a central theme in organizational theory, underpinning decisions on organizational structure, specialization, search, and firm boundaries among many others (Burns and Stalker, 1961; Thompson, 1967; March, 1991; Richardson, 1996; Eisenhardt et al., 2010; Toh and Kim, 2013).

Given the two competing effects, prior contingency research suggests that constraining resource adjustment can be good or bad for innovation depending on how much a firm needs to adjust its resources, for example, having a positive effect in a stable environment but a negative effect in a volatile

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environment where firm resources quickly become obsolete (March, 1991; Eisenhardt and Martin, 2000; Winter, 2003). Extending the prior emphasis on industry- and task-level considerations, I examine a firm's competitive position as a critical yet overlooked contingency that creates asymmetrical incentives to adjust resources and shifts the relative importance of the two competing effects. Notably, research on competitive interactions (Anderson and Cabral, 2007; Lerner, 1997; Reinganum, 1983) theorizes that firms take varying levels of risk based on their competitive position. With less to lose (or more to gain), laggards challenge the leaders by increasing investment in innovation and also pursuing high-variance, disruptive technologies whereas leaders focus on safer yet more incremental innovations.

Building on this leader-laggard dynamics, I argue that a constraint on resource adjustments does not uniformly affect firm innovation at all times, but asymmetrically penalizes firms when they are in a laggard position and must actively adjust resources to challenge leaders. Specifically, because employment protection increases the cost of releasing resources that turn out to be unproductive, it constrains laggards in their ability to experiment with new resources, resulting in fewer and more incremental innovations. In contrast, I expect employment protection to have limited effects for leaders because they focus on exploiting existing resources with limited adjustment requirements. The proposed argument distinguishes between a firm's incentives to adjust resources from its ability to do so and emphasizes that successful firm innovation requires both. To test these predictions empirically, I leverage staggered restrictions to the "employment-at-will" doctrine by U.S. state courts from 1973 to 2000 that prohibited firms from dismissing their employees without due cause and thereby increased the cost of adjusting the workforce (Autor et al., 2007). My empirical strategy exploits the interaction between state-level variations in the adoption timing of employment protection laws and changes in a firm's competitive position defined at the industry level. The incongruence in state and industry boundaries allows controlling for industry- or state- factors and making more rigorous causal claims.

I find several sets of findings in support of the proposed theory based on patent-based measures of innovation. As my baseline, I first find that falling into a laggard position causes a 3.5% increase in the

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number of firm patent applications and a 2.4% increase in market value. Employment protection, specifically the adoption of the implied contract exception (or simply IC), fully moderates this increase. To better understand the constraint on resource adjustment as the underlying mechanism, I next examine whether all technologies and industries are affected equally. Looking across different types of patents, I find that the decline in a laggard's patents is concentrated in radical technologies that require substantial adjustments to existing resources as well as high-quality patents that accumulate the most citations. Looking across industries, IC actually increases innovation by firms in low-velocity industries, but this positive effect is uncovered only after controlling for a firm's competitive position, pointing to the material risk of its omission. The effects are absent prior to the adoption and peak with three-year lags and are robust across various specifications, firm subsamples, and alternative measures of a firm's competitive position. Lastly, I show that IC reduces both the hiring of new external inventors as well as the firing of existing inventors by laggard firms.

This study contributes to long-standing research on the consequences of constraining firm action and resource adjustment. By theoretically and empirically distinguishing between firms that have the incentive to adjust resources *versus* those that do not, its findings demonstrate that constraints on resource adjustments actually constrain radical innovation, though they can still have some positive effects. They articulate the process and the black box between constraints on resource adjustment and innovation in a way that explains why the relationship is more complex than a simple average effect. More broadly, this study addresses a gap at the intersection of competitive strategy and organizational theory that explores the tradeoff between resource and adjustment effects (or efficiency and flexibility). Given the asymmetric importance of adjustment effects to laggards, the optimal balance between resource and adjustment effects depends not only on industry-level dynamism (e.g., high vs. low velocity) or task characteristics (radical vs. incremental) but also on a firm's competitive position that continuously shifts over time. Even within an industry, firms in a leader or laggard position work on different tasks that demand competing

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capabilities. Recognizing this simple insight can resolve empirical inconsistencies in studies that only consider task- and industry-level characteristics.

2. Theory and Hypotheses

2.1. Constraining Resource Adjustment: Good or Bad for Innovation?

As the creation and implementation of new ideas or products, innovation involves a significant degree of trial-and-error while experimenting with new resources (March, 1991). Most attempts at innovation fail, including over 95% of new product developments (Schilling, 2015), and require firms to quickly release resources that turn out to be unproductive and make room for new ones. Even upon the discovery of valuable technology through R&D, its commercialization requires adjustments to multiple parts of the value chain, including the skill mix of employees, the production process, complementary assets, and broader tangible and intangible resources (Henderson and Clark, 1990; Teece, 1986; Kaul, 2012; Wu et al., 2014). As a result, constraining a firm's ability to adjust existing resources increases both the cost and risk of experimenting with new resources and in turn, decreases innovation with a bias towards projects that do not require drastic adjustments. I refer to these negative effects as "adjustment effects."

However, there are also significant costs to maintaining flexibility, and constraining a firm's ability to adjust resources can actually enhance firm innovation. Agency research suggests that increased job security from restricting a firm's ability to dismiss employees can motivate greater employee effort, increasing the returns to investing in innovation (Acharya et al., 2014; Griffith and Macartney, 2014). The consequent reduction in employee turnover increases a firm's incentive to invest in employee training and the willingness of employees to develop more firm-specific, specialized knowledge and undertake riskier projects (Collins and Smith, 2006; Sauermann and Cohen, 2010; Manso, 2011; Samila and Sorenson, 2011). The increased job security may also help to recruit and retain higher quality talent at lower cost, as often seen in government agencies (Mastracci, 2009). More generally beyond human resources, Bloom et al. (2013) propose that low adjustment ability, combined with a negative demand shock, can actually

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stimulate innovation by reducing the opportunity cost of experimenting with the "trapped" resources. While recognizing that these effects are varied and can differ across specific resources and contexts, I term the overall positive effects on existing resources as "resource effects."[1]

Managing this tradeoff between flexibility in adjusting resources and efficiency in utilizing existing resources represents a central theme in organizational research that manifests across varied streams of research, including learning and employee turnover (March, 1991), organizational structure (Burns and Stalker, 1961; Jansen et al., 2006), specialization (Hannan and Freeman, 1977; Toh and Kim, 2013), and commitment (Ghemawat, 1991) among many others. Increased commitment, for example in the form of vertical integration that gives up "efficient abandonment processes (Adner and Levinthal, 2004)," allows for more efficient exploitation of resources but also risks trapping firms in a rigid position (Richardson, 1996). Similarly, long-term contracts that result in slow employee turnover permit efficient accumulation and exploitation of internal knowledge but also preclude fast learning and adaptation (March, 1991).

While differing in their specific operationalization, these streams of literature explore the common theme of how "constraint on action" (Davis et al., 2009: 415) affects performance, and suggest that the relative importance of the two effects depends critically on how much a firm needs to adjust resources. Notably, the ability to adjust resources confers limited advantage in a stable environment where success rests on the efficient use of existing resources (Winter, 2003). Conversely, in a disruptive environment that quickly obsolesces existing resources, increasing the productivity of existing resources provides limited benefits, and can even be harmful by delaying the adoption of new requisite resources (Eggers, 2012).

I incorporate a firm's competitive position into this contingency approach that has singularly focused on industry- or task-level consideration (Burns and Stalker, 1961; Woodward, 1965; March,

[1] For example, Bradley, Kim, and Tian (2015) find unionization to decrease innovation and suggest increased moral hazard and slack as underlying mechanisms. While there is no clear consensus, providing job security is generally considered a necessary evil in managing the highly idiosyncratic and risky innovation process (Manso, 2011).

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1991). The constant shifts in a firm's competitive position – driven by the erosion of a leader's advantage by laggards and the upward and downward reversion to the mean in firm performance – represent one of the most robust findings in management research (McGahan and Porter, 1999; Wiggins and Ruefli, 2005), but there has been a surprising lacuna of research that examines how a firm's competitive position imposes varying incentives to adjust resources. This results in an overly static depiction of firm innovation process where the quantity and the types of firm innovation remain disconnected from a firm's competitive position. Below, I use employment protection as a specific instantiation of a constraint on resource adjustment that differentially affects a firm based on its competitive position.

2.2. *When* Do Firms Pursue Innovation?

Complementing a vast body of innovation research that relates industry-level competitive intensity to firm innovation (e.g., Aghion et al., 2005; Hashmi, 2013), a subset of industrial organizations research looks within an industry and emphasizes heterogeneity in the incentive to innovate. A firm's incentives to invest in R&D and innovation does not remain constant but critically depends on its position relative to competitors. In particular, models of R&D and technology race provide a formal analysis of the strategic interactions across two (groups of) competing firms where a firm's payoff depends on its position relative to the other. The core assumption is that innovation creates a "winner-takes-most" structure where a disproportionate share of profits or market share accrues to winners (e.g., Autor et al., 2017).[2]

With less to lose (or more to gain), firms in a laggard position become more risk-seeking and invest in disruptive innovations whereas leader firms become risk-averse and invest in low-variance innovation projects that are more incremental (Anderson and Cabral, 2007) or imitative (Ross and Sharapov, 2015).[3] Aside from investing in more radical innovation (i.e., types of innovation), it is also

[2] The predictions are most stark in a "winner-takes-all" setting but remain valid as long as the payoff from winning the race is convex and not linear (i.e., the second derivative is positive).
[3] Toh and Kim (2013) address a related question on technological breadth. They show a counterintuitive result that a winner-takes-all structure can incentivize firms to increase technological specialization in times of high technological uncertainty rather than spread their bets.

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rational for a laggard firm to invest more heavily in innovation (i.e., quantity of innovation) (Reinganum, 1983). These racing models suggest that firms actively adjust both the size and composition of their innovation portfolio, and technological leadership cycles across different firms over time. Such variable incentives to invest in innovation also serves as one of the core assumptions in behavioral models of organizational risk-taking (Cyert and March, 1963) as well as evolutionary models of firm adaptation (Nelson and Winter, 1982).

The increased incentives of laggards to invest in innovation present one of the key insights from IO economics research that draws a stark contrast with broader patterns of firm resource adjustment (Anderson or Cabral, 2007). Namely, leaders increase investment in resources, such as employment and capital expenditure, and grow while laggards reduce investments and shrink in size. However, with few notable exceptions (Lerner, 1997; Ross and Sharapov, 2015), research on the competitive dynamics of firm innovation remains largely theoretical with limited empirical support and has been challenged with models that produce competing predictions (e.g., Gilbert and Newbery, 1982).[4] There are also several cases of radical innovations by leader firms, such as Kodak, Polaroid, and Xerox (e.g., Benner, 2010), and the relationship between competition and innovation has yielded "seemingly endless variations (Gilbert, 2006:159)." In resolving these empirical and theoretical inconsistencies, I build upon leader-laggard dynamics as a context that shapes firm incentives to invest in innovation but focus on its interactions with a firm's resource adjustment ability as a critical yet understudied determinant of the actual firm response.

I argue that employment protection does not constrain all firms uniformly at all times but asymmetrically penalizes firms when they are occupying a laggard position. The adjustment effects are highly variable, increasing in importance with the degree of the required adjustments. The constraint falls mainly upon laggards who must actively release existing resources that turn out to be unproductive and

[4] Notably, there are models of pre-emption where leaders (incumbents), not laggards (new entrants), invest more heavily in innovation. The competing prediction rests critically on the degree to which these models assume the payoff from innovation to be uncertain. For a review of various contingencies, refer to Reinganum (1989) and Gilbert (2006).

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experiment with new resources. In contrast, it is expected to have limited effects on leaders, which tend to focus on exploiting existing resources. This contingent and option-like characterization of adjustment ability closely parallels the conceptualization of dynamic capabilities (Helfat et al., 2007; Kogut and Kulatilaka, 2001). As a higher-order routine, the ability to adjust resources remains dormant in a stable environment and becomes operative only when changes in the external environment require significant adjustments to a firm's resource bundle (Eisenhardt and Martin, 2000). Based on the asymmetrical adjustment requirement, I hypothesize that:

> Hypothesis 1 (H1): *Employment protection constrains innovation by firms in a laggard position but has limited effects on innovation by firms in a leader position.*

2.3. When Do Firms Pursue *Radical* Innovation?

Beyond negatively affecting the innovation of laggards generally, adjustment effects specifies the types of innovation that are most likely to be constrained. As discussed, falling into a laggard position incentivizes a shift toward disruptive, high variance innovations (Anderson and Cabral, 2007). These are also precisely the types of innovations that require accessing new resources as well as substantial adjustments to existing resources (Griffith and Macartney, 2014) and as a result, are most likely to be affected by the negative adjustment effects of employment protection.

Despite its wide acceptance, the premise that a constraint on resource adjustment stifles radical innovation has found equivocal support across different empirical contexts, definitions of radical innovation, and specific technology fields (Adler et al., 1999; Akkermans et al., 2009; Damanpour and Aravind, 2012). Griffith and Macartney (2014) find a higher share of radical patents by subsidiaries of multinational companies in low protection countries, and Benner and Tushman (2002) show that standardizing the production processes increases the overall pace and number of innovation but crowds out explorative innovations. However, some studies draw the opposite conclusion that the constraint on resource adjustment actually enhances radical innovations (e.g., Cardinal, 2001; Jansen et al., 2006). I argue that the equivocal findings arise from overlooking a firm's competitive position. Because firms dynamically adjust their share of investments in radical and incremental innovations over time, examining

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whether the constraint increases or decreases the average level of radical innovation results in an underspecified test with a significant bias against the adjustment effect. Incorporating competitive dynamics helps to identify when firms are most likely to shift towards more radical innovations (i.e., H1: firms in a laggard position) and in turn, be penalized by employment protection.

> H2*: Employment protection asymmetrically constrains radical innovation by laggards relative to incremental innovation.*

3. Data and Empirical Approach

3.1. Proxies for Innovation

I follow related research and use patent-based measures of firm innovation. I use patent count for each firm-application year to proxy for the quantity of innovation and the number of citations received to proxy for its quality. Patent citation counts have been shown to be a reasonable proxy for patent quality, with only a small number of citations accumulating to incremental patents (Hall et al., 2005). I weigh the citation received with a truncation index created by Hall et al. (2001) that adjusts for different paces of citation accumulation for different application years and take its log given the skewness in the number of citations received. As an alternative dependent variable, I obtain data from Kogan et al. (2017) who measure a patent's market value based on 3-day abnormal returns in response to news of its grant by the US Patent Office. They also conduct an independent exercise of linking patent application files to Compustat and provide an improved match over the expanded time period of 1926 to 2010.

3.2. Employment Protection

There are substantial challenges to measuring a firm's ability to adjust resources. It is not directly observable and does not leave paper trails as patents do. Employment protection laws provide a uniquely suitable context by imposing a concrete constraint on a firm's ability to take one specific action with respect to one type of resource: *releasing employees*. Generally, employment protection is described as "restrictions placed on the ability of the employer to utilize labor (Addison and Teixeira, 2003:85)." The U.S. historically supported an "employment-at-will" doctrine, which allowed employers to fire their employees without any cause, advance notice, or restriction. Since the early 1970s through 1990s,

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however, different states have gradually adopted common law exceptions that restrict an employer's ability to fire at-will and increase the risk and cost of dismissing employees (Autor et al., 2007). These restrictions are commonly referred to as "wrongful discharge laws," and consist of three different classes: implied contract exception (IC), good faith exception (GF), and public policy exception (PP). I provide a brief summary of them here based on Autor et al. (2007).[5]

An implied contract exception becomes effective when an employer promises not to terminate a worker without "just cause," decreasing the pace with which firms can reconfigure their human resources. Such a promise can be made in several forms: a verbal promise ("You have a job here as long as you want."); expectations arising from past performance ("No one with evaluation above X gets fired."); and usual company practices ("You are given at least two official warnings before being let go."). The good faith exception prohibits employers from firing workers to deprive them of earned benefits, such as sales commissions or pension bonuses. The public policy exception provides workers with protections against discharges that would prevent them from upholding public policy, such as whistleblowing an employer's illegal activity. Of the three exceptions, the implied contract exception has been shown to have the strongest effect on employment patterns and firm performance, decreasing state-level employment by 0.8% (Autor et al., 2006), increasing outsourcing (Autor, 2003), and reducing firm profitability (Bird and Knopf, 2009). Acharya et al. (2014) also find the good faith exception to encourage firm innovation and entrepreneurship. Hence, I focus on estimating the effects of the implied contract exception while controlling for the good faith exception.

One major concern is whether the adoption timing of the implied contract exception was a function of a state's innovation activities or performance. I first verify that each adopting state is well balanced in its share of leader and laggard firm-year observations. Next, I estimate Weibull hazard models where the failure event is the adoption of the implied contract exception.[6] The analysis rejects that

[5] For detailed adoption schedules for each state and descriptions of precedent-setting Supreme Court cases, refer Autor (2003: Appendix A).
[6] The analysis closely follows Acharya et al. (2014)'s tests for the exogenous adoptions of the good faith exception.

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IC's adoption was related to state- or firm-level innovative activities (as proxied by the number of patents, citations, or R&D spending each year) or firm performance (as proxied by a firm's laggard status or the state's share of laggard firms each year). In addition, the use of triple-differences as the empirical strategy, described below, allows for a causal interpretation of the findings as long as the treatment (IC) does not systemically correlate with a variable that creates the third difference, a firm's competitive position (Giroud and Muller, 2010). The frequent changes in a firm's position as a leader or laggard make the violation of this condition unlikely. Notably, 52% of the laggards in the sample switch their position to being a leader in the following year. Refer to Appendix A for more detailed descriptions of the implied contract exception, the overall number of states that have adopted it, and test results on the exogeneity of the adoptions.

3.3. Firm Competitive Position

Prior research has relied on two metrics in assessing a firm as a leader or laggard: financial and technological performance. The two are highly correlated (e.g., Kogan et al., 2017), and I rely on industry-adjusted ROA as the main measure of a firm's relative competitive position. ROA has accumulated robust evidence of influencing firm risk-taking as well as external evaluation of firm and managerial performance (e.g., Chen and Miller, 2007; Greve, 2003), and has also been used in previous research that explores the effects of employment protection (Bird and Knopf, 2009) as well as other policy changes (e.g., Giroud and Muller, 2010). Moreover, because products embed multiple technologies (Eggers and Kaul, 2018) and firms often "know" more than they make from a technological standpoint (Brusoni et al., 2001), technological performance provides a noisy signal of a firm's position relative to competitors. Using total shareholder returns (TSR) as alternative financial metric yields consistent results.

Beyond a duopoly setting with only two firms where a firm's position as a leader or laggard is transparent (e.g., IBM vs. AMD) (Goettler and Gordon, 2011), specifying a firm's competitive position presents a complex task. In my baseline specification, I use a simple binary variable *Laggard* that is equal to one if a firm's performance (P_{it}) is lower than industry benchmark (IB_{it}). IB_{it} is defined as the median

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ROA at four-digit SIC level for each fiscal year. This measure is intuitive but does not reflect the potential convexity in the cost of adjusting resources (Zhang, 2005), an issue we address in section 4.4.

3.4. Control Variables

In addition to firm fixed effects, all specifications include year and 3-digit SIC code interacted fixed effects (Year × SIC3) to control for any industry level trends, such as technological uncertainty, product lifecycle (Furr and Snow, 2014), and any other time-varying shocks that are unrelated to IC and changes in a firm's competitive position. I control for factors related to a firm's innovation performance, including firm size (log of sales), industry revenue growth rates, and industry concentration based on the Herfindahl index and its square term (Aghion et al., 2005). Innovation research emphasizes firm financial slack as an important determinant of risk-taking, and I include four different measures of a firm's financial resources, including 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 (Chen and Miller, 2007). Because of significant data attrition, I do not control for a firm's asset tangibility which can serve as a collateral to securing a loan in the main specification, but its inclusion does not qualitatively change any of the results. All industry level controls are constructed at the four-digit SIC level in line with the prior construction of a firm's relative competitive position. The results are robust to additionally controlling for market-to-book ratio, firm age, and state-year controls, including the total number of patents and citations, and the number of firm entries based on first-time patent applications as well as total revenue, capital investments, and R&D spending by public firms, or excluding all control variables other than firm and year fixed effects.

3.5. Empirical Approach

I use the following specification in testing the interaction between the adoptions of the implied contract exception (*IC*) and a firm's competitive position (*Laggard*):

$$Y_{ist} = \alpha_i + \alpha_t + \beta_1 IC_{st-n} + \beta_2 Laggard_{it-n} + \beta_3 IC_{st-n} \times Laggard_{it-n} + X_{ist} + \varepsilon_{ist} \tag{1}$$

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where i, s, and t index a firm, state, and year, respectively. n is the number of lags before the current time period t. The effects of employment protection laws are expected to arise with some lags, usually ranging between one to four years, given the nature of legislative shocks and patents as the dependent variable (e.g., Acharya et al., 2014; Cerqueiro et al., 2016). As labor contracts are governed by state laws, I follow previous research in using the state of firm headquarters, reported in Compustat, as governing the firm's overall contracts (Bird and Knopf, 2009; Acharya et al., 2014). While some firms maintain multiple R&D labs across different states, I find that there is a very high overlap in the state of firm headquarters and the state of the (first) inventor's address as documented in the USPTO application.[7] IC_{st} is an indicator variable that equals 1 if the implied contract exception has been adopted in state s at year t. $Laggard_{it}$ is a binary variable that equals 1 if a firm performance is below the industry benchmark at year t. In this asymmetric linear adjustment model, $IC_{st} \times Laggard_{it}$ allows the coefficient of IC_{st} to vary based on a firm's competitive position (Enders and Granger, 1998) and has been used to examine the effects of adverse shocks on firms' adjustment behavior (Hamermesh and Pfann, 1996). In this triple-difference specification, IC_{st} creates a standard difference-in-differences where the first difference compares the effect on the dependent variable before and after the legislative shock and the second difference takes the difference in the first difference across firms headquartered in the treated and non-treated states. $Laggard_{it}$ identifies the extent to which firms increase or decrease innovation when its performance falls below an industry average. The primary variable of interest is the third difference, captured as the interaction between $Laggard_{it}$ and IC_{st}. This variable estimates the extent to which the effect of $Laggard_{it}$ varies before and after the adoption of IC. All standard errors are clustered at the state level and corrected for heteroskedasticity. Block-bootstrapping at the firm, state-firm, or state-year level produces similar standard errors (for these alternative clustering approaches, refer to Flammer and Kacperczyk, 2016).

3.6. Data

[7] The median and mean value of the overlap are 100% and 69.5%, respectively. The high degree of overlap unfortunately does not permit exploiting a within-firm, across-location effect of employment laws.

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My starting sample is the universe of Compustat firms and their patent portfolio recorded in the latest NBER patent database from 1973 to 2000 (Hall et al., 2001). Since performance variable ROA is a ratio that can take extreme values, I winsorize the sample at the 99th and 1st percentile. Finally, I drop financial firms (SIC 6000-6999) and government enterprises (SIC>7999) from the sample since they are subject to different regulatory rules, and 4-digit SIC codes with less than eight firms as they do not allow forming meaningful quartiles of firm performance. All of the results are robust to their inclusion. My main sample consists of 56,443 firm-year observations. I adopt coding by Autor et al. (2006) for the adoption timing of the implied contract exception in each state.[8] Table 1 reports the sample statistics. The sample statistics, such as the average number of firm patents and firm size, are broadly consistent with Acharya et al. (2014).

--Insert Table 1 about here--

4. Results

4.1. Competitive Dynamics of Firm Innovation

Table 2 estimates equation (1) with two and three-year lags. In Models (1) and (2) that only include IC_{t-2} and $Laggard_{t-2}$ respectively, both are statistically insignificant. Simultaneously including the two in Model (3) makes little difference. However, in Model (4) that includes their interaction $IC_{t-2} \times Laggard_{t-2}$, $Laggard_{t-2}$ achieves statistical and economical significance ($p<0.01$). Firms produce 3.2% more patents when they are in a laggard position. Lending support to the main argument (H1), the increase is fully moderated by the negative and significant $IC_{t-2} \times Laggard_{t-2}$. These results are consistent with models of technology races that predict laggards to increase innovation (e.g., Lerner, 1997; Reinganum, 1983) against preemption models where leaders invest more heavily in innovation (e.g., Gilbert and Newberry, 1982). Model (5) repeats Model (4) using a three-year lag and finds consistent results.

[8] Available for download at http://economics.mit.edu/faculty/dautor/data/autdonschw06.

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Models (6) - (10) use the market value of patents (Kogan et al., 2017) as the alternative dependent variable.[9] While showing a consistent pattern, the inclusion of $IC_{t-2} \times Laggard_{t-2}$ generates more drastic differences. $Laggard_{t-2}$ is negative with high statistical significance ($p<0.01$) in Models (7) and (8), indicating that the total market value of innovation actually decreases when firms occupy a laggard position. However, $Laggard_{t-2}$ switches to being positive and significant ($p<0.10$) with the inclusion of $IC_{t-2} \times Laggard_{t-2}$ in Model (9). $IC_{t-2} \times Laggard_{t-2}$ again takes the opposite sign of $Laggard_{t-2}$ and is negative and significant (H1). Using the total number of citations (log) as the dependent variable yields consistent results (Appendix D).

These findings have important implications. These results first highlight the ability to dismiss employees flexibly as a critical yet highly contingent determinant of innovation. They complement existing research on competitive interactions, technology races, and behavioral research on performance feedback that focuses exclusively on incentives or motivations to innovate while neglecting substantial differences in a firm's ability to adjust resources (cf. Eggers and Kaul, 2018). With respect to the dynamics of firm innovation and performance, they also demonstrate a firm's ability to adjust resources as a critical determinant of whether a firm experiences upward reversion or a downward spiral. There is a downward spiraling among some laggard firms where "failure leads to search and change which leads to failure which leads to more search (Levinthal and March, 1993:106)" but also a robust tendency for mean reversion in firm performance (e.g., McGahan and Porter 1999). Firms in a laggard position can be an important and successful source of innovation but only when they are unencumbered in their ability to adjust and experiment with resources.

Figure 1 graphs the dynamic effects of the adoption of the implied contract exception. Similar to Bertrand and Mullainathan (2003), I divide the adoption of IC laws into separate time periods with six indicator variables for each state: IC^{year-2}, IC^{year-1}, IC^{year0}, IC^{year+1}, IC^{year+2}, *and* IC^{year+2}. IC^{year-2} and

[9] The larger sample size comes from the improved match between Compustat and USPTO application files by Kogan et al. (2017).

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IC^{year+2} take the value of 1 two years before and after the adoption of *IC*, and $IC^{year>2}$ takes the value of 1 three years after the adoption of *IC* and thereafter. In Figure 1A, the independent effects of *IC* are statistically insignificant with the exception of the temporary significance of IC^{year+2}. This positive effect is examined more carefully below. Figure 1B graphs the coefficients of *IC*'s interactions with $Laggard_{t-3}$. The penalizing effect on laggards is not related to IC^{year-2}, IC^{year-1}, or IC^{year0} but becomes significant one year after the adoption of *IC* (IC^{year+1}) with respect to the number of patents and three years after ($IC^{year>2}$) with respect to the patent value, respectively. The significant $IC^{year>2}$ indicates that the effects persist long term.[10] The patterns are consistent with the notion that the effect of employment protection takes some time to affect patents and address the issue of reverse causation. Refer to Appendix B for results with various lags of $Laggard_{it}$.

---Insert Table 2 about here**--**

--------------------------------------Insert Graph 1A and 1B about here**---------------------------------------**

4.2. Are All Technologies Equally Affected?

Table 3 tests whether the negative effects on innovation are more pronounced for radical technologies that require experimenting with new resources (H2). In identifying patents that contain more radical technologies, I obtain a measure of patent novelty from Eggers and Kaul (2018). They assess a patent to contain novel technology if it combines technology classes that have not been frequently combined before by other patents in the same USPTO's technology class (3-digit *nclass*) in the past five years.[11] Models (1) – (4) examine the number of firm-year patents (log) that fall into the top 10%, 25%, and 50%, and bottom 50% of the novelty score. Consistent with H2, the penalizing effect of IC_{t-2} on laggards (i.e., $IC_{t-2} \times Laggard_{t-2}$) is stronger in patents with high novelty scores but entirely absent in patents with scores in the bottom 50%.

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[10] IC_{t-n} with long lags continue to remain significant with its interaction with $Laggard_{t-3}$, including IC_{t-5} or IC_{t-10}.
[11] Data accessible at https://sites.google.com/stern.nyu.edu/jpeggers/data?authuser=0. The requirement for calculating the historical patterns in citation reduces the time window to 1981-2000.

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Models (5) and (6) examine the effects on high-quality patents that accumulate the top 5% and 10% of citations in their technological class each year. These right-tail patents are considered to arise from engaging in "hit-or-miss" projects that require risky experimentation with new resources (Hall et al., 2001; Cerqueiro et al., 2016). The decrease in a laggard's patents is concentrated in these high-quality patents. In particular, close to 40% of the overall decrease in a laggard's patents are concentrated in the top 5% patents. As the flip side of the increased "hit" patents by laggard firms, Model (7) examines whether the increased experimentation also results in more "miss" patents that receive zero citations (Levinthal and March, 1993). I again find positive and significant $Laggard_{t-2}$ and its moderation by $IC_{t-2} \times Laggard_{t-2}$. Lastly, Model (5) examines the count of distinct 3-digit patent classes (*nclass*) in which a firm files for patents each year. It proxies the level of risk-taking and experimentation based on the breadth of technological search rather than its direction. I similarly find positive and significant $Laggard_{t-2}$ and its full moderation by negative and significant $IC_{t-2} \times Laggard_{t-2}$.

In addition to providing further evidence on the constraint on resource adjustment as the underlying mechanism, these results contribute to a more nuanced understanding of the costs of employment protection. To the extent that challenging leaders centers on discovering a few breakthrough ideas even at the risk of many "misses," employment protection imposes substantive penalties on laggards and their ability to innovate. These results also suggest that contrary to conventional belief, struggling incumbents can be an important source of radical innovation. Identifying their importance, however, poses two hurdles: (i) looking within a shifting subset of firms occupying a laggard position (ii) accounting for significant heterogeneity in their ability to adjust resources.

--Insert Table 3 about here**--**

4.3. Are All Industries Equally Affected?

Table 4 examines whether the implied contract exception has different effects across high and low velocity sectors with the rapid and slow pace of technological change. Each 4-digit SIC code is assigned as a high or low velocity sector based on the mean value of the speed at which patents accumulate

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citations (Fabrizio and Tsolmon, 2014). This measure closely resembles the notion of a half-life, commonly used in science, and intends to capture the speed at which a new technology is adopted. For example, in the pharmaceutical industry, the majority of citations are accumulated within the first three years a patent is granted whereas patents in petroleum and natural gas industries continue to accumulate citations after six years.[12] Models (1) and (2) show somewhat surprising results. While $IC_{t-3} \times Laggard_{t-3}$ are negative and significant across both slow- and high-velocity sectors, IC_{t-3} is actually positive and significant in the low-velocity sector with respect to the number of patents (log). This positive effect is consistent with Acharya et al. (2014) and Griffith and Macartney (2014), but qualifies its importance to a low-velocity sector.

Figure 2 graphs result from a dynamic specification using the six indicator variables (IC^{year-2}, IC^{year-1}, IC^{year0}, IC^{year+1}, IC^{year+2}, *and* $IC^{year>2}$). In the low-velocity sector, IC_{t-n} actually turns positive two years after the adoption and persists afterwards. This positive effect is uncovered only when a firm's competitive position and its interaction with *IC* ($IC_{t-3} \times Laggard_{t-3}$) are taken into account. This provides further evidence (in addition to Table 2) that the impact of under-specification from omitting a firm's competitive position is material and may underpin some of the inconsistent results in prior studies. Without explicitly accounting for a firm's competitive position, a researcher only observes the sum of the positive resource and negative adjustment effect with a bias towards a null finding. This underpins why Acharya et al. (2014) do not uncover the negative effects of IC laws and instead conclude on a null effect.

---Insert Table 4 about here**---**

---------------------------------------Insert Graph 2A and 2B about here**---------------------------------------**

4.4. Mechanisms: Constraint on Resource Adjustment

[12] Specifically, I calculate (i) the share of citations accumulated by a patent within the first three years of its grant and check robustness to using (ii) the share of citations made to patents granted in the last three years. I use a three year window because it is the median value of the average citation lag. Using longer or shorter lags yields qualitatively consistent results. Three largest high velocity SIC code are 2834 (pharmaceuticals), 3674 (semiconductor), and 4911 (electric devices). Three largest low velocity SIC code are 1311 (crude petroleum and natural gas), 5411 (grocery stores), and 5812 (eating places).

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The analyses so far focus on the *consequences* of constraining resource adjustment on patent-based outcomes, as predicted by the proposed theory. I next conduct four additional analyses to better understand the constraint on resource adjustment as driving the decrease in innovation by laggards.

Inventor Turnover I first use the disambiguated inventor database by Li et al. (2014) and investigate whether the implied contract exception actually constrains adjustments in human resources. Autor et al. (2007) document that the implied contract exception reduces the turnover of blue collar workers, but its effect on inventor mobility has not yet been established. Each patent application contains information on the name of the inventor and its assignee (oftentimes its employer) and provides a rare opportunity to examine firm-level turnover in human resources. Following Bernstein (2015) and Marx et al. (2009), "New hire" is an inventor who produces his or her first patent at a given firm after producing at least one patent at a different firm in prior, and "Fire" is an inventor who produces at least one patent at a given firm and at least one patent at a different company afterward. Refer to Data Appendix for a more detailed description of how inventor movements are identified and its limitations.

Table 5 reports results on the hiring and firing of inventors (log) during a three window ($t+0$, $t+1$, and $t+2$). Positive and significant $Laggard_{t-3}$ indicates that firms actively reorganize their human resources by increasing both hiring and firing in response to falling behind. The hiring and firing are moderated by negative $IC_{t-3} \times Laggard_{t-3}$, consistent with the increased cost of adjusting resources from the implied contract exception. Overall, the results present reduced inventor turnover as one of the channels through which employment protection constrains innovation by laggard firms.[13]

---Insert Table 5 about here**--**

Ability *versus* Effort I next examine whether the negative effect of employment protection (H1) stems from decreasing efforts at (radical) innovation or decreasing a firm's ability to translate these efforts into output more productively (Ahuja et al., 2008; Eggers and Kaul, 2018). Firms with limited ability to adjust

[13] Because "Fire" contains both involuntary and voluntary turnovers, "Leaver" may be more descriptively accurate. However, rather than the overall number of inventors that leave the firm, *Laggard* and $IC \times Laggard$ capture the share of the turnover that is related to low performance, which likely contains a higher share of involuntary turnover.

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resources may not attempt to experiment with resources and innovate in the first place. Model (1) verifies that laggard firms increase R&D intensity, as documented by prior research (Greve, 2003; Chen and Miller, 2007).[14] However, in contrast to prior results on patents, $Laggard_{t-1} \times IC_{t-1}$ does not achieve statistical significance. Models (2) and (3) repeat the main analysis on patent counts and their market value but include firm R&D spending (log) as an additional control variable. With the inclusion of this new variable that proxies for the amount of effort, $Laggard_{t-3}$ is no longer significant, but $IC_{t-3} \times Laggard_{t-3}$ remains significant with a marginal decrease in magnitude.

These results indicate decreased ability as the primary mechanism and demonstrate the importance of distinguishing between the inputs and outputs of the innovation process. Firms in a laggard position increase innovation efforts even with employment protection in place, but whether the increased efforts translate into output depends on a firm's ability to release old and obtain new resources.

---Insert Table 6 about here--

Convexity in Adjustment Response The binary measure of $Laggard_{it}$ is obtuse in that it does not discriminate between laggards with performance moderately and significantly below the leaders who may need more adjustments. Laggards, however, are constrained in the extent to which they can experiment with new resources because the cost of adjusting resources is highly convex, especially with respect to releasing resources (Hamermesh and Pfann 1996; Zhang, 2005).[15] For example, laying off 100 people is exponentially more costly and disruptive compared to laying off 10 people. As a result, the magnitude of resource adjustment should increase with declining performance up to a certain point but plateau afterward from the exponential increase in the cost of making further adjustments. Consistent with the convexity, Lerner (1997) finds in the disk-drive industry that middle laggards with technological performance in the third quartile are as likely as the bottom laggards with performance in the fourth

[14] The specification directly follows Chen and Miller (2007), including the shorter lag of one year (vs. two or three year lags on patents). This is because R&D spending is an input to the innovation process that can be more immediately adjusted.
[15] This exponential increase in adjustment cost arises in part from the limited reversibility of investments in resources, for example from the lack of secondary markets and the specialized nature of resources.

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quartile to increase innovation. If the constraint on resource adjustment is indeed the underlying mechanism, the marginal effect of employment protection should be the largest on firms with performance in the third quartile (middle laggards) that most aggressively adjust their resources, rather than the fourth quartile (bottom laggards).

To reflect this non-linear relationship, I revise the binary $Laggard_t$ and form linear splines of firm performance relative to the industry performance benchmark. I start by identifying the difference between a firm's performance (P_{it}) and the industry benchmark: $P_{it} - IB_{it}$. I then form two additional knots at the 25th and 75th percentiles that result in four continuous variables covering each quartile of the annual performance. For brevity, I label the four linear splines created as *Quartile 1* (top 25th percentile), *Quartile 2* (25-50th percentile), *Quartile 3* (50-75th percentile), and *Quartile 4* (bottom 25th percentile). *Quartile 3* and *Quartile 4* take negative values by construction, and I take their absolute values for the ease of interpretation.

In Table 7, I find positive and significant $Quartile\ 3_{t-3}$ and $Quartile\ 4_{t-4}$ (i.e., laggard firms) and its moderation by negative and significant $IC_{t-3} \times Quartile3_{t-3}$ and $IC_{t-3} \times Quartile\ 4_{t-3}$ with respect to the overall number of patents (Model 1), radical patents with a novelty score in the top 10% (Model 2), and top 10% patents in terms of received citation (Model 3), and the market value of patents (Model 5). The effect sizes are four to eight times larger for $Quartile\ 3_{t-4}$ and $IC_{t-3} \times Quartile\ 3_{t-3}$ relative to $Quartile\ 4_{t-4}$ and $IC_{t-3} \times Quartile\ 4_{t-3}$. These results based on linear spline provide a more nuanced and precise test of the underlying mechanism but involves specifying multiple variables that are also less intuitive in interpretation.

One potential concern is that the threat to survival, rather than the convexity of the adjustment costs, underpins the weaker marginal effects on the bottom quartile firms (March and Shapira, 1987). In Models (4) and (6), I restrict the sample to firms with low risk of bankruptcy by excluding those with debt ratio in the top ten percentile. These firms continue to show convexity in adjustment responses. Excluding

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the top tenth or twentieth percentile of Altman Z-score or financial constraint based on Kaplan-Zingales index yields consistent results.

---Insert Table 7 about here**--**

Laggard position *or* Declining Performance There is some concern that declining performance, not falling into a laggard position, prompts firms to increase innovation. In Table 8, I restrict the sample to firms that experience an *increase* in nominal performance (ROA at t-3 is higher than ROA at t-4) but get categorized as a laggard because the performance still falls below the industry competitor. The analysis takes advantage of the difference in the nominal ROA and industry-adjusted ROA; industry-adjusted ROA can be negative and qualify a firm as a laggard even while the nominal ROA is positive and improving. All of the results remain robust. The sample of firms with decreasing performance also shows consistent results (unreported).[16]

---Insert Table 8 about here**--**

4.5. Robustness Checks and Limitations

The empirical strategy based on the staggered adoptions of IC makes alternative mechanisms unlikely, and I focus on the stability of the results across various subsamples for robustness checks. To conserve space, I briefly summarize the key results and discuss them more fully in Appendix D. First, I replicate Acharya et al. (2014) who find positive effects of the good faith exception and null effects of the implied contact exception. This indicates that the differing conclusions derive from the incorporation of competitive dynamics, not from differences in the dataset in use. The results are robust to including more granular Year$\times$SIC4 fixed effects; excluding all control variables other than firm and year fixed effects; excluding seven states that never adopt IC; excluding the three largest patenting states (California, New York, and Texas); expanding the time period to 1970 – 2000 using patent count data from Kogan et al.

[16] The analysis helps to address the alternative explanation that some firms are experiencing a decrease in ROA and qualifying as a laggard because they are foregoing short-term profits and investing in (radical) innovative projects that will show up as patents in 2-3 years.

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(2017); restricting the sample to firms with at least one patent in the firm history; and using a sample that drops firm-year observations five years after the adoption of the implied contract exception.

There are also important limitations to the findings. In particular, there are several sources of downward bias, including noisy identifications of a firm's competitive position due to the diversified nature of a firm's product portfolio and partial exposure to IC from multi-location firms. The observed effects of employment protection on firm innovation (both positive and negative) should be considered as falling closer to their lower bounds. With the exception of Montana, employment protection laws only increase in strength without repeals and re-adoptions. Concluding whether a decrease in employment protection enhances innovation by laggards – the converse of my finding – requires further research. Moreover, the scope of the paper is limited to a firm's internal innovative activities, but firms may also respond to falling into a laggard position by accessing external resources either through firm acquisitions (Kaul, 2012) or more targeted patent-level transactions through markets for technology (Arora et al., 2014; Lungeanu et al., 2016).

Lastly, whether the findings would generalize to a voluntary (endogenous) constraint on resource adjustment poses an important question. Resource constraint is often the outcome of a strategic decision by the management team (Ghemawat, 1991) and not the accidental result of a policy shock. This necessitates reliance on quasi-natural experiments to make causal arguments. However, the issue goes beyond dealing with endogeneity. It is difficult to conclude whether a decrease in laggards' innovation is due to motivation or ability through an examination of voluntary adoptions. I expect the main theoretical proposition – that the adjustment effect matters more for firms in a laggard position – to be applicable across both voluntarily and involuntarily imposed constraints.

5. Discussion and Conclusion

How does the ability to adjust resources affect firm innovation? Theoretical research challenges the intuitive positive relationship: being able to adjust resources more flexibly ("adjustment effects") comes at the cost of reduced efficiency in utilizing existing resources ("resource effects"). In fact, the few prior

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empirical studies on employment protection point to the dominance of the less obvious resource effects (Acharya et al., 2014; Griffith and Macartney, 2014). I examine this tradeoff in the context of employment protection and find that constraining the ability to adjust resources asymmetrically affects firms when they occupy a laggard position. In uncovering this elusive relationship (Gilbert, 2006), this study emphasizes the importance of considering a firm's ability to adjust resources along with its incentives to invest in innovation. The two are considered in largely independent streams of literature – resource adjustment in capability research and incentive for innovation in behavioral and competitive strategy research – and have not been put together with few notable exceptions (Eggers and Kaul, 2018).[17]

While generalizing these findings beyond the particular context of employment protection laws requires much caution, the premise that a firm's competitive position critically affects the tradeoff between adjustment and resource effects informs contingency research, behavioral research on performance feedback, and policy formulation. In managing the tradeoff between resource and adjustment effects (or efficiency and flexibility), organizational research emphasizes taking a contingency approach based on the industry and task characteristics of the firm (e.g., Eisenhardt and Martin, 2000; Cardinal, 2001). However, even the basic premise that flexibility matters more in a fast-moving environment has been challenged (Damanpour and Aravind, 2012; Toh and Kim, 2013; Schilke, 2014). My findings suggest that the prior contingency approach presents a partial view of the firm resource adjustment and adaptation process that does not take into account changes in a firm's competitive position. Had I not considered a firm's competitive position, controlling for various output or input characteristics and including a host of industry level controls still would have yielded a misleading null effect of employment protection in slow-moving industries (Figure 2A). Even within an industry, firms in a leader or laggard

[17] The separate emphasis traces back to Schumpeter (Malerba and Orsenigo, 1995). His earlier work focuses on incentives, highlighting small entrepreneurial firms with little risk of cannibalization as the primary source of innovation. His later work, however, focuses on ability of large firms who can better afford large R&D labs and withstand failures.

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position work on different tasks that demand competing capabilities, and the constant shifts in a firm's competitive position preclude a straightforward answer to whether flexibility or efficiency is better.

I also note the equifinality in predictions of racing models and performance feedback research in the tradition of Behavioral Theory of the Firm (Cyert and March, 1963). Although the two are based on contrasting assumptions of economic incentives based on winner-takes-all (Anderson and Cabral, 2007:598) and behavioral motivations based on social comparison theory (Greve, 2003:63), they converge on the nonlinear payoff function and its implications, especially the increase in risk-taking and innovation by laggards. The convergence between the two research streams extends beyond innovation dynamics to general patterns of firm investment. Recent IO economics research utilizes increased computational capacity to solve competitive interactions that are analytically intractable (Ericson and Pakes, 1995). One key takeaway is that Markov perfect equilibria (MPE) can be approximated by considering only two factors: a firm's own state and expected long-run average state of the industry (Weintraub et al., 2008). To the extent that the current industry benchmark serves as a reasonable proxy for the average state of the industry in the future or the firm's future state based on reversion to the mean, this draws a close parallel to making investment decisions based on historical and social reference points. It is perhaps not very surprising that organizational behavior with as robust support as reference dependence coincides with economic rationality, even if inadvertently (Davis et al., 2009). Understanding more precisely the conditions under which the two diverge promises to be an interesting area of future research.

Finally, this study has implications for evaluating and designing labor market policy. The highly contingent importance of adjustment and resource effects points to an unforeseen set of tradeoffs. Restricting employee dismissal and protecting employees from the unlimited power of employers come at the cost of penalizing *some* underdog firms and decreasing inventor mobility. Unfortunately, stagnation in the labor market tends to reduce employment opportunities for younger and inexperienced workers disproportionately. In the face of increasing social inequality where winners seem to win continuously

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and increase their dominance (Piketty and Saez, 2003), there are increasing calls to protect employees and limit competition. As early as 1942, Schumpeter predicted in *Capitalism, Socialism, and Democracy* that the middle class, increasingly disgruntled by the growing lack of meaningful work and rising unemployment, will demand a welfare state that constrains entrepreneurship and technological progress. Given the penalties on laggard firms and the adverse effects of rising industry concentration on wages (e.g., Benmelech et al., 2018), it is unclear whether the push towards more liberal labor market policies will result in more egalitarian outcomes.

Most of the current research on employment protection and broader public policy, such as non-compete covenants, unionization, and employment subsidies, also focuses on assessing the average effects over time, ignoring the asymmetrical effects on laggard firms. The complex and dynamic set of tradeoffs based on a firm's competitive position advocates the questions of *when* and *where,* rather than *whether* employment protection is good or bad, as a more productive direction of inquiry. I hope that the leader-laggard dynamics documented in this study provides a useful framework that can be applied to research on broader factor market policy. Given the wide-ranging unintended consequences of legislative shocks on firm innovation, the role of U.S. state courts and the weight (or lack thereof) given to economic logic in their deliberations raise pressing concerns.

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Table 1. Sample Statistics

Variables	Obs.	Mean	SD	Min	Max
Number of patents$_t$ (log)	56,443	0.71	1.21	0.00	8.38
Market value of patents$_t$ (log)	89,017	0.60	1.45	0.00	6.45
Implied Contract$_{t-3}$	56,443	0.55	0.50	0.00	1.00
Laggard$_{t-3}$	56,443	0.43	0.50	0.00	1.00
Industry revenue growth$_t$	56,443	0.13	0.14	-1.03	1.34
Debt ratio$_t$	56,443	0.26	0.98	0.00	210.57
Financial slack: Current ratio$_t$	56,443	2.95	9.90	0.00	1719.25
Financial slack: Sales ratio$_t$	56,443	1.24	46.40	-1032	6998.00
Distance from bankcrupcy$_t$	56,443	4.37	39.52	-8009	1487.74
Total asset$_t$ (log)	56,443	4.62	2.04	0.01	12.40
Industry concentration (HHI)$_t$	56,443	1.12	1.51	-0.05	8.56
R&D spending$_t$ (log)	56,443	0.23	0.16	0.02	0.95

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Table 2. Effects of the Implied Contract Exception on Firm Innovation

DV:	Number of patents$_t$ (log)					Patent value$_t$ (log)				
	n=2				*n=3*	*n=2*				*n=3*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Implied Contract (IC)$_{t-n}$	0.005		0.000	0.024	0.011	0.013		0.005	0.034	0.034
	[0.030]		[0.032]	[0.033]	[0.033]	[0.026]		[0.030]	[0.028]	[0.029]
Laggard$_{t-n}$ (=1)		0.000	0.000	0.032***	0.035***		-0.016***	-0.017***	0.016*	0.024***
		[0.007]	[0.007]	[0.012]	[0.011]		[0.006]	[0.006]	[0.010]	[0.009]
Laggard$_{t-n}$ × IC$_{t-n}$				-0.045***	-0.053***				-0.048***	-0.055***
				[0.015]	[0.016]				[0.014]	[0.017]
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*
R-squared	0.85	0.85	0.85	0.85	0.86	0.87	0.87	0.87	0.87	0.87
N	60,996	62,673	60,769	60,769	56,443	97,012	103,528	96,590	96,590	89,017

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level.

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Figure 1A: Dynamic Effects of IC on Firm Innovation

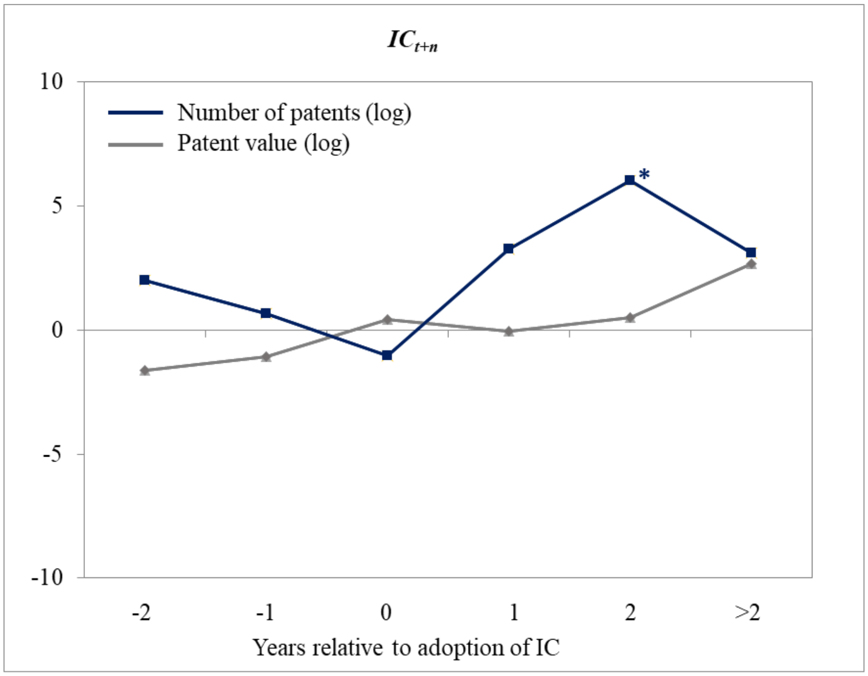
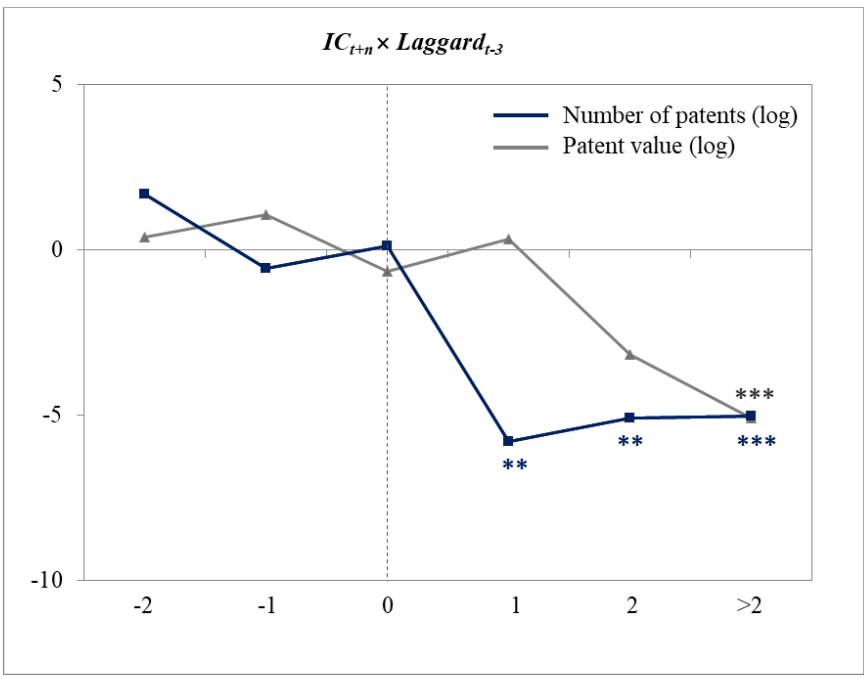


Figure 1B: Dynamic Effects of IC on Laggards



Note: *p<0.1; **p<0.05; ***p<0.01

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Table 3. Are All Technologies Equally Affected?

DV:	Number of patents$_t$ (log)							Active Patent Classes$_t$ (log)
	Patent Novelty				Received Patent Citations			
	Top 10%	Top 25%	Top 50%	Bottom 50%	Top 5%	Top 10%	Zero citation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implied Contract (IC)$_{t-2}$	0.003	0.005	-0.003	-0.010	0.005	0.013	0.004	0.022
	[0.014]	[0.020]	[0.030]	[0.028]	[0.013]	[0.016]	[0.017]	[0.025]
Laggard$_{t-2}$	0.019*	0.021*	0.039**	0.025	0.023***	0.030***	0.026***	0.025***
	[0.010]	[0.013]	[0.017]	[0.017]	[0.004]	[0.006]	[0.009]	[0.010]
Laggard$_{t-2}$ × IC$_{t-2}$	-0.027**	-0.034**	-0.049***	-0.027	-0.020***	-0.029***	-0.025*	-0.031***
	[0.013]	[0.014]	[0.019]	[0.020]	[0.006]	[0.008]	[0.013]	[0.012]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.77	0.82	0.85	0.84	0.75	0.79	0.72	0.85
N	47,131	47,131	47,131	47,131	55,966	55,966	55,966	60,769

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level.

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Table 4. Are All Industries Equally Affected?

DV:	Number of patents$_t$ (log)		Patent value$_t$ (log)	
	Low Velocity	High Velocity	Low Velocity	High Velocity
	(1)	(2)	(3)	(4)
Implied Contract (IC)$_{t-3}$	0.047**	-0.069	0.042	0.016
	[0.023]	[0.064]	[0.026]	[0.049]
Laggard$_{t-3}$	0.035**	0.037	0.016	0.042**
	[0.015]	[0.026]	[0.011]	[0.019]
Laggard$_{t-3}$ × IC$_{t-3}$	-0.051**	-0.061*	-0.053**	-0.065**
	[0.022]	[0.034]	[0.024]	[0.032]
Controls	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*
R-squared	0.86	0.86	0.88	0.87
N	35,957	20,486	56,805	32,212

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level.

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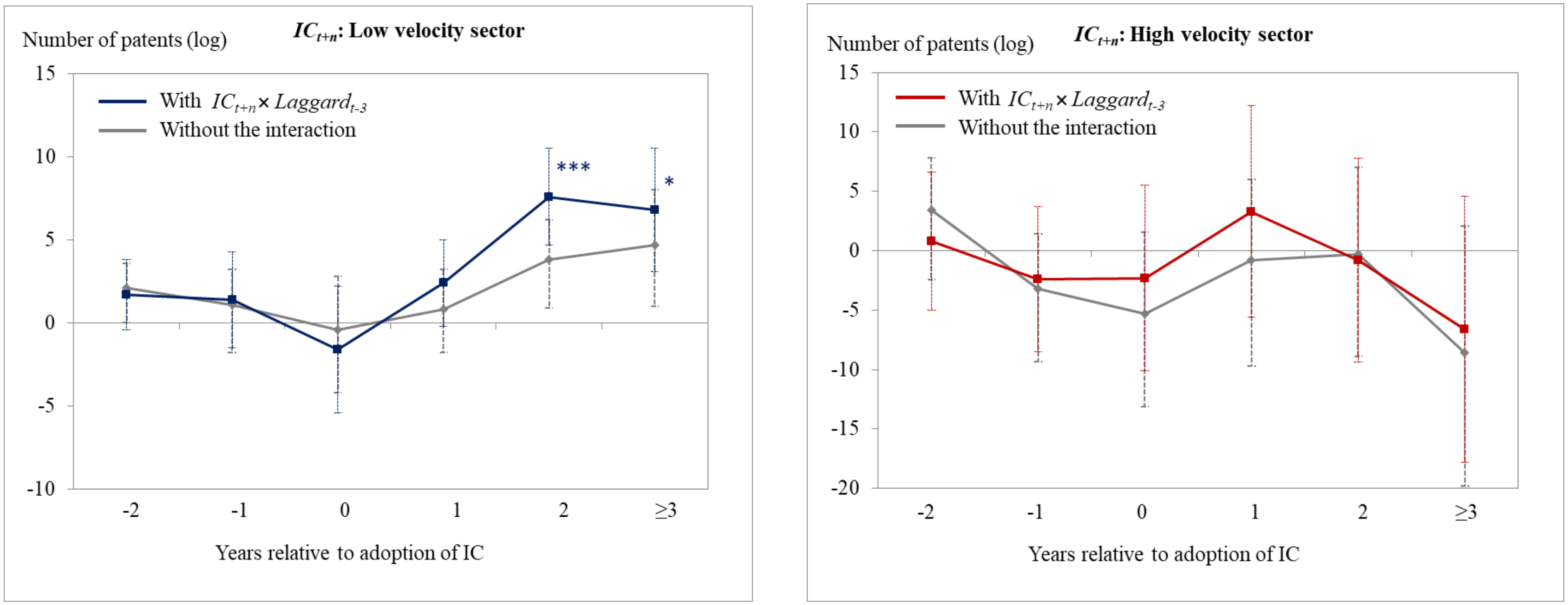
Figure 2A and 2B: Dynamic Effects of IC in Low and High Velocity Sectors



Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level. Dashed lines represent the standard errors.

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Table 5. Employment Protection and Inventor Turnover

	New hire$_{t0+t1+t2}$	Fire$_{t0+t1+t2}$
	(1)	(2)
Implied Contract (IC)$_{t-3}$	0.044 [0.047]	0.031 [0.044]
Laggard$_{t-3}$	0.099*** [0.023]	0.090*** [0.020]
Laggard$_{t-3}$ × IC$_{t-3}$	-0.140*** [0.041]	-0.110*** [0.033]
Controls	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*
Firm FE	*yes*	*yes*
R-squared	0.79	0.74
N	50,488	50,488

Table 6. Effort *versus* Ability

	R&D Intensity$_t$	Number of patents$_t$ (log)	Patent market value$_t$ (log)
	n=1	*n=3*	*n=3*
	(1)	(2)	(3)
Implied Contract (IC)$_{t-n}$	-0.002 [0.002]	0.009 [0.031]	0.033 [0.027]
Laggard$_{t-n}$ (=1)	0.004** [0.002]	0.017 [0.011]	0.009 [0.008]
Laggard$_{t-n}$ × IC$_{t-n}$	0.000 [0.003]	-0.039** [0.016]	-0.044*** [0.017]
R&D spending (log)$_{t-3}$		0.168*** [0.034]	0.200*** [0.036]
Controls	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*
R-squared	0.652	0.859	0.876
N	54,009	56,443	89,017

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level.

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Table 7. Employment Protection and Convexity in Adjustment Costs

	Number of patents$_t$ (log)				Patent value$_t$ (log)	
	All	Top 10% Novelty	Top 10% Citations	High slack firms	All	High slack
	(1)	(2)	(3)	(4)	(5)	(6)
Implied Contract (IC) $_{t\text{-}3}$	-0.018 [0.027]	-0.039 [0.026]	-0.008 [0.017]	-0.022 [0.027]	-0.001 [0.025]	0.001 [0.027]
Quartile 1 $_{t\text{-}3}$ } Leader	-0.184 [0.117]	-0.142 [0.118]	-0.164** [0.064]	-0.255** [0.128]	-0.076 [0.081]	-0.107 [0.091]
Quartile 2 $_{t\text{-}3}$ } Leader	-0.022 [0.181]	0.015 [0.170]	-0.207** [0.099]	0.064 [0.215]	-0.355* [0.198]	-0.344* [0.191]
Quartile 3 $_{t\text{-}3}$ } Laggard	0.325** [0.143]	0.413** [0.187]	0.181*** [0.066]	0.359* [0.188]	0.332*** [0.122]	0.326** [0.152]
Quartile 4 $_{t\text{-}3}$ } Laggard	0.063** [0.031]	0.044 [0.028]	0.049** [0.024]	0.114** [0.044]	0.098*** [0.025]	0.122*** [0.043]
Quartile 1 $_{t\text{-}3}$ × *IC* $_{t\text{-}3}$	0.317* [0.164]	0.288** [0.129]	0.318*** [0.097]	0.460** [0.181]	0.339** [0.151]	0.348** [0.173]
Quartile 2 $_{t\text{-}3}$ × *IC* $_{t\text{-}3}$	0.137 [0.288]	-0.007 [0.276]	0.240 [0.219]	0.158 [0.319]	0.738** [0.290]	0.801** [0.344]
Quartile 3 $_{t\text{-}3}$ × *IC* $_{t\text{-}3}$	-0.395** [0.184]	-0.413* [0.211]	-0.153* [0.079]	-0.474** [0.216]	-0.313** [0.152]	-0.314* [0.172]
Quartile 4 $_{t\text{-}3}$ × *IC* $_{t\text{-}3}$	-0.055* [0.033]	-0.045 [0.030]	-0.036 [0.023]	-0.095** [0.042]	-0.078*** [0.028]	-0.081* [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	0.86	0.85	0.79	0.86	0.87	0.88
N	56,443	43,178	56,443	49,531	89,017	76,390

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level.

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Table 8. Laggard Position *versus* Nominal Performance

	Number of patents$_t$ (log)		Patent value$_t$ (log)
	All	Top 10% Novelty	
	(1)	(2)	(3)
Implied Contract (IC)$_{t-3}$	0.011 [0.048]	-0.006 [0.023]	0.040 [0.039]
Laggard$_{t-3}$ (=1)	0.034* [0.018]	0.037* [0.020]	0.029** [0.013]
Laggard$_{t-3}$ × IC$_{t-3}$	-0.049* [0.025]	-0.044** [0.020]	-0.060*** [0.021]
Controls	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*
R-squared	0.88	0.85	0.88
N	30,097	22,827	47,576

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level.

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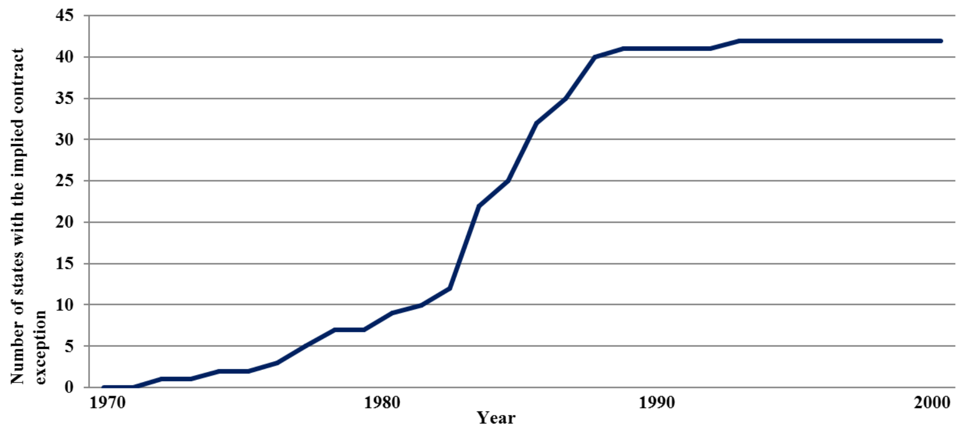
Appendix A: Implied Contract Exception

Figure A. Adoption of the implied contract exception



The graph shows the number of U.S. states that have adopted the implied contract exception. The data is from Autor, Donohue, and Schwab (2006).

The precise nature and the magnitude of the cost imposed by the implied contract exception when dismissing employees remain controversial, especially because it can be nullified by explicitly stipulating the at-will employment contract.[18] Prior studies and interviews with HR managers point to three types of costs. The first is administrative (Condon and Wolff 1985). The implied contract exception induced firms to document employee problems in writing and pushed dismissal decisions to higher levels of management. While the administrative costs themselves were not very significant, they did have the effect of slowing employee adjustments until the end of the evaluation cycle. The second and the largest cost stemmed from the uncertainty of potential lawsuits. Until the late 90s, the legal scope of the implied contract exception remained highly unclear which inflated the threat of potential employee lawsuits. When litigated, employers lost, for example in 68% of the cases in California between 1980 and 1986, with an average penalty of over half a million dollars per case (Dertouzos, Holland, and Ebener, 1988). The last relates to managerial costs. Manager interviews indicate that being implicated in wrongful discharge lawsuits is highly damaging to a manager’s career. Few companies are willing to promote someone under an active lawsuit, even though these lawsuits usually take several years to be resolved. In sum, the implied contract exception represents one of the most extensively discussed and empirically verified legal constraints on a firm’s adjustment ability with significant implications prior to the 2000s.

One major concern is whether the adoption timing of the implied contract exception was a function of a state’s innovative performance. I estimate Weibull hazard models where the failure event is the adoption of IC. Table A1 reports the coefficients from a Weibull hazard model, where the “failure event” is the adoption of the implied contract exception in 43 U.S. 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 (Acharya et al., 2014) but I also check for robustness at the firm level in Table A2.

[18] In fact, a survey by Sutton and Dobbin (1996) find that the share of firms that explicitly reserve their “right to fire” increased from fewer than 5% in 1955 to 29% in 1985.

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Duration model for passage timing of the implied contract exception

Table A1: State Level

	Event: Adoption of Implied Contract Exception$_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of patents $_{state,t-1}$ *(log)*	-0.039				-0.040		
	[0.092]				[0.092]		
Number of citations $_{state,t-1}$ *(log)*		-0.011				-0.012	
		[0.079]				[0.080]	
State R&D $_{state,t-1}$ *(log)*			-0.075				-0.075
			[0.080]				[0.080]
Share of laggard firms $_{state,t-1}$				0.135	0.055	0.056	0.058
				[1.276]	[1.291]	[1.336]	[1.101]
N	730	730	813	813	729	729	813

Table A2: Firm level

	Event: Adoption of Implied Contract Exception$_t$				
	(1)	(2)	(3)	(4)	(5)
Number of patent $_{firm,t-1}$ *(log)*	0.002				-0.061
	[0.045]				[0.047]
Number of citations $_{firm,t-1}$ *(log)*		0.006			
		[0.022]			
R&D Spending $_{firm,t-1}$ *(log)*			0.03		0.073
			[0.053]		[0.054]
Debt $_{firm,t-1}$				-0.004	-0.123
				[0.009]	[0.104]
N	26,629	26,629	47,636	47,544	26,585

Note: Robust standard errors are clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Lastly, each adopting state is well-balanced in its share of leader and laggard firm-year observations. I find this to be consistent with the empirical design. A firm's competitive position is defined at the industry level – with no obvious correlation to state-level trends.

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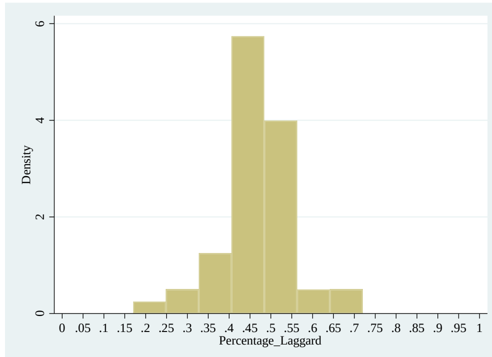
By-State Distribution



x-axis (*% Laggard*) indicates the percentage of firm-year observations occupying a laggard position for each state from 1973 to one year prior to the adoption of the implied contract exception.

In addition to passing a battery of additional checks (John et al., 2015; Serfling, 2016), Autor and colleagues emphasize institutional details surrounding IC adoption to further buttress the claim of exogeneity. The adoption of the implied contract exception was concerned with "enhancing fairness in employment relationships and consistency with general contracting principles rather than economic concerns (Acharya et al. 2014: 328)" and "because a court's issuance of a new precedent is an idiosyncratic function of its docket and the disposition of its justices, the timing of a change to the common law is likely to be in part unanticipated (Autor 2003: 16)."

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Appendix B: Dynamic Specification with Lags of *Laggard*

Table B reports the coefficients from a dynamic specification and their interaction with lags of $Laggard_{it-n}$. It verifies that the falling into a laggard position increases firm patents with three-year lags, addressing concerns of reverse causality.

DV:	Number of Patents$_t$ (log)				
	Run simultaneously				
	n = 0	n = 1	n = 2	n = 3	
$Laggard_{t-n}$	0.022 [0.016]	0.017 [0.017]	0.006 [0.012]	0.011 [0.012]	
$IC^{2yr\ before} \times Laggard_{t-n}$	-0.033 [0.035]	-0.004 [0.037]	0.038 [0.039]	0.013 [0.039]	
$IC^{1yr\ before} \times Laggard_{t-n}$	0.054 [0.042]	-0.021 [0.036]	-0.037 [0.036]	0.010 [0.036]	
$IC^{0yr} \times Laggard_{t-n}$	-0.027 [0.022]	-0.003 [0.029]	-0.003 [0.021]	0.011 [0.021]	
$IC^{1yr\ after} \times Laggard_{t-n}$	-0.031 [0.048]	-0.013 [0.053]	0.042 [0.044]	-0.069* [0.044]	
$IC^{2yr\ after} \times Laggard_{t-n}$	-0.025 [0.049]	0.001 [0.055]	-0.017 [0.044]	-0.031 [0.044]	
$IC^{>2yr\ after} \times Laggard_{t-n}$	-0.026 [0.024]	-0.022 [0.018]	-0.008 [0.014]	-0.035** [0.014]	
Implied Contract (IC)$^{2yr\ before}$					0.021 [0.027]
Implied Contract (IC)$^{1\ yr\ before}$					-0.001 [0.027]
Implied Contract (IC)$^{0\ yr}$					-0.002 [0.038]
Implied Contract (IC)$^{1yr\ afer}$					0.036 [0.035]
Implied Contract (IC)$^{2yr\ after}$					0.068* [0.038]
Implied Contract (IC)$^{>2yr\ after}$					0.047 [0.056]
Controls			*yes*		
Firm FE			*yes*		
Year × State of ops. FE			*yes*		
R-squared			0.85		
N			57,975		

Note: Robust standard errors are clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

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Appendix C: With a Full Set of Control Variables

The following table shows Table 2 Models (5) and (10) with full sets of control variables. The good faith exception has a positive effect on firm innovation, consistent with Acharya et al. (2014). The results verify that the differing conclusions derive from the incorporation of competitive dynamics, not from differences in the dataset in use.

	Number of patents$_t$ (log)	**Patent value$_t$ (log)**
Implied Contract (IC)$_{t-3}$	0.011 [0.033]	0.034 [0.029]
Good Faith (GF)$_{t-3}$	0.079* [0.044]	0.128*** [0.033]
Laggard$_{t-3}$	0.035*** [0.011]	0.024*** [0.009]
Laggard$_{t-3}$ × IC$_{t-3}$	-0.053*** [0.016]	-0.055*** [0.017]
Laggard$_{t-3}$ × GF$_{t-3}$	-0.064** [0.026]	-0.059*** [0.021]
Debt$_t$	-0.003 [0.005]	-0.001 [0.005]
Financial slack$_{t,\ Current\ ratio}$	0.000 [0.000]	0.000 [0.000]
Financial slack$_{t,\ Working\ capital}$	0.000 [0.000]	0.000 [0.000]
Distance from Bankcrupcy$_t$	0.000 [0.000]	0.000 [0.000]
ln(Total_Asset)$_t$	0.216*** [0.020]	0.218*** [0.021]
Herfindahl$_t$	-0.174 [0.255]	0.017 [0.408]
Herfindahl^2_t	0.183 [0.305]	-0.136 [0.503]
Industry growth$_t$	0.004 [0.032]	0.011 [0.035]
Firm fixed effects	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*
R-squared	0.86	0.87
N	56,443	89,017

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level.

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Appendix D: Robustness (Section 4.5)

Model (1) includes a more granular Year × 4-digit SIC interacted fixed effects (vs. Year × 3-digit SIC fixed effects used in the baseline specification). Model (2) replaces Year × 3-digit SIC FE with simple year fixed effects. Model (3) excludes all control variables other than firm and year fixed effects. Model (4) excludes states that do not adopt IC until 2000 because they may differ fundamentally from the adopting states and serve as a poor control group. Pennsylvania and Florida are two such states. Model (5) requires that a firm has at least one patent in its corporate history to be included in the sample. Model (6) expands the time window to 1970-2000, utilizing the expanded coverage from Kogan et al. (2018). Model (8) drops firm-year observations three years after the adoption of the implied contract exception. Model (9) categorizes firms as a laggard based on total shareholder returns, not ROA. Model (10) uses the total number of citations as the alternative dependent variable.

	DV: Number of patents$_t$ (log)								DV: Total number of citations
	Year × SIC4 FE	Exclude potentially endogenous control variables		Only eventual IC adoptiong states	At least one patent in firm history	Time period: 1970-2000	(4) + Drops 5 yrs after IC adoption	*Laggard* based on TSR	
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)
Implied Contract (IC)$_{t-3}$	0.011	0.020	0.032	-0.009	0.017	0.007	0.005	0.011	0.029
	[0.029]	[0.039]	[0.035]	[0.030]	[0.033]	[0.026]	[0.010]	[0.033]	[0.056]
Laggard$_{t-3}$ (=1)	0.038***	0.027**	0.019*	0.045**	0.046***	0.020***	0.009	0.035***	0.047**
	[0.011]	[0.012]	[0.012]	[0.018]	[0.013]	[0.006]	[0.009]	[0.011]	[0.021]
Laggard$_{t-3}$ × IC$_{t-3}$	-0.052***	-0.047***	-0.081***	-0.058***	-0.064***	-0.031**	-0.031**	-0.053***	-0.087***
	[0.014]	[0.017]	[0.017]	[0.020]	[0.017]	[0.012]	[0.015]	[0.016]	[0.031]
Controls	*yes*	*yes*	*no*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*no*	*no*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.86	0.84	0.83	0.86	0.85	0.87	0.91	0.86	0.78
N	56,443	56,443	64,797	45,783	44,255	106,613	31,992	56,443	56,443

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors clustered at the state level.

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Data Appendix: Disambiguated inventor database (Table 4)

I start with the database by Li et al. (2014) that disambiguates the names of inventors contained in all of the USPTO patents and assigns a unique identification to each inventor. I first merge this DB with the latest NBER patent DB (Hall, Jaffe, and Trajtenberg, 2001) to identify i) the assignee firm for each patent and ii) GVKEY. Some inventors file multiple patents in a given year, and I take the assignee firm associated with the last patent filed in a given year as the employer of the inventor. I record firm A (based on GVKEY) to have hired a new external inventor if the inventor has worked for a different company previously or produced patents as an independent inventor between year t-3 and t-1. There are two notable exceptions. First, in the case of firm A (Year 1) – "missing" (Year 2) - firm A (Year 3), I replace missing (Year 2) with firm A. "Missing" (Year 2) is likely from an assignment issue and is not considered as a new inventor hire. Second, I exclude cases where an inventor is considered a new hire because of transitioning from missing GVKEY to non-missing GVKEY despite sharing the same PDPASS (a company identifier assigned by Hall et al., 2001) across the transitioning years.

While providing complete coverage of all inventors that file for patents, the precise date of an inventor's move from firm A to firm B cannot be identified based on the NBER dataset. An inventor's employer is revealed only when the inventor files for a patent (as assignees), and unless an inventor files for patents consecutively without a gap year, the precise year of the movement cannot be identified. For example, it is unclear which year (2001 vs. 2002 vs. 2003) inventor A moved to firm Y from firm X in the following case.

Inventor A – Patent 1 – Year 2000 – Firm X
Inventor A – Patent 2 – Year 2003 – Firm Y

I record the year of application for the new patent (2003) as the year of movement. Note that this is an upper bound for the year of the movement. Some inventors have significant gaps in between patents, and I restrict the sample to inventors with less than four-year gaps to reduce the noise. All of the results are robust to using a mid-point year (2002, rounded up), but this affects the number of lags after which the implied contract exception becomes significant.

Lastly, there is a significant number of spelling errors and mistakes in reported assignee names (e.g., KELLY COMPANY INC vs. KELLEY COMPANY INC) that result in false classification. As long as these errors do not systemically correlate with firm performance and the adoption of the implied contract exception, any inferences remain valid.

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