Shielding Firm Value: Employment Protection and Process Innovation*

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Abstract

An increase in labor dismissal costs leads firms to increase process innovation, namely innovation that reduces production costs, especially in industries with a large share of labor costs in total costs. Firms with high innovation ability adjust their production methods and mitigate the effects of increased labor rigidity. They exhibit larger increases in process innovation and capital intensity, and larger decreases in employment and employment growth. This allows them to increase labor productivity, operating performance, and ultimately to avoid value losses. Our evidence highlights that, by facilitating the adjustment of the input mix when market conditions change, innovation ability is a key driver of firm performance.

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1. Introduction

Frictions in labor markets that make a firm's labor input rigid and costly to adjust lead to higher production costs and operating leverage. Such frictions can thus reduce a firm's value both by decreasing its expected future cash flows and by increasing its cost of capital.[1] To mitigate the impact of these frictions, firms reduce their financial leverage (Simintzi, Vig, and Volpin (2015), Serfling (2016)) or reorganize their production activity by substituting capital for rigid labor and by outsourcing production (Autor (2003), Autor, Kerr, and Kugler (2007)). However, it is often overlooked that in order to take advantage of a higher, more cost-effective, capital-labor ratio a firm must be able to develop new production methods that are appropriate for that capital-labor ratio (Jones (2005)). The ability to invent new production methods is thus critical for a firm's success in mitigating the impact of labor markets frictions on its value, yet little is known about this role of innovation empirically.

In this paper, we examine how a firm's innovation ability shapes the adjustment of its production techniques and ultimately affects its performance following an increase in labor dismissal costs—a key source of labor rigidity. Such costs make layoffs costly and labor difficult to adjust (Autor, Kerr, and Kugler (2007)). The resulting operating leverage effectively increases the cost of labor relative to other inputs making cost-effective to firms to substitute capital for labor. We first study the effect of labor rigidity on a firm's invention of new cost-saving production methods—process innovations. We then study how a firm's ex-ante innovation ability drives the adjustment of its production input mix in response to increased labor rigidity, and thereby moderates the impact of higher labor rigidity on its productivity, operating performance, and market value. Our evidence shows that, by facilitating the adjustment of the input mix when conditions in input markets change, innovation ability is a key driver of firm performance.

Using textual analysis of patent claims, we create novel measures of innovation that distinguish *process innovations*, which refer to inventions of new methods used to adjust firms' production (Scherer (1982, 1984), Eswaran and Gallini (1996)) from other non-process innovations. Stilted legalistic language and the use of consistent vocabulary across firms and

[1] A large literature discusses the effects of various labor market frictions on firms' operations and performance, including Clark (1984), Abowd (1989), Besley and Burgess (2004), Autor, Kerr, and Kugler (2007), Messina and Vallanti (2007), Atanassov and Kim (2009), Chen, Kacperczyk, and Ortiz-Molina (2011), Agrawal and Matsa (2013), Donangelo (2014), Favilukis and Lin (2016), Campello et al. (2018), and Favilukis, Lin, and Zhao (2019), among many others. See Matsa (2018) for a broader discussion of labor market frictions in corporate finance.

over time allows us to accurately distinguish patent claims that describe process innovations from those that do not. Our main measures thus count the number of process and non-process claims contained in patents filed by each firm in a given year. To account for the heterogeneity in patent quality, we also use citation-weighted counts of process and non-process patents. To highlight the importance of understanding what economic mechanisms drive the creation of process innovations, we document a significant steady increase in the share of process innovation in total innovation over time, from 19.5 % in 1975 to 32.2% in 1997, the last year in our sample, and continuing to increase afterward.

We use a difference-in-differences methodology based on the staggered adoption of the "good faith" exception to the common law "employment at will" doctrine by U.S. state courts between 1973 and 1995. This doctrine gives employers unlimited discretion to fire employees at any time. The good faith exception significantly restricts this discretion because it serves as a general prohibition against firing workers without just cause and it thus opens firms to potentially costly litigation if they lay off workers (Dertouzos and Karoly (1992), Kugler and Saint-Paul (2004), Autor, Kerr, and Kugler (2007)). Prior work further shows that the adoption of this exception leads to a significant increase in labor adjustment costs and operating leverage (Autor, Kerr, and Kugler (2007), Serfling (2016)).

We find that, following the adoption of the good-faith exception, firms located in adopting states increase their process innovation by 6.1% to 8.9% relative to firms in other (non-adopting) states. This increase in process innovation becomes statistically and economically significant four years after the adoption. Further, the increase in process innovation is more pronounced in industries where labor costs account for a larger share of production costs, and thus are more impacted by the law. The adoption of the good-faith exception does not, however, materially affect non-process innovation. These results suggest that higher labor adjustment costs lead firms to increase their innovation efforts focused on developing new production methods.

The evidence supports a causal interpretation of our results. First, the good-faith exception concerns firms' firing decisions rather than innovation outcomes or production technique choices, and its recognition follows from court decisions made by independent judges in specific cases rather than from changes in state legislation that are potentially contentious. Second, in addition to firm and year fixed effects, our results hold controlling for various time-varying firm characteristics, as well as controlling for the state's business environment and political leaning. When possible, we also include state fixed effects interacted with year fixed effects, which ensures that state-specific time-varying omitted variables cannot explain our findings. Third, the pre-treatment trends in the innovation of firms in treated and control states are indistinguishable. Fourth, the adoption of the good-faith exception in neighboring states does not affect a firm's innovation, suggesting that local economic shocks correlated with the adoption of the good-faith exception are unlikely to drive our results. Fifth, our results are unlikely to be driven by a differential impact across states of increased patent enforcement in the early 1980s and associated surge in patenting activity (Lerner and Seru (2017)). Our results hold controlling for time-varying differences in patent filings across states, if we restrict our sample to the 1975-1990 period (which precedes the most significant surge in patenting occurred during the 1990s), or if we exclude firms in the states of California and Massachusetts (which historically harbor a large fraction of patenting firms).

An increase in employment protection in a firm's state of headquarters can also increase the job security of its inventors employed in that state and, through this mechanism, lead them to exert more effort in innovation (Acharya, Baghai, and Subramanian (2014)). If such effort was focused on processes, this rationale could explain our results. Employment contracts are typically governed by labor laws in the state where the employee works, so the adoption of the good-faith exception in a firm's state of headquarters does not affect the job security of inventors the firm employs in other states. Inconsistent with job security alone driving our results, we find that the adoption of the good-faith exception in a firm's state leads to an increase in its process innovation even if the majority of its lead inventors are located in other states or if the lead inventors are dispersed across several states.

Next, we show that firms with high ex-ante innovation ability respond to increased labor dismissal costs by developing considerably more process innovations compared to those with low ex-ante innovation ability. Non-process innovation remains largely unaffected even for high ex-ante innovation ability firms. Furthermore, consistent with our intuition that innovation ability helps firms mitigate the negative consequences of labor market rigidities, we also find that firms with high ex-ante innovation ability reduce their total employment and employment growth, and increase their capital intensity. Such adjustments in production input mix are insignificant for low innovation ability firms. These results suggest that, when an increase in labor rigidity makes the labor input more costly, innovation ability facilitates the creation of process innovations which firms then deploy as new production methods.

Finally, we show that the ex-ante ability to innovate and adjust production methods helps firms mitigate the adverse effects of labor market rigidities on their performance. Following the adoption of the good-faith exception, we document significant increases in the productivity of labor for high innovation ability firms. We also find that high innovation ability firms maintain their profitability and avoid market value losses, while low innovation ability firms fare much worse. Our results thus suggest that innovation ability allows firms to shield their value from labor market shocks.

Our paper advances the literature that examines how frictions in labor markets affect corporate policies and outcomes. It is closely related to prior work that shows how employment protection creates operating leverage and, through this mechanism, impacts corporate investment and financing decisions (Autor, Kerr, and Kugler (2007), Simintzi, Vig, and Volpin (2015), Serfling (2016), Bai, Fairhurst, and Serfling (2019)).[2] Contrary to Bai et al. (2019), who find a negative effect of employment protection on average firm investment, we show that firms with higher ex-ante ability to innovate are those who invest more in capital to offset the value losses from the increased rigidity. This evidence is consistent with the view in Jones (2005), who highlights that the availability of new production techniques suited for different capital-labor ratios affects firms' ability to change their input mix and thus shapes production functions.

A few prior studies examine how frictions in labor markets affect innovation. Acharya, Baghai, and Subramanian (2014) argue that employment protection incentivizes inventors to exert effort and find that the adoption of the good faith exception leads to an increase in firms' overall innovation. We distinguish between process and non-process innovation, and highlight another channel through which labor protection affects innovation, namely, the need to invent new processes that allow firms to adjust their production methods and mitigate the negative impact of labor rigidity on their values. Bradley, Kim, and Tian (2017) show that an increase in labor unionization leads to a decrease in innovation, because unions can hold up the firm and demand higher wages once the firm has incurred the sunk cost of innovation, which reduces the firm's ex-ante incentives to innovate. This suggests that different types of labor markets frictions impact firms' innovation differently. Bena and Simintzi (2019) show that large U.S. multinational firms reduce their process innovation

[2] Similarly, Autor et al. (2016), Bloom, Draca, and Van Reenen (2016), and Hombert and Matray (2018) show that innovative firms differentiate their products in response to competition from lower-cost foreign rivals.

after their access to "cheap" offshore labor improves. We instead focus on changes in the effective price of domestic labor that affect all U.S. firms, and show that employment protection boosts process innovation allowing firms to reduce their reliance on domestic labor.

A broader corporate finance literature examines what factors stimulate innovation, such as governance (Atanassov (2013), Balsmeier, Fleming, and Manso (2017)), ownership structure (Aghion, Van Reenen, and Zingales (2013), Bena et al. (2017)), organization (Lerner, Sørensen, and Strömberg (2011), Ferreira, Manso, and Silva (2014), Seru (2014)), managerial compensation (Manso (2011), Ederer and Manso (2013)), capital structure (Atanassov, Nanda, and Seru (2007)), litigation risk (Cohen, Gurun, and Kominers (2016)), corporate taxes (Mukherjee, Singh, and Žaldokas (2017)), and the supply of credit (Amore, Schneider, and Žaldokas (2013)). We further highlight that the distinction between process and non-process innovation might be useful in understanding what drives innovation.

Our paper is also related to the academic and public debates around the view that the introduction of new technologies which support automation makes labor redundant, leading to job displacement, lower wages, and more inequality (Autor, 2015; Autor, Levy, and Murnane, 2002; Autor and Dorn, 2013).) It is thus important to understand how the incentives for automation respond to policy intervention. Our evidence highlights that employment protection increases labor costs and thus directly affects firms' incentives and efforts to invent new production methods that facilitate the substitution of capital for labor, which can negate some of the intended benefits for workers. More generally, a potential unintended consequence of increased labor protection is that it could, in fact, accelerate automation and thereby lead to job displacement that is permanent in the long-run.

The paper is organized as follows. Section 2 discusses our conceptual framework and hypotheses. Section 3 discusses our measures of process and non-process innovation, the data, and our identification strategy. Section 4 examines the impact of labor rigidity on innovation. Section 5 focuses on how ex-ante innovation ability affects the adjustment of production methods and firm performance. Section 6 concludes.

2. Higher labor costs and new production techniques

Jones (2005) highlights that adjustments to a firm's input mix inherently require inventions of new production techniques and that the availability of such inventions constrains a firm's ability to do such adjustments. Specifically, he notes that "production techniques" are ideas regarding how to organize production efficiently for specific capital-labor ratios. Such techniques specify a series of instructions to transform inputs into output based on that capital-labor ratio. If a firm wants to change its capital-labor ratio, this renders its original production technique obsolete and thus needs to discover a new one that is appropriate for the new capital-labor ratio. Hence, production functions represent the substitution possibilities across different production techniques, which in turn depend on the extent to which new techniques that are appropriate for different capital-labor ratios are discovered.

Embedding the production function with input substitution possibilities described above into the profit maximization problem of the firm implies that changes in the relative price of inputs incentivize firms to change their capital-labor ratios, which requires the availability of new production methods to support the new desired capital-labor ratios. Hence, there is a direct link between changes in the relative costs of production inputs and innovation in new production methods. This intuition dates back to John Hicks (1932), who noted that *"...a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind—directed to economizing the use of a factor which has become relatively expensive..."*

Consider for example the introduction of assembly lines in automotive production in the early 1900's. High labor costs and inefficiencies in production required that profit-maximizing automakers substitute machines for workers to reduce production costs, but this was unfeasible within the "craftmanship" approach to production predominant at the time. The substitution could only be implemented using a new way to organize the production process targeted at a higher capital-labor ratio. This led to a revolutionary new production technique – the "assembly line", which was credited to Ransom Olds (he patented the "stationary assembly line", and introduced it to produce the Oldsmobile Curved Dash model in his Lansing, Michigan factory in 1901) and Henry Ford (he created the "moving assembly line", and introduced it to produce the Model T in his Lansing Park, Michigan factory in 1913). This innovation led to huge productivity gains and cost savings, including a dramatic reduction in production time while using less manpower per automobile, which translated into much lower final prices, higher production volumes, and higher profit margins for these automakers.[3]

[3] By 1916 the price of Ford's Model T had fallen to $360 from its debut price of $850 in 1908 and sales were more than triple their 1912 level. The Model T was discontinued in 1927, accounting for nearly half of all automobiles

In the context of this paper, we focus on an increase in the effective price of labor (relative to capital) associated with changes in labor laws that increased employment protection. Following the above intuition, our hypothesis is that increases in employment protection lead firms to invent new cost-saving production methods that allow firms to substitute capital for labor. Further, the discussion above suggests that firms with greater innovation ability are better able to implement the required substitution of capital for labor and thus to mitigate the impact of higher labor costs on their performance.

3. Innovation measures and empirical framework

3.1 Process vs. non-process innovation

The conceptual distinction between process and non-process innovation is at the heart of our conceptual framework, empirical tests, and interpretation of the results. Prior literature highlights that process innovation refers to a new way to produce an existing good and aims to improve a firm's own production methods to lower its production costs (Scherer (1982, 1984), Link (1982), Cohen and Klepper (1996), Eswaran and Gallini (1996)). In contrast, non-process innovation generally refers to inventions sold to others, such as new or improved products that the firm aims to sell to either final consumers or other firms.

An example of process innovation is the "assembly line" (discussed in Section 2), which led to many related patents after the original idea. A recent one (published in 2005) is Ford Motor's patent *"Manufacturing assembly line and a method of designing a manufacturing assembly line"* (US20050044700A1), which contains *"A method of designing a manufacturing process line. A process is identified as a set of discrete steps. A subset of steps is assigned to one of a plurality of standardized work cells. The work cells include a standardized workpiece presenter and a standardized processing tool. Additional subsets of discrete steps are assigned to a standardized work cell until the design for the manufacturing process is completed."*

Other examples of Ford's process innovation include *"Wheel manufacture"* (US3859704A), granted in 1975, which describes *"a process for the production of vehicular wheels and finds particular utility in wheels in which a steel rim must be united to a magnesium or aluminum spider. The aluminum or magnesium spider is united to the steel rim by a combination of adhesive action and metal interlocking since steel is essentially*

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sold in the world to that date. The Olds Motor Works Co. (founded by Ransom Olds) was bought by General Motors in 1908. General Motors discontinued the "Oldsmobile" brand in 2004, after a production run of 96 years.

unweldable to either aluminum or magnesium." and *"Method for motor vehicle interior climate control"* (US20170144505A1), describing *"A method for climate control for an interior of a motor vehicle includes acquiring climatically relevant data of the interior and/or surroundings of the vehicle, creating a thermodynamic model of a vehicle climate system […], the model including […], introducing into the interior a quantity of air having a temperature different from an existing interior temperature [further details omitted]."*

Examples of Ford's non-process patented innovation include *"Motor vehicle body mount"* (US3622194A), granted in 1971, describing *"A body mount for connecting a motor vehicle body part to a motor vehicle frame…[description of body mount omitted]"*, and various patents grated in 2018 such as *"Airbag for oblique vehicle impacts"* (US9963101B2), describing *"An airbag system includes an inflator and an airbag in communication with the inflator. [further details omitted]",* its *"Head rest with a compartment for a travel pillow"* (US10093205B2), its *"Keyless vehicle door latch system with powered backup unlock feature"* (US20180051493A1), and its *"Direct injection fuel pump"* (US10006426B2), among others.

The adoption of new processes might require innovation in new equipment that supports the new processes. For example, Ford's patent *"Methods and systems for assisted direct start control"* (US20170341637A1) first describes *"A method of controlling a vehicle system including an engine that is selectively shut-down during engine idle-stop conditions, comprising: … [further details omitted]"* and then *"A vehicle system, comprising: a powertrain including wheels, an engine, a torque converter having a lock-up clutch, and an automatic transmission including a forward clutch; wheel brakes; and a control system configured to selectively shut-down the engine during engine idle-stop conditions …[further details omitted]"*. Process innovation can also aid subsequent non-process innovation by the same or other firms in related fields. For example, Ford Motor's process patent granted in 1975 *"Wheel manufacture"* (US3859704A) discussed above is cited by subsequent non-process patents, such as ITT Corp's *"Aluminum alloy motorcycle wheel having an extruded rim shrink fitted and resin bonded to a die cast hub-spoke unit"* (US4256348A) granted in 1981.

3.2 Distinguishing process and non-process innovation in patent filings

We use the process and non-process innovation measures developed by Bena and Simintzi (2019). Specifically, our main dependent variables separately measure a firm's patented process and non-process innovation output and are extracted from the texts of patent grants. To this end, our measure relies on the critical defining element of a patent:

the list of specific "claims". The claims define – in technical terms – what subject matter the patent protects and the scope of protection conferred. For this reason, the list of specific claims in a patent is the primary subject of examination in patent prosecution and crucial in patent litigation cases.

As detailed in Bena and Simintzi (2019), our measure is based on the full texts of all utility patents awarded by the United States Patent and Trademark Office (USPTO) from January 1976 to December 2012. The patent texts are then parsed to extract the section that contains the list of patent claims. Finally, with the use of standard textual analysis techniques, claims can be unambiguishly distinguished within each patent as either process or non-process claims. This is aided by the very legalistic and stilted language used in drafting claims, e.g., process claims always refer to *"A method for ..."* or *"A process for ..."* (or minor variations), followed by a verb (typically in gerund form). For example, the list of 23 claims in Ford's patent *"Method of assembling a vehicle from preassembled modular components"* (US6493920B1) reads *"1. A method of assembling a vehicle, the method comprising; … [full description omitted]"*; *"2. The method of claim 1 wherein the roof panel is made of material selected from the group consisting of aluminum and magnesium."*; and all remaining claims also begin *"The method of claim…"*.

To see how the standardized legal language used in the drafting of patent claims allows to accurately distinguish process from non-process claims, note that the most frequent bigrams of words in process claims that do not appear among the top 1,000 bigrams of words in non-process claims are (after word stemming and in the order of frequency): "compris-step", "method-compris", "said-method", "process-prepar", "process-compris", "step-provid, "aqueous-solut", "step-form", "alkali-metal", "effect-amount", "process-produc", "method-produc", "method-manufactur", "compris-contact", "method-form", and "method-make".[4] See Bena and Simintzi (2019) for more detail.

3.3 Matching of patents to firms and measures of process and non-process innovation

To match patent filings to firms in Compustat we follow Bena, Ferreira, Matos, and Pires (2017). We first search each patent grant document and identify the names of patent assignees, the country of these assignees, and whether each assignee is a U.S. corporation, a

[4] Non-process claims use very different unique words. For example, in June 21, 2004 Apple Inc. filed a *"Integrated sensing display"* non-process patent (US 7535468 B2), whose first and second claims read *"1. A device comprising a display panel..."* and *"2. The device of claim 1, wherein the image elements are located in a..."*.

non-U.S. corporation, an individual, or a government body. Using this information, we then match patents to firms in Compustat. Our matching algorithm involves two main steps. First, we standardize patent assignee names and firm names, focusing on unifying suffices and dampening the non-informative parts of firm names. Second, we apply multiple fuzzy string matching techniques to identify the firm, if any, to which each patent belongs.[5]

We measure a firm's annual process and non-process innovation in two ways. The first approach exploits the fact that each and every patent can be broken down into the individual process and non-process claims it contains. Thus, a firm's *Process Claims* is computed by summing the number of process claims contained in all of its patents filed in each year. Similarly, a firm's *Non-Process Claims* is computed by summing the number of non-process claims contained in all of its patents filed in each year. Both variables are set to zero for firm-years with no patents. The advantage of these measures is that they capture *all* process and non-process innovations patented by a firm. However, they ignore differences in the quality of innovations protected by each specific claim in a patent, because there are no claim-level indicators of quality (e.g., citations are for entire patents and not for individual claims).

Our second approach uses the number of citations received by each patent to account for the differences in the scientific merit of innovations (Hall, Jaffe, and Trajtenberg (2001, 2005), Jaffe and Trajtenberg (2002)). To ensure a clear distinction between process and non-process innovations, we focus on patents that contain only process claims (Process Patents) or only non-process claims (Non-Process Patents), but not both.[6] *C-W Process Patents* is the citations-weighted number of process patents and *C-W Non-Process Patents* is the citations-weighted number of non-process patents filed by a firm in each year, respectively. Both measures are set to zero for firm-years with no process or no non-process patents.

Figure 1 shows that, together with an overall increase in the total number of claims (process and non-process) during our sample period (which mirrors the increase in patenting documented in prior studies), there is a steady increase in the share of process innovation. For the average firm in our sample, the share of process claims in total claims was 24.5% over the entire sample period, but this share rose steadily from 19.5% in 1975 (first year in our sample) to 32.2% in 1997 (last year in our sample). Although outside our sample period, this trend continued in subsequent years, leading to a share of almost 40% in 2010. Hence,

[5] See Bena, Ferreira, Matos, and Pires (2017) for more detail on the matching procedure and a comparison of the matches to those in the NBER patent database.
[6] Process patents and non-process patents account for 70.3% of all patents in our data.

process innovation is becoming an increasingly important component of overall innovation.

In Panel A of Table 2, we examine which industries account for the bulk of process innovation. We report the share of each two digit SIC industry in the total number of process claims contained in all patents over the period 1975-97 as well as the subperiods 1975-80, 1981-85, 1986-90, and 1991-97. Manufacturing industries account for the majority of process innovation, with Chemicals & allied products (SIC 28), Electronic & electrical equipment (SIC 36), and Machinery & computer equipment (SIC 35) at the top of this list, although communications (SIC 48) and business services (SIC 73) account for a sizeable fraction as well. Interestingly, some industries have increased their shares in process innovation over the years (SICs 36, 35, 38, and 73) and some have decreased their shares (SICs 28, 29, and 33), while the shares of other industries remained largely unchanged (SIC 37, 48, and 26).

In Panel B, we examine the importance of process innovation relative to total innovation for the same industries identified in Panel A. Specifically, we report the shares of process claims in the total number of (process and non-process) claims contained in all patents for the period 1975-97 as well for the subperiods 1975-80, 1981-85, 1986-90, and 1991-97. Over our entire sample period, process innovation accounts for a large fraction of patented innovation in those industries that generate the bulk of process innovation. In all of these industries process innovation accounts for at least a quarter of the innovation in the industry and in some (petroleum refining, primary metal industries, business services) it accounts for about half. Importantly, consistent with the aggregate trend, for most industries there is a large and steady increase in the share of process innovation over the years.

3.4 Wrongful discharge

To estimate the causal effect of labor dismissal costs on firms' process and non-process innovation, we use a difference-in-differences approach based on the variation in these costs associated with the staggered adoption of "wrongful discharge laws" by U.S. state courts between the late 1970s and the early 1990s. Prior work extensively discusses these laws and their economic significance as a source of exogenous variation in labor dismissal costs (Dertouzos and Karoly (1992), Miles (2000), Kugler and Saint-Paul (2004), Autor, Donohue, and Schwab (2004, 2006), Autor, Kerr, and Kugler (2007)). Recently, Acharya, Baghai, and Subramanian (2014) and Serfling (2016) further validate this setting for identification purposes.

The legal framework regarding worker dismissals prevailing at the beginning of the

1970s was centered around the common law doctrine of "employment at will". This doctrine sustained a legal presumption that employers could fire workers *at will*, that is, "for good cause, bad cause, or no cause" (a quote from Payne vs. Western & Atlantic Railroad, Supreme Court of Tennessee, 1884), which gave employers unlimited discretion in firing workers. Between 1973 and 1995, courts in 46 states set new legal precedents recognizing three exceptions to employment at will usually referred to as "wrongful discharge laws". These exceptions significantly limited employers' discretion to fire workers, opened them to potentially costly litigation, and generated uncertainty about when employers could terminate workers with impunity. The survey of public firms' managers conducted by Dertouzos, Holland, and Ebener (1988) indicated that 46% of managers feared potential losses arising from such lawsuits, while Jung (1997) and Boxold (2008) document economically significant awards to plaintiffs.

The key legal change we use to gauge an increase in labor dismissal costs is the adoption of the *"good-faith exception"* to the employment at will doctrine by state courts. This exception represents an implied covenant to terminate employment only in good faith and fair dealing, which essentially prevents employers from firing workers for any "bad cause". The good-faith exception represents the largest deviation from at-will employment and is the most far reaching. It gives employees both a contract and a tort cause of action in the event they are dismissed, allowing them to seek compensation for both contractual losses and emotional distress, as well as punitive damages that imply highly uncertain amounts. Importantly, it serves as a general prohibition against terminating any worker without just cause (economic necessity or poor performance) and thus could have sweeping consequences (Dertouzos and Karoly (1992), Kugler and Saint-Paul (2004), and Autor, Kerr, and Kugler (2007)).

State courts adopted two other exceptions to the employment at will doctrine during this period that had less impact on firms. We include them as control variables in our analyses. One is the "*implied-contract exception"*, which protects workers from discharges when there is an implicit promise that the firm will not fire workers without good cause.[7] The other is the *"public-policy exception"*, which protects workers against discharges that would thwart an important public policy, such as, performing jury duty, filing a worker's compensation

[7] Such promises follow from the language in employment contracts and personnel manuals, or from expectations of continuing employment based on the length of service and prior promotions. In practice, employers can reword these documents to clearly indicate that employment contracts are at will (Miles (2000), Autor, Kerr, and Kugler (2007)) and employers indeed took such steps (Sutton and Dobbin (1996)).

claim, reporting an employer's wrongdoing, or refusing to commit perjury.[8]

Prior work highlights that the adoption of the good-faith exception significantly increases hiring and firing costs, ultimately increasing labor adjustment costs and operating leverage. Using plant-level data from the Census Bureau, Autor, Kerr, and Kugler (2007) show that the adoption of this exception reduces employment volatility, both in the intensive (within-plant) and the extensive (plant entry/exit) margins.[9] Further, in a sample of public firms, Serfling (2016) shows that it leads to a reduction in the volatility of employment and in the likelihood that a firm fires workers when its earnings decrease; it also leads to an increase in the elasticity of changes in earnings to changes in sales and in the volatility of profits.

The adoption of the good-faith exception is unlikely to be driven by changes in economic or political conditions in the state that could be correlated with firms' incentives to innovate. It occurs in judiciary decisions by state courts and not through a potentially contentious legislative process in the state. The judges are independent and largely immune to political pressure from interested parties, and thus base their decisions on the merits of the specific case. Further, Walsh and Schwarz (1996) document three key reasons why judges adopt these exceptions: enhancing fairness in employment relationships, assuring consistency with established principles of contract law, and following similar rulings in other states. Last, Acharya, Baghai, and Subramanian (2014) and Serfling (2016) show that the adoption of the good-faith exception is not driven by changing political conditions, economic conditions, or in other labor regulation in the state, and that such rulings were not anticipated. Hence, it provides plausibly exogenous variation in employment protection in our study of innovation.

3.5 Data and variables

The sample spans the period 1975-1997 and is based on the publicly traded firms in the Compusat dataset. As in Bloom, Schankerman and Van Reenen (2013), it includes all non-financial and non-utility firms headquartered in the U.S. that filed at least one patent with the United States Patent and Trademark Office (USPTO) during this period, for a total of 44,898 firm-year observations. We define all variables in the Appendix. The corresponding summary statistics are in Table 1.

[8] This exception is of minor legal and economic significance, because large compensation amounts are rare and courts limit public policy cases to clear violations of specific legislative commands rather than violations of a vaguer sense of public obligation (Edelman, Abraham, and Erlanger (1992), Autor, Donohue, and Schwab (2006)).
[9] Also consistent with these legal changes affecting hiring decisions, Kugler and Saint-Paul (2004) further show that the good-faith exception reduced the re-employment probability of unemployed relative to employed workers.

To merge the wrongful discharge law indicators and other state level variables into our dataset, we rely on a firm's historical state of headquarters.[10] To this end, we use the "company header history" file in the legacy CRSP/Compustat Merged database. This file provides, for each firm, the time frame for each verified historical state of headquarters and allows us to accurately track changes in the headquarter state over time. When this information is missing for a particular year, we use the firm's next or last verified state of headquarters if available. In this way, we obtain the historical state of headquarters for 75% of the observations in our sample. The remaining 25% of observations correspond to firms with no data available in the company header history file. Most these firms have the last reporting year in Compustat between 1975 and 1990 and especially in the early part of our sample. For these firms, we use the state of headquarters reported in the "company header file", which is the state of headquarters as of the firm's last reporting year. For these firms, the last recorded headquarter state we use is close in time to most of their observations.[11]

4. Results

4.1 Econometric specification

To identify the effect of wrongful discharge laws on process and non-process innovation, we estimate the following difference-in-differences regression:

$$y_{i,s,t} = \beta_1 Good\ Faith_{s,t} + \beta_2 Implied\ Contract_{s,t} + \beta_3 Public\ Policy_{s,t} \\ + \delta X_{i,s,t-1} + \alpha_i + \mu_t + \varepsilon_{i,s,t}$$

where i denotes firm, s denotes the firm's state of headquarters, and t denotes year. The dependent variables y are *Log(1 + Process Claims), Log(1 + Non-Process Claims), Log(1 + C-W Process Patents),* and *Log(1 + C-W Non-Process Patents)*. The three indicator variables for whether the state recognizes the corresponding exception to the employment at will doctrine are *Good Faith*, *Implied Contract*, and *Public Policy*, respectively. The vector X includes lagged firm-level control variables (*Log(1 + Patent Stock)*, *Log(1 + R&D Stock), Log(Sales)*, and *Log(M/B)*) and state-level control variables (*State GDP Growth* and *State Political Balance*). As in Bloom, Schankerman and Van Reenen (2013), we control for differences in a

[10] According to employment law, the relevant jurisdiction for a wrongful discharge lawsuit is the state where the employee works. Firms often employ workers in different states, but data restrictions only allow us to identify a firm's state of headquarters, where most of a firm's workers are typically employed.
[11] For example, if a firm last appears in Compustat in 1985, the company header file records the state of headquarters in 1985 and we use this state in all prior years as well.

firm's stock of knowledge using lagged patent stock and lagged R&D stock, as well as for other relevant firm characteristics. Further, the inclusion of the state-level control variables alleviates concerns that changes in a state's economic conditions or political environment correlated with both the adoption of wrongful discharge legislation and innovation could confound our inferences. Last, α_i is a firm fixed effect, which controls for firm characteristics that do not vary over our sample period, and μ_t is a year fixed effect, which absorbs time-varying shocks affecting all firms. In all specifications, standard errors are clustered by state.

Our empirical approach is aided by the staggered adoption of wrongful discharge laws, which allows us to use a time-varying control group that provides a counterfactual for how firms' innovation would have evolved in the treated states had they not adopted such legislation. The key coefficient of interest is β_1, which gauges the causal effect of the adoption of the good-faith exception on innovation. This coefficient captures the change in innovation for firms in adopting (treated) states relative to the contemporaneous change in innovation for firms in non-adopting (control) states. The causal interpretation hinges on the parallel trends assumption that the pre-treatment trends in innovation are the same for both treated and control groups. We provide timing tests in support of this assumption in the next section.

4.2 Impact of labor dismissal costs on process vs. non-process innovation

Table 3 reports the results of pooled (panel) OLS regressions that implement our main difference-in-differences approach discussed in Section 4.1. In Panel A, the dependent variables are *Log(1 + Process Claims)* in columns (1)-(2) and *Log(1 + C-W Process Patents)* in columns (3)-(4). The adoption of the good-faith exception leads to a statistically significant increase in the process innovation of firms in adopting states relative to that of firms in non-adopting states both in specifications with and without control variables.[12] This effect is also economically significant: In models without control variables, process innovation increases by 13.4% when measured by process claims and it increases by 9.1% when measured by citations-weighted process patents. When we include the control variables the magnitudes decrease to 8.9% and 6.1%, respectively.

In Panel B, the dependent variables are *Log(1 + Non-Process Claims)* in columns (1)-(2)

[12] The inclusion of control variables helps alleviate the concern that differences between firms in treatment and control states could confound our inferences given the lack of truly random assignment to these groups. However, it is conceivable that some of these variables (in particular the firm-level controls) could be affected by the adoption of wrongful discharge laws and bias our estimates. Hence, both specifications are useful in assessing the effect of wrongful discharge laws on innovation.

and *Log(1 + C-W Non-Process Patents)* in columns (3)-(4). Consistent with the possibility that the introduction of new production methods might sometimes require supporting non-process innovation (or generate it as a by product), the estimated effect of the adoption of the good faith exception on non-process innovation is positive. However, it is statistically insignificant in three out of the four specifications and only marginally significant in specification (3). The effect of *Good Faith* on non-process innovation is much smaller in economic magnitude than its effect on process innovation reported in Panel A.

Overall, the results in Table 3 provide support for the hypothesis that labor market rigidities that increase the effective price of labor lead firms to tilt their innovation efforts toward developing new production processes. Consistent with the discussion in Section 3.4 and prior evidence that the good-faith exception places the greatest rigidities on labor markets, we find no effect of the other two exceptions on firms' process or non-process innovation. Hence, we include *Implied Contract* and *Public Policy* in all subsequent analyses, but in the remainder of the paper we focus on the good-faith exception.

Next, we examine the dynamics of the differences in *Process Claims* and in *Non-Process Claims* between treated and control firms around the adoption of the good-faith exception. To this end, we use empirical models analogous to those in columns 2 and 4 of Table 3 but replace *Good Faith* by the indicator variables *Good Faith -3*, *Good Faith -2*, *Good Faith -1*, *Good Faith 0*, *Good Faith +1*, *Good Faith +2*, *Good Faith +3*, *Good Faith +4*, and *Good Faith 5+*, which are equal to one if the firm's state of headquarters adopts the exception in the respective years.

The results of these tests are reported in Figures 2a (process claims) and 2b (non-process claims). Figure 2a shows that there is no statistically or economically significant difference in the process innovation of firms in treated and control states prior to the adoption of the good-faith exception. This evidence is consistent with the parallel-trends assumption behind our difference-in-differences identification. The figure also suggests that the increase in the process innovation of treated firms manifests gradually over time. It starts two years after the adoption and ultimately leads to a statistically and economically significant persistent difference in process innovation between treated and control firms four years after the adoption (the coefficients of *Good Faith +4* and *Good Faith 5+* statistically significant at the 5% level). This pattern is consistent with a reasonable lag between the shift in the focus of firms' innovation efforts at the time of the adoption and the actual patenting of new processes. Figure 2b shows that there are no differences in the non-process innovation of firms in treated and control states in the years before or after the adoption of the good-faith exception.

To better understand what drives the results in Figure 2a, in Figure 3 we plot the levels of process innovation separately for treated and control firms around the adoption of the good-faith exception. To this end, we proceed in three steps. First, we retain the variation in *Process Claims* that is unexplained by firm fixed effects and year fixed effects (i.e., we adjust it by removing time-invariant differences across firms and time trends common to all firms). Second, for each adoption event, we construct a dataset of treated firms (in the adopting state) and control firms (in never adopting states) over the years -3 to +10 relative to the adoption year for the treated state (year 0). We require that firms are in the data in both year -1 and year 0. Third, we pool all events together in to a single dataset in event time, going from year -3 to year +4 and then years 5+ (averaging *Process Claims* over the years +5 to +10). Figure 3 shows that the process innovation of firms in control states remains fairly constant over the years -3 to 5+. This indicates that changes in the process innovation of firms in the control group do not explain the dynamics of the differences in the process innovation between treated and control firms illustrated in Figure 2a. The process innovation of firms in treated states instead follows the same pattern as the one demonstrated in Figure 2a, suggesting our results are driven by a surge in the process innovation of firms in states that adopted the good-faith exception.

4.3 Cross-sectional heterogeneity: industry labor cost share

To further examine what drives the impact of higher labor dismissal costs on innovation, we ask whether the effect of the adoption of the good-faith exception on innovation is related to the importance of labor costs in the industry's cost structure. Firms' incentives to invent new cost-saving production processes in response to the adoption of the good-faith exception are arguably greater in industries for which labor costs account for a larger fraction of production costs. If higher labor adjustment costs drive the observed increase in process innovation documented in Table 3, the adoption of the good-faith exception should have a larger impact on process innovation in such industries.

To investigate this issue, in Table 4 we augment our main specification to include *LaborCostShr* and *Good Faith* × *LaborCostShr*, where *LaborCostShr* is the labor cost share of the firm's 3-digit SIC industry (see the Appendix for details on the construction of this variable). To facilitate the interpretation of the estimated coefficients, *LaborCostShr* is standardized to have mean zero and standard deviation of one before forming the interaction.

In all regression models, we include the same control variables as in Table 3. We consider a specification with firm fixed effects and year fixed effects and another one with firm fixed effects and state fixed effects interacted with year fixed effects. In the latter, we fully control for any unobservable time-varying state-level factors that could confound our results.

The results in columns (1)-(4) show that the adoption of the good-faith exception leads to a larger increase in process innovation in industries for which labor costs account for a larger share of production costs: The coefficient of *Good Faith* × *LaborCostShr* is positive and statistically significant, both when we measure process innovation using process claims in columns (1)-(2) or citations-weighted process patents in columns (3)-(4). The estimates imply that, in industries whose *LaborCostShr* is one-standard deviation higher than the sample mean, the increase in process innovation is 5.9 to 6.7 percentage points larger when process innovation is measured by process claims and 5.3 to 5.9 percentage points larger when it is measured by citations-weighted process patents. The results in columns (5)-(8) show that the recognition of the good-faith exception has no effect on non-process innovation, regardless of the share of labor costs in total costs in the firm's industry: The coefficients of *Good Faith* and of *Good Faith* × *LaborCostShr* are generally positive but statistically insignificant in all four regression specifications.

Overall, the results in Table 4 provide evidence that is consistent with the view that an increase in labor dismissal costs leads firms to increase their efforts to develop new cost-saving process innovation as they seek to mitigate the impact of increased labor rigidity on their operations. They also highlight the likely reason why non-process innovation is unaffected, that is, non-process innovation does not aim to improve production methods to reduce costs as required by the treatment.

4.4 Alternative explanations

In Table 5, we examine if our main results could be due to unobserved changes in local economic conditions that drive both the passage of wrongful discharge laws and the increase in process innovation. To this end, we augment our main specification in Table 3 to include *Good Faith Neighbor*, which is an indicator variable equal to one if a "neighboring state" (adjacent to the firm's state of headquarters) has adopted the good-faith exception by year t and zero otherwise, alongside with *Good Faith*. If economic conditions that are common to bordering states drive the results, then we should see an increase in process innovation for firms in states that do not adopt the legal change but share a common border with adopting states. However, in columns (1)-(2) we find no effect of *Good Faith Neighbor* on a firm's process innovation measured by process claims or by citations-weighted process patents, while the coefficient of *Good Faith* remains positive and statistically significant. Columns (3)-(4) further show no effect of *Good Faith Neighbor* on a firm's non-process innovation.

Lerner and Seru (2017) caution that a stronger enforcement of patent rights in the period which coincides with the early period of our sample led to a surge in patenting activity that may have differentially affected innovation across states. Specifically, stronger patent rights could have differentially impacted geographically-clustered fields of innovation, causing differential trends in innovation across states that could confound our inferences. To alleviate this concern, in Table 6 we use various approaches to control for these possible patterns in the data.

In Panel A, we focus on process innovation, measured by process claims in columns (1)-(3) and citations-weighted process patents in columns (4)-(6). First, in columns (1) and (4) we add the (lagged) logarithm of the mean number of patents filed by other firms located in the firm's state, *Log(State Patents)*, as an additional explanatory variable. The estimated effect of *Good Faith* on process innovation is very similar to that in the baseline results. Second, in columns (2) and (5) we repeat the analysis over the 1975-1990 period, that is, the period before the explosive growth in patents observed post 1990, which occurred with different intensities across states. Despite the lower statistical power associated with a smaller sample and set of events, the coefficient of *Good Faith* remains statistically and economically significant. Last, in column (3) and (6) we exclude from the sample two states, California and Massachusetts, which showed the highest patent growth over our sample period and account for a large share of patenting activity in the U.S. Again, the estimated coefficient of *Good Faith* remains positive and significant. Panel B repeats the same analyses using the two non-process innovation measures as the dependent variables, but the coefficient of *Good Faith* remains statistically insignificant in all tests. Overall, we find that our results are robust to the concerns outline above.

We also investigate another potential mechanism through which the adoption of the good-faith exception in a firm's state of headquarters could lead to an increase in the firm's process innovation. The adoption of this exception in the firm's state of headquarters increases job security not only for the firm's production workers (the focus of our conceptual arguments), but also for the firm's inventors employed in that state. Increased job security of a firm's inventors employed at headquarters can incentivize them to exert more effort in their innovation activities (Acharya, Baghai, and Subramanian (2014)). If for some reason such additional effort is largely focused in developing new processes, then the job security mechanism could explain our baseline results in Table 3. We note, however, that this mechanism alone cannot easily explain why the increase in process innovation is larger in industries with a larger share of labor costs in total costs as we document in Table 4.

To shed further light on whether increased job security drives our main results, we analyze the text of each patent grant document and extract the state of the lead inventor's business address. This allows us to identify patents for which the lead inventor is employed in a state other than the firm's state of headquarters. For such inventors, their job security is generally unaffected by the adoption of the good-faith exception in the firm's state of headquarters, because their employment contracts with the firm are typically signed under the labor laws of the state where they actually work.

Our tests reported in Table 7 are thus based on the importance of the location of a firm's inventors. Whether lead inventors are employed in the firm's state of headquarters or in other states is crucial to the job security mechanism: The effect of *Good Faith* on process innovation should be weaker when the firm's inventors are employed in other states and thus unlikely to experience an increase in their job security. In contrast, the mechanism we highlight is that increased employment protection in a firm's state of headquarters (where most of its production workers are located) incentivizes the firm to develop cost-saving process innovation. In this view, the state in which the firm's inventors are located is unimportant and should be unrelated to the impact of *Good Faith* on process innovation.

In Panel A, we examine whether the impact of *Good Faith* on process innovation depends on the location of the firm's inventors. To this end, we augment our main specification to include interactions of *Good Faith* with two indicator variables. The first is equal to one if more than 50% of the lead inventors listed in all patents the firm applied for in a given year are located outside the firm's state of headquarters and zero otherwise (*Majority Inventors Outside*). The second is equal to one if no state concentrates more than 50% of the lead inventors listed in all patents the firm applied for in a given year and zero otherwise (*Disperse Inventors*). In columns (1)-(4) the dependent variable is based on process claims and in columns (5)-(8) it is based on citations-weighted process patents. We consider a specification with firm fixed effects and year fixed effect and another with firm fixed effects and state fixed effects interacted with year fixed effects. The estimated coefficients of *Good Faith* × *Majority Inventors Outside* and *Good Faith* × *Disperse Inventors* are statistically insignificant in all eight specifications we consider. For completeness, Panel B reports the results of analogous tests for non-process innovation. Again, the coefficients on both interactions are statistically insignificant. In sum, increased inventor job security is unlikely to be the driver of our results.

4.5 Robustness tests

We now discuss the results of two additional tests that help assess the robustness of our main results in Table 3. These results are reported in tables A1-A2 of the Online Appendix.

First, in Table A1 we examine the robustness of our results based on citations-weighted patents (columns (3)-(4) in both panels of Table 3) to the choice of the weighting scheme. In columns (1)-(2) and (5)-(6) we use raw (unweighted) patent counts (*Process Patents* and *Non-Process Patents*). In columns (3)-(4) and (7)-(8) we use market value-weighted counts (*V-W Process Patents* and V-*W Non-Process Patents*) from Kogan et. al. (2017). The results in columns (1)-(4) continue to indicate a positive and statistically significant impact of the adoption of the good-faith exception on process innovation. Compared to the analogous results in Panel A of Table 3, the coefficient of *Good Faith* is smaller in magnitude when the dependent variable is not weighted and similar when it is value weighted. The results on non-process innovation in columns (5)-(8) are also consistent with those reported in Panel B of Table 3. Once the control variables are included in the regressions, there is not statistically significant impact of the adoption of the good-faith exception on non-process innovation. Further, the coefficients of *Good Faith* are positive but smaller than for process innovation.

In Table A2, we restrict attention to firm-years with at least one process or non-process patent and examine the impact of *Good Faith* on the share of process innovation in the firm's total (process and non-process) innovation computed in four alternative ways: using the number of claims of each type (*Process Share in Claims*), the number of citations-weighted patents of each type (*Process Share in C-W Patents*), the number of unweighted patents of each type (*Process Share in Patents*), and the number of value-weighted patents of each type (*Process Share in V-W Patents*), respectively. The regression specifications are analogous to those in Table 3. Across all specifications, we find that the adoption of the good-faith exception leads to a statistically significant increase in the share of process innovation. The estimated coefficients of *Good Faith* in the specifications with control variables indicate that the share of process innovation increases by 2.1 percentage points when the dependent variable is *Process Share in Claims* (or 8.6% relative to the sample mean for this variable) and by 3 percentage points when the dependent variable is *Process Share in C-W Patents* (or

15.1% relative to the sample mean for this variable). The results based on *Process Share in Patents* and *Process Share in V-W Patents* are very similar: The share of process innovation increases by 15.7% and 15.8% relative to the sample mean of these variables, respectively.

5. Innovation ability, adjustment of production methods, and firm performance

The discussion in Section 2 highlights the importance of a firm's *ex-ante* innovation ability in the adjustment of its production techniques to changing conditions in input markets and thus as a source of value. We thus examine whether firms with greater ex-ante innovation ability exhibit greater adjustments of their production methods and input mix in response to increased labor dismissal costs and how such ability ultimately affects firms' performance.

Following Bloom and Van Reenen (2002), our measure of ex-ante innovation ability is a firm's stock of patents (also referred to as "stock of knowledge" in the economics literature). Although firms do not necessarily patent all their inventions, this measure is arguably a good proxy for a firm's innovation ability in general. In Table 8, we examine how a firm's ex-ante innovation ability affects the response of its innovation to an increase in labor adjustment costs. To this end, we augment our regressions of process and non-process innovation on *Good Faith* to include an interaction of *Good Faith* with the firm's lagged stock of patents *Log(1 + Patent Stock)*, which is standardized to a mean of zero and standard deviation of one.[13] The coefficient of *Good Faith* × *Log(1 + Patent Stock)* thus allows for a direct comparison of the effect for the top patenting firms (firms with *Log(1 + Patent Stock)* one-standard deviation above the mean) and for the scarcely patenting firms (firms with *Log(1 + Patent Stock)* one-standard deviation below the mean) to the effect for the average firm. We also include all the control variables used in our main specification in Table 3. We consider a specification with firm fixed effects and year fixed effects and another with firm fixed effects and state fixed effects interacted with year fixed effects. Columns (1)-(4) report the results for the two measures of process innovation and columns (5)-(8) report those for the two measures of non-process innovation.

The estimated coefficient of *Good Faith* × *Log(1 + Patent Stock)* is positive and statistically significant in columns (1)-(4). These results imply that, relative to a firm with

[13] The *Patent Stock* corresponding to a *Log(1 + Patent Stock)* at the sample mean, one-standard deviation above the mean, and one-standard deviation below the mean are 4.5, 26.4, and 0.11 patents, respectively.

the stock of patents at the sample mean, for firms with a one-standard deviation above the sample mean stock of patents, the adoption of the good-faith exception leads to an increase in process innovation that is 8.1% to 9.8% higher when measured with process claims and 15.1% to 15.5% when measured with citations-weighted process patents. The estimated coefficient of *Good Faith* × *Log(1 + Patent Stock)* is statistically insignificant in all specifications that use non-process innovation as the dependent variables (columns (5)-(8)). These results suggest that high innovation ability firms choose to develop new processes to facilitate the introduction of new production methods when labor adjustment costs increase.

In Table 9, we examine how a firm's ex-ante innovation ability allows firms to adjust their employment and capital intensity in response to the adoption of the good-faith exception. We consider four alternative dependent variables: the annual percentage change in employment, *Employment Growth*, in columns (1)-(2); the level of employment, *Log(Employment)*, in columns (3)-(4); the capital-labor ratio, *Log(K/L)*, in columns (5)-(6); and capital expenditures per employee, *Log(Capex/Emp)*, in columns (7)-(8). As in Table 8, we include *Good Faith* and *Good Faith* × *Log(1 + Patent Stock)* and all control variables in the regressions, and we consider specifications with firm fixed effects and year fixed effects and also with firm fixed effects and state fixed effects interacted with year fixed effects.

The coefficient of *Good Faith* is negative when the dependent variables are employment growth and employment level, and positive when the dependent variables are the capital-labor ratio and capital expenditures per employee. This suggests that the typical firm, that is, the firm with *Log(1 + Patent Stock)* at the sample mean, reduces employment and substitutes capital for labor, but the coefficients are statistically insignificant. Importantly, the coefficients of *Good Faith* × *Log(1 + Patent Stock)* are statistically significant for all dependent variables, indicating that firms with high innovation ability exhibit more pronounced adjustments of their input mix following the adoption of the good faith exception. Specifically, the firm with a one-standard deviation above the sample mean stock of patents experiences a one percentage point larger decrease in employment growth, a 6.7%-7.9% larger decrease in employment, a 6.7%-7.4% larger increase in the capital-labor ratio, and a 9.1%-10.1% larger increase in the capital expenditures per employee, relative to the firm with stock of patents at the sample mean.

In Table 10, we ask if the impact of the adoption of the good-faith exception on a firm's labor productivity, operating performance, and equity value depends on its ex-ante ability to innovate. The dependent variables are labor productivity measured by sales per employee, *Log(Sales/Emp)*, operating performance measured by operating income before depreciation scaled by assets, *Profit*, and shareholder value measured by the market-to-book equity ratio, *Log(ME/BE)*. The key explanatory variables of interest are *Good Faith* and *Good Faith* × *Log(1 + Patent Stock)*. We include all control variables in the regressions, and we consider specifications with firm fixed effects and year fixed effects and those with firm fixed effects and state fixed effects interacted with year fixed effects.

In columns (1)-(2), the dependent variable is *Log(Sales/Emp)*. Consistent with the typical firm (with *Log(1 + Patent Stock)* at the sample mean) taking measures to boost labor productivity, we find a positive but small and statistically insignificant coefficient of *Good Faith*. Importantly, the coefficient of *Good Faith* × *Log(1 + Patent Stock)* is positive and statistically significant in both specifications. A firm with innovation ability one-standard deviation above the sample mean increases its labor productivity by 5.9%-6.9% after the adoption of the good-faith exception, relative to a firm with innovation ability at the sample mean.[14] This evidence is consistent with that in Dinlersoz and Wolf (2018), who use the Census Bureau's Survey of Manufacturing Technology to report that more automated establishments are less production labor intensive and exhibit greater productivity of labor.

In columns (3)-(4), the dependent variable is *Profit*. The coefficient of *Good Faith* in column (3) is negative but small and statistically insignificant. Thus, the increase in labor rigidity has little impact on the profitability of a firm with innovation ability at the sample mean. The key result is that the coefficient of *Good Faith* × *Log(1 + Patent Stock)* is positive and statistically significant in both specifications. Hence, firms with greater ex-ante innovation ability exhibit better operating performance when labor dismissal costs increase. The estimates in column (3) imply that the adoption of the good faith exception leads to a 0.6 percentage-point increase in the profitability of firms with innovation ability one-standard deviation above the sample mean, relative to a firm with innovation ability at the mean.

Last, in columns (5)-(6), we use *Log(ME/BE*) as the dependent variable to examine how a firm's ex-ante innovation ability ultimately shields shareholder value when labor dismissal costs increase. The coefficient of *Good Faith* reported column (5) suggests a negative effect of increased labor rigidity on the equity value of a firm with innovation ability at the sample

[14] Besides lower employment, labor productivity can also increase for other reasons, e.g., if the adoption of new production methods leads firms to substitute unskilled for skilled labor (Autor and Katz (1999), Autor, Levy, and Murnane (2003), Autor and Dorn (2013)), if higher firing costs lead firms to more carefully select new hires and ultimately increase the quality of its workforce, or because of an increase in the physical capital per worker.

mean, but it is statistically insignificant. Importantly, in both specifications the coefficients of *Good Faith* × *Log(1 + Patent Stock)* are positive and statistically significant. The estimates in column (5) imply that a firm with innovation ability one-standard deviation above the sample mean experiences a 4.5% increase in its equity value after the adoption of the good-faith exception, relative to a firm with innovation ability at the sample mean.

In sum, the results in Table 10 suggest that, through the process innovation mechanism we describe, high innovation ability firms are better able to adjust their production techniques, boost the productivity of their labor, and thereby maintain their performance, ultimately avoiding economically significant value losses when increased labor rigidity hurts their business. More generally, our evidence highlights that innovation ability is a key determinant of a firm's success in adjusting to changing conditions in input markets and, ultimately, a key driver of firm value.

6. Conclusions

Our evidence highlights that increases in labor rigidity steer firms' innovation activities toward process innovation that facilitates the required adjustment of production methods – a substitution of capital for labor – and thereby mitigates the negative effects of such rigidity on firm value. More broadly, our findings suggest that high innovation ability allows firms to more easily adjust their strategies when business conditions change and that, through this mechanism, innovation ability is a key driver of firms' performance.

From a public policy point of view, we highlight the unintended (or at least not fully understood) consequences of labor regulation that aims to benefit employees. Labor laws that increase employment protection or otherwise make labor costlier ultimately lead firms to take actions to mitigate the impact of these laws on their performance. This can negate some of the benefits of employment protection sought by the regulation. Autor (2003) documents an increase in outsourcing. We highlight another mechanism, namely, a change in corporate R&D policy towards introducing production methods that are less reliant on labor inputs.

Our study also stresses the importance of distinguishing different types of innovation. Prior studies examine the impact of regulatory changes on overall innovation, but such changes do not have to affect all types of innovation in the same way. The new measures of process innovation we develop in this paper can thus aid future research that seeks to understand the determinants of innovation.

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Appendix: Variable Definitions

Process and non-process innovation measures

Process Claims	The number of process claims contained in all patents filed (and ultimately awarded) by the firm in each year.
Non-Process Claims	The number of non-process claims contained in all patents filed (and ultimately awarded) by the firm in each year.
C-W Process Patents	The citations-weighted number of process patents filed (and ultimately awarded) by the firm in each year. Citations received are counted, for each patent, over the period that ends 3 years after the patent award year. Process patents are patents that contain only process claims.
C-W Non-Process Patents	The citations-weighted number of non-process patents filed (and ultimately awarded) by the firm in each year. Citations received are counted, for each patent, over the period that ends 3 years after the patent award year. Non-Process patents are patents that contain only non-process claims.

Wrongful Discharge Laws indicators (from Autor, Donohue, and Schwab (2006)):

Good Faith	Indicator variable equal to one if the firm's state of headquarters has adopted the Good Faith exception to the "firing at will" doctrine by year *t*, and zero otherwise.
Implied Contract	Indicator variable equal to one if the firm's state of headquarters has adopted the Implied Contract exception to the "firing at will" doctrine by year *t*, and zero otherwise.
Public Policy	Indicator variable equal to one if the firm's state of headquarters has adopted the Public Policy exception to the "firing at will" doctrine by year *t*, and zero otherwise.

Additional Good Faith variables

Good Faith -3	Indicator variable equal to one if the firm's state of headquarters will adopt the Good Faith exception in three years, and zero otherwise.
Good Faith -2	Indicator variable equal to one if the firm's state of headquarters will adopt the Good Faith exception in two years, and zero otherwise.
Good Faith -1	Indicator variable equal to one if the firm's state of headquarters will adopt the Good Faith exception in the following year, and zero otherwise.
Good Faith 0	Indicator variable equal to one if the firm's state of headquarters adopted the Good Faith exception in the current year, and zero otherwise.
Good Faith +1	Indicator variable equal to one if the firm's state of headquarters adopted the Good Faith exception the year before, and zero otherwise.
Good Faith +2	Indicator variable equal to one if the firm's state of headquarters adopted the Good Faith exception two years before, and zero otherwise.
Good Faith +3	Indicator variable equal to one if the firm's state of headquarters adopted the Good Faith exception three years before, and zero otherwise.

Good Faith +4	Indicator variable equal to one if the firm's state of headquarters adopted the Good Faith exception four years before, and zero otherwise.
Good Faith 5+	Indicator variable equal to one if the firm's state of headquarters adopted the Good Faith exception five or more years before, and zero otherwise.
Good Faith Neighbor	Indicator variable equal to one if a "neighboring state", that is, a state adjacent to the firm's state of headquarters, has adopted the Good Faith exception by year t, and zero otherwise.
Employment and capital intensity variables	
Employment Growth	Annual growth rate of a firm's employment (*emp*).
Log(Employment)	Logarithm of a firm's employment level (*emp*).
Log(K/L)	Logarithm of a firm's capital-labor ratio defined as property, plant, and equipment (*ppent*) divided by employment (*emp*).
Log(Capex/Emp)	Logarithm of a firm's capital expenditures per employee defined as capital expenditures (*capex*) divided the employment (*emp*).
Labor productivity, profitability, and shareholder value measures	
Log(Sales/Emp)	Logarithm of sales (*sale*) dividend by the number of employees (*emp*).
Profit	Operating income before depreciation (*oibdp*) divided by assets (*at*); winsorized at the top/bottom 5% of the annual distribution.
Log(ME/BE)	Natural logarithm of the market value of equity (*prcc_f* × *csho*) divided by the book value of equity (*at* - *lt*).
Control variables	
Patent Stock	A firm's patent stock computed by adding its patents since 1872 and assuming an annual depreciation rate of 15%.
R&D Stock	A firm's R&D stock computed by adding its R&D spending (*xrd*) since 1950 and assuming an annual depreciation rate of 15%.
Log(Sales)	The logarithm of a firm's sales (*sale*).
Log(M/B)	The logarithm of a firm's market value of assets (the sum of the market value of equity, *csho* × *prcc_f*, the book value of long term debt, *dltt*, and the book value of debt in current liabilities, *dlc*) scaled by the book value of assets (*at*).
State GDP Growth	Annual growth rate of state GDP in current dollars (Source: U.S. Bureau of Economic Analysis).
State Political Balance	Fraction of a state's congress members in the U.S. House of Representatives that belong to the Democratic Party (Source: History, Art & Archives, U.S. House of Representatives).
Other variables	
LaborCostShr	The average labor cost share in the firm's 3-digit SIC industry. For each firm, dollar labor costs are computed as the Compustat number of employee's (*emp*) times the

	average wage rate in the firm's industry obtained from the Quarterly Census of Employment and Wages provided by the U.S. Bureau of Labor Statistics. Next, the dollar labor costs are divided by the firm's cost of goods sold (*cogs*). Last, firm cost shares are averaged across all firm-years in each 3-digt SIC industry.
Log(State Patents)	The logarithm of the mean number of patents filed (and ultimately awarded) in each year by firms headquartered in the same state as the firm. Patents filed by the firm itself are excluded from the calculation of the mean.
Majority Inventors Outside	Indicator variable equal to one if more than 50% of the lead inventors listed in all patents the firm applied for in a given year are located outside the firm's state of headquarters, and zero otherwise. The lead inventor is the first inventor listed on the patent grant document.
Disperse Inventors	Indicator variable equal to one if no U.S. state concentrates more than 50% of the lead inventors listed in all patents the firm applied for in a given year, and zero otherwise. The lead inventor is the first inventor listed on the patent grant document.

Figure 1: The figure reports the average number of total (process and non-process) claims (left axis) and the average share of process claims in total claims (right axis) for firms in our sample over the period 1975-1997.

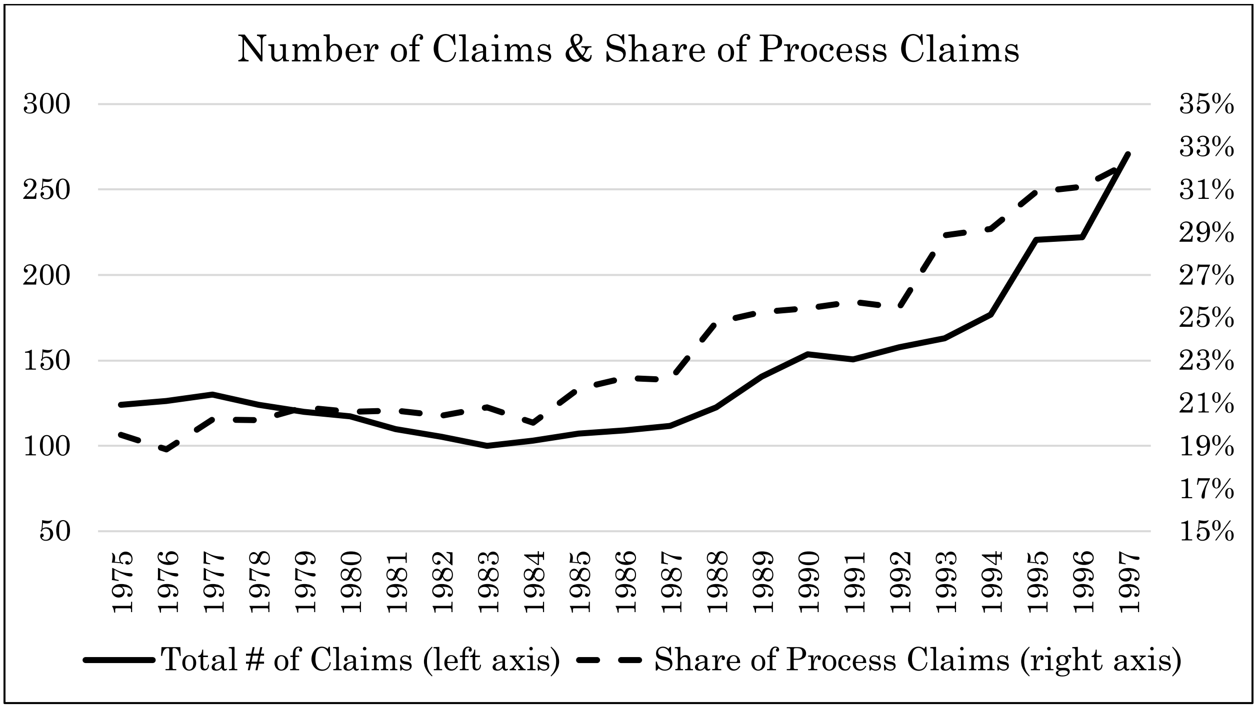

Figure 2: The figures report the differences in *Process Claims* (Figure 2a) and in *Non-Process Claims* (Figure 2b) between treated and control firms around the adoption of the Good Faith exception (year 0). The differences are estimated using empirical models analogous to those in columns 2 and 4 of Table 3, but replacing *Good Faith* by *Good Faith -3*, *Good Faith -2*, *Good Faith -1*, *Good Faith 0*, *Good Faith +1*, *Good Faith +2*, *Good Faith +3*, *Good Faith +4*, and *Good Faith 5+* (see the Appendix for definitions). The dots indicate the estimated coefficients of these indicators and the dashes above / below indicate the upper and lower bounds of the 95% confidence intervals.

Figure 2a

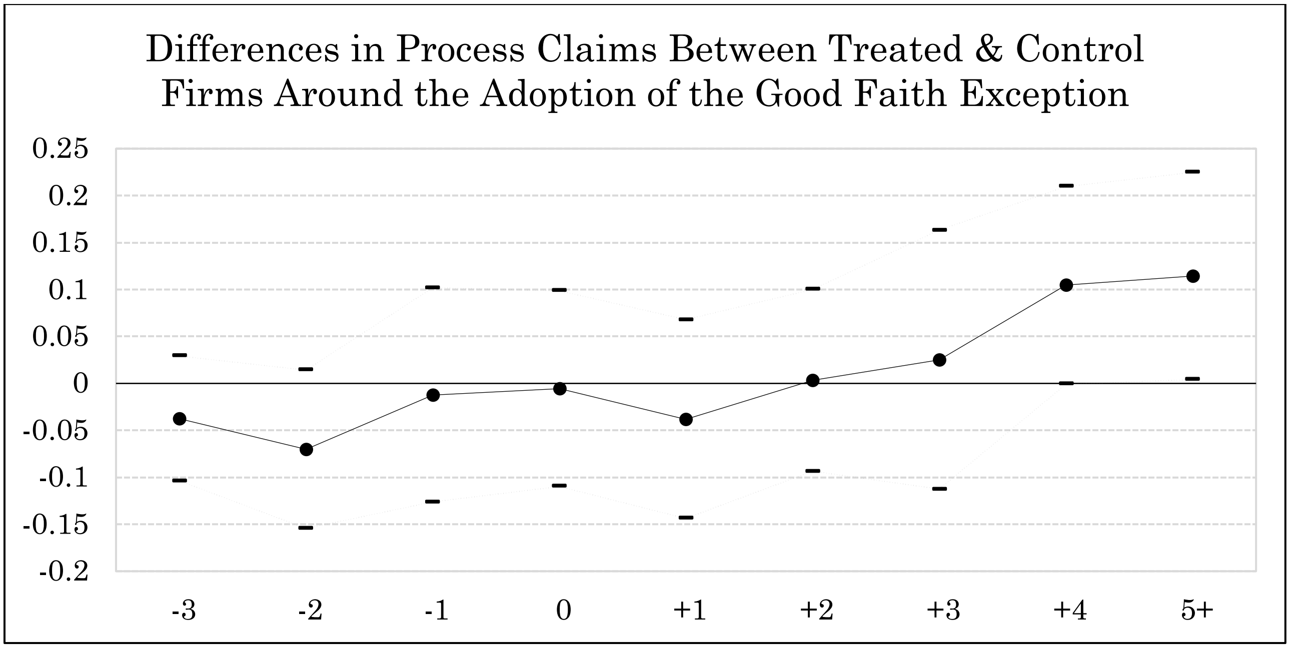

Figure 2b

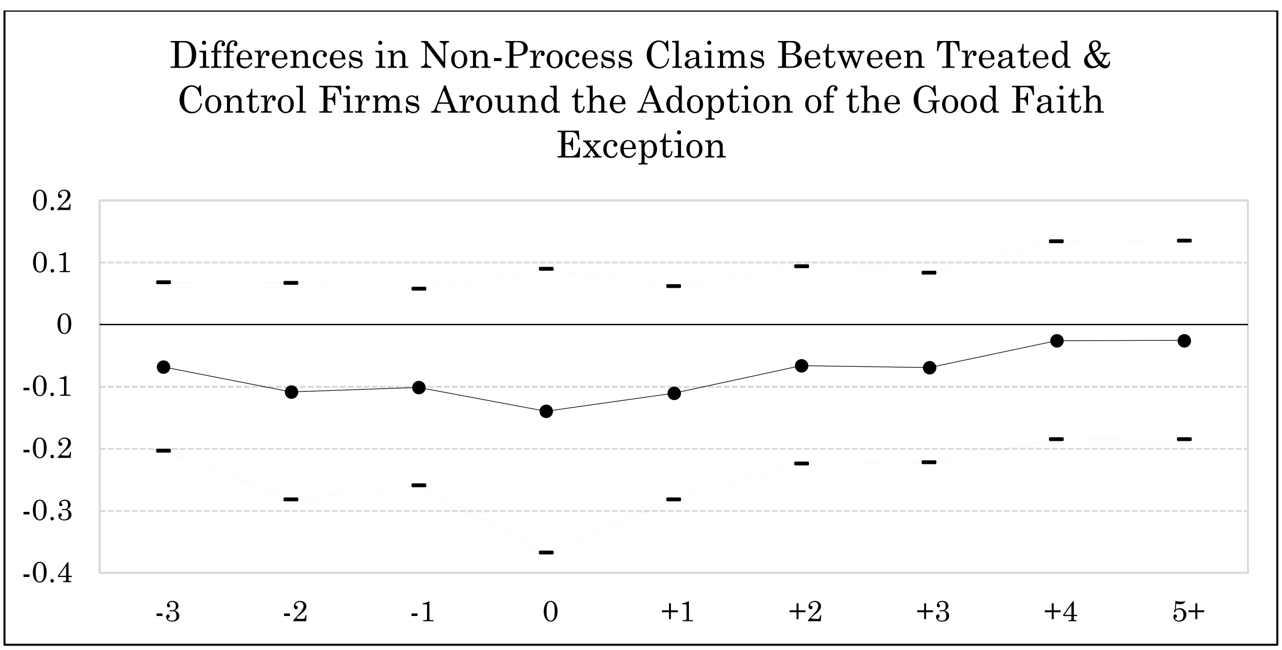

Figure 3: The figure reports the values of *Process Claims* for treated and control firms around the adoption of the Good Faith exception. The data is constructed in three steps. First, using the sample in our main tests, we retain the variation in *Process Claims* that is unexplained by firm fixed effects and year fixed effects (i.e., we adjust the original variable by removing time-invariant differences across firms and time trends common to all firms). Second, for each adoption event, starting from our main sample, we construct a panel dataset of treated firms (in the adopting state) and control firms (in never adopting states) over the time frame -3 to +10 years relative to the adoption year for the treated state (year 0). We require that firms are in the data in both year -1 and year 0. Third, we pool all events together in to a single dataset in event time, going from year -3 to year +4 and then years 5+ (averaging *Process Claims* over the years +5 to +10).

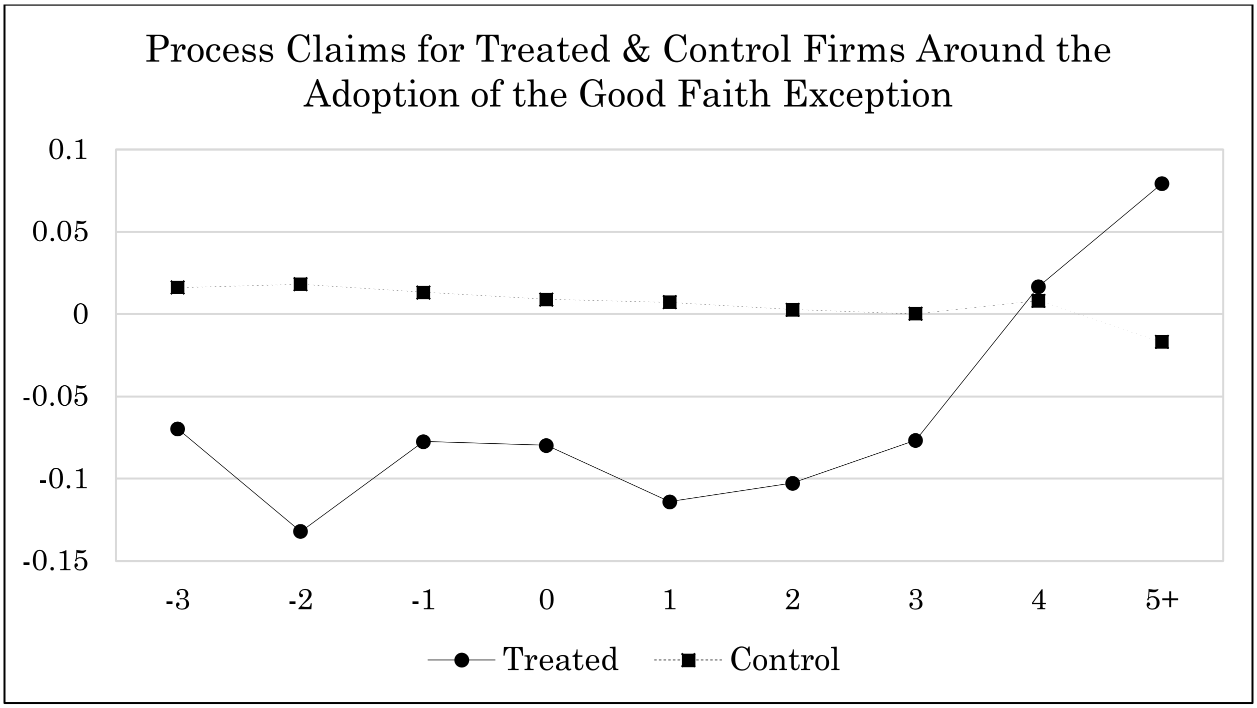

Table 1: Summary Statistics

The sample spans the period 1975-1997. It includes all non-financial and non-utility firms headquartered in the U.S. that filed at least one patent with the USPTO during this period and for which we can compute the key variables. All variables are defined in the Appendix.

	Mean	Sd. Dev.	Pctile 10	Median	Pctile 90
Process and non-process innovation measures					
Log(1 + Process Claims)	1.133	1.825	0.000	0.000	4.025
Log(1 + Non-Process Claims)	1.872	2.195	0.000	0.000	5.017
Log(1 + C-W Process Patents)	0.507	1.214	0.000	0.000	2.303
Log(1 + C-W Non-Process Patents)	1.126	1.658	0.000	0.000	3.664
Wrongful Discharge Laws indicators					
Good Faith	0.238	0.426	0.000	0.000	1.000
Implied Contract	0.638	0.480	0.000	1.000	1.000
Public Policy	0.654	0.476	0.000	1.000	1.000
Employment and capital intensity variables					
Employment growth	0.037	0.254	-0.189	0.023	0.288
Log(Employment)	0.283	2.054	-2.375	0.262	3.046
Log(K/L)	2.988	1.086	1.725	2.911	4.359
Log(Capex/Emp)	1.424	1.197	0.000	1.383	2.917
Labor productivity, profitability, and shareholder value measures					
Log(Sales/Emp)	4.543	0.793	3.665	4.536	5.461
Profit	0.108	0.141	-0.053	0.136	0.249
Log(ME/BE)	0.494	0.857	-0.497	0.423	1.553
Control variables					
Log(1 + Patent Stock)	1.708	1.609	0.000	1.314	3.984
Log(1 + R&D Stock)	1.830	1.928	0.000	1.302	4.623
Log(Sales)	4.691	2.264	1.930	4.687	7.617
Log(M/B)	0.116	0.715	-0.630	-0.018	1.085
State GDP Growth	0.077	0.036	0.035	0.075	0.124
State Political Balance	0.602	0.164	0.435	0.600	0.833

Table 2: Process Innovation Across Industries

Panel A reports the shares of two-digit SIC industries in all patented process innovation (measured by process claims) over the period 1975-97 as well for the subperiods 1975-80, 1981-85, 1986-90, and 1991-97. Industries are ranked by their shares over the period 1975-97 in descending order, with the top 10 industries reported in detail and the rest combined into the category "All other industries". Panel B reports the shares of process innovation in total patented innovation (measured by process and non-process claims) for the same two-digit SIC industries identified in Panel A, also over the period 1975-97 as well for the subperiods 1975-80, 1981-85, 1986-90, and 1991-97.

Panel A: Distribution of Process Innovation Across Industries

SIC2	Industry description	1975-97	1975-80	1981-85	1986-90	1991-97
28	Chemicals & allied products	23.5%	29.2%	28.2%	27.8%	18.8%
36	Electronic & electrical equipment	17.8%	9.9%	12.5%	13.9%	23.1%
35	Machinery & computer equipment	15.1%	6.8%	7.8%	11.4%	21.1%
29	Petroleum refining	9.8%	17.3%	17.9%	11.1%	4.7%
38	Instruments etc.	9.2%	6.5%	6.2%	9.8%	10.8%
37	Transportation equipment	6.5%	6.4%	6.9%	8.8%	5.7%
48	Communications	3.4%	3.7%	4.1%	4.4%	2.8%
26	Paper & allied products	2.6%	1.9%	2.0%	3.1%	2.7%
73	Business services	1.7%	0.2%	0.2%	0.4%	3.0%
33	Primary metal industries	1.6%	3.2%	2.0%	2.2%	0.8%
	All other industries	8.8%	15.0%	12.2%	7.3%	6.5%

Panel B: Share of Process Innovation in Total Innovation for Selected Industries

SIC2	Industry description	1975-97	1975-80	1981-85	1986-90	1991-97
28	Chemicals & allied products	38.9%	35.1%	39.6%	40.1%	40.0%
36	Electronic & electrical equipment	28.2%	17.2%	20.8%	23.9%	34.5%
35	Machinery & computer equipment	27.3%	13.7%	19.9%	24.2%	32.5%
29	Petroleum refining	59.4%	58.5%	61.7%	56.6%	60.5%
38	Instruments etc.	25.9%	19.4%	20.5%	25.5%	29.1%
37	Transportation equipment	21.8%	17.7%	21.0%	21.8%	24.1%
48	Communications	29.1%	19.7%	24.1%	28.2%	41.5%
26	Paper & allied products	25.1%	21.7%	21.5%	23.6%	27.8%
73	Business services	41.6%	10.4%	15.3%	29.8%	46.3%
33	Primary metal industries	45.8%	49.8%	43.6%	49.4%	40.2%
	All other industries	30.1%	31.3%	32.1%	27.3%	29.5%

Table 3: Wrongful Discharge Laws and Process vs. Non-Process Innovation

The table reports the results of OLS regressions of process innovation and non-process innovation on *Good Faith,* the other Wrongful Discharge Laws indicators (*Implied Contract* and *Public Policy*), lagged controls variables (*Log(1+ Patent Stock)*, *Log(1+R&D Stock)*, *Log(Sales)*, *Log(M/B)*, *State GDP Growth*, and *Political Balance*), as well as firm fixed effects and year fixed effects. In Panel A, the dependent variables are *Log(1+Process Claims)* and *Log(1+C-W Process Patents)*. In Panel B, the dependent variables are *Log(1+Non-Process Claims)* and *Log(1+C-W Non-Process Patents)*. All other variables are defined in the Appendix. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Impact of Good Faith on process innovation

	Process Claims		C-W Process Patents	
	(1)	(2)	(3)	(4)
Good Faith	0.134***	0.089***	0.091***	0.061**
	(4.456)	(2.959)	(3.062)	(2.119)
Implied Contract	0.002	-0.022	0.002	-0.016
	(0.030)	(-0.561)	(0.054)	(-0.626)
Public Policy	-0.022	-0.002	-0.030	-0.018
	(-0.509)	(-0.062)	(-0.939)	(-0.811)
Log(1 + Patent Stock)		0.422***		0.281***
		(14.699)		(7.876)
Log(1 + R&D Stock)		0.178***		0.114***
		(6.090)		(5.849)
Log(Sales)		0.105***		0.037***
		(6.785)		(2.930)
Log(M/B)		0.074***		0.045***
		(4.454)		(4.750)
State GDP Growth		-0.347		-0.387
		(-1.026)		(-1.461)
State Political Balance		-0.112		-0.042
		(-1.353)		(-0.690)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	44,898	44,898	44,898	44,898
Adjusted R^2	0.706	0.728	0.713	0.733

Panel B: Impact of Good Faith on non-process innovation

	Non-Process Claims		C-W Non-Process Patents	
	(1)	(2)	(3)	(4)
Good Faith	0.070	0.027	0.054*	0.021
	(1.488)	(0.567)	(1.758)	(0.789)
Implied Contract	0.007	-0.012	-0.003	-0.018
	(0.135)	(-0.256)	(-0.073)	(-0.586)
Public Policy	-0.002	0.019	-0.005	0.010
	(-0.039)	(0.478)	(-0.130)	(0.284)
Log(1 + Patent Stock)		0.416***		0.336***
		(11.246)		(11.644)
Log(1 + R&D Stock)		0.142***		0.106***
		(4.086)		(4.506)
Log(Sales)		0.189***		0.120***
		(9.653)		(8.271)
Log(M/B)		0.107***		0.094***
		(5.274)		(6.080)
State GDP Growth		-0.407		-0.175
		(-0.921)		(-0.594)
State Political Balance		-0.067		-0.022
		(-0.917)		(-0.351)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	44,898	44,898	44,898	44,898
Adjusted R^2	0.677	0.694	0.715	0.733

Table 4: Cross-Sectional Variation in the Effect of Good Faith on Innovation – The Role of the Industry Labor Cost Share

The table reports the results of OLS regressions of process and non-process innovation on *Good Faith* that further interact *Good Faith* with the average labor cost share in the firm's 3-digit SIC industry, *LaborCostShr* (standardized to a mean of zero and standard deviation of one). The dependent variables are *Log(1+Process Claims)* in columns (1)-(2), *Log(1+C-W Process Patents)* in columns (3)-(4), *Log(1+Non-Process Claims)* in columns (5)-(6), and *Log(1+C-W Non-Process Patents)* in columns (7)-(8). All regressions include *Implied Contract* and *Public Policy* and the lagged controls variables (*Log(1+Patent Stock)*, *Log(1+R&D Stock)*, *Log(Sales)*, *Log(M/B)*, *State GDP Growth*, and *Political Balance*). All variables are defined in the Appendix. Specifications (1), (3), (5), and (7) include firm fixed effects and year fixed effects. Specifications (2), (4), (6), and (8) include firm fixed effects and state fixed effects interacted with year fixed effects. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Process Innovation				Non-Process Innovation			
	Process Claims		C-W Process Patents		Non-Process Claims		C-W Non-Process Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good Faith	0.095***		0.066**		0.030		0.022	
	(2.829)		(2.116)		(0.641)		(0.823)	
Good Faith × LaborCostShr	0.059*	0.067**	0.053*	0.059**	0.013	0.017	-0.001	0.001
	(1.777)	(2.056)	(1.962)	(2.328)	(0.328)	(0.385)	(-0.036)	(0.028)
LaborCostShr	0.047	0.048	0.019	0.025	0.107***	0.109***	0.071***	0.078***
	(1.372)	(1.280)	(0.820)	(1.007)	(3.383)	(3.797)	(2.725)	(3.113)
Other WDLs & Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
State × Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	44,860	44,765	44,860	44,765	44,860	44,765	44,860	44,765
Adjusted R^2	0.728	0.729	0.733	0.733	0.694	0.695	0.733	0.733

Table 5: Adoption of the Good Faith Exemption in Neighboring States

The table reports the results of OLS regressions of process and non-process innovation on *Good Faith* and an indicator variable *Good Faith Neighbor* for whether a "neighboring state" (a state adjacent to the firm's state of headquarters) has adopted the Good Faith exception by year *t* and zero otherwise. The dependent variables are *Log(1+Process Claims)* in column (1), *Log(1+C-W Process Patents)* in column (2), *Log(1+Non-Process Claims)* in column (3), and *Log(1+C-W Non-Process Patents)* in column (4). All regressions include *Implied Contract* and *Public Policy*, the lagged controls variables (*Log(1+Patent Stock)*, *Log(1+R&D Stock)*, *Log(Sales)*, *Log(M/B)*, *State GDP Growth*, and *Political Balance*), as well as firm-fixed effects and year fixed effects. All variables are defined in the Appendix. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Process Innovation		Non-Process Innovation	
	Process Claims	C-W Process Patents	Non-Process Claims	C-W Non-Process Patents
	(1)	(2)	(3)	(4)
Good Faith	0.086***	0.063**	0.022	0.016
	(2.999)	(2.208)	(0.465)	(0.628)
Good Faith Neighbor	-0.021	0.013	-0.039	-0.040
	(-0.555)	(0.729)	(-0.946)	(-1.475)
Other WDLs & Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	44,898	44,898	44,898	44,898
Adjusted R^2	0.728	0.733	0.694	0.733

Table 6: Controlling for Time Trends in Innovation

The table reports the results of OLS regressions of process innovation and non-process innovation on *Good Faith,* the other Wrongful Discharge Laws indicators (*Implied Contract* and *Public Policy*), lagged controls variables (*Log(1+Patent Stock), Log(1+R&D Stock)*, *Log(Sales)*, *Log(M/B)*, *State GDP Growth*, and *Political Balance*), as well as firm fixed effects and year fixed effects. In Panel A, the dependent variables are *Log(1+Process Claims)* in columns (1)-(3) and *Log(1+C-W Process Patents)* in columns (4)-(6). In Panel B, the dependent variables are *Log(1+Non-Process Claims)* in columns (1)-(3) and *Log(1+C-W Non-Process Patents)* in columns (4)-(6). For both panels, columns (1) and (4) include *Log(State Patents),* defined as the logarithm of the mean number of patents filed by firms headquartered in the firm's state in each year (the patents filed by the firm itself are excluded in the calculation of this mean), as an additional control variable. For both panels, columns (2) and (4) estimate the benchmark specification restricting the sample to the period 1975-1990, and columns (3) and (6) estimate the benchmark specification excluding the states of California and Massachusetts from the sample. All variables are defined in the Appendix. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Effect of Good Faith on process innovation

	Process Claims			C-W Process Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Good Faith	0.080***	0.081***	0.122***	0.056**	0.052*	0.068**
	(2.726)	(2.704)	(4.920)	(2.142)	(1.964)	(2.056)
Log(State Patents)	0.091**			0.050		
	(2.309)			(1.620)		
Sample	Full	1975-90	Excl. CA & MA	Full	1975-90	Excl. CA & MA
Other WDLs & Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,898	29,328	35,326	44,898	29,328	35,326
Adjusted R^2	0.728	0.756	0.740	0.733	0.786	0.761

Panel B: Effect of Good Faith on non-process innovation

	Non-Process Claims			C-W Non-Process Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Good Faith	0.015	-0.009	0.030	0.013	-0.008	-0.004
	(0.299)	(-0.184)	(0.551)	(0.514)	(-0.342)	(-0.109)
Log(State Patents)	0.118**			0.077*		
	(2.018)			(2.008)		
Sample	Full	1975-90	Excl. CA & MA	Full	1975-90	Excl. CA & MA
Other WDLs & Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,898	29,328	35,326	44,898	29,328	35,326
Adjusted R^2	0.694	0.718	0.702	0.733	0.766	0.745

Table 7: Effect of Good Faith on Process vs. Non-Process Innovation – Lead Inventor's State of Location

The table reports the results of OLS regressions of process and non-process innovation on *Good Faith* that further interact *Good Faith* with two variables that capture the location of inventors relative to the location of the firm. The first is an indicator variable equal to one if more than 50% of the lead inventors listed in all patents the firm applied for in a given year are located outside the firm's state of headquarters and zero otherwise (*Majority Inventors Outside*). The second is an indicator variable equal to one if no state concentrates more than 50% of the lead inventors listed in all patents the firm applied for in a given year and zero otherwise (*Disperse Inventors*). In Panel A, the dependent variables are *Log(1+Process Claims)* in columns (1)-(4) and *Log(1+C-W Process Patents)* in columns (5)-(8). In Panel B, the dependent variables are *Log(1+Non-Process Claims)* in columns (1)-(4) and *Log(1+C-W Non-Process Patents)* in columns (5)-(8). All regressions include *Implied Contract* and *Public Policy* and the lagged controls variables (*Log(1+Patent Stock)*, *Log(1+R&D Stock)*, *Log(Sales)*, *Log(M/B)*, *State GDP Growth*, and *Political Balance*). All variables are defined in the Appendix. Specifications (1), (3), (5), and (7) include firm fixed effects and year fixed effects. Specifications (2), (4), (6), and (8) include firm fixed effects and state fixed effects interacted with year fixed effects. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Regressions of process innovation on Good Faith interacted with Majority Inventors Outside and Disperse Inventors

	Process Claims				C-W Process Patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good Faith	0.084***		0.073**		0.055*		0.053*	
	(2.896)		(2.339)		(1.891)		(1.966)	
Good Faith × Majority Inventors Outside	0.047	0.030			0.084	0.073		
	(0.501)	(0.345)			(0.989)	(0.826)		
Majority Inventors Outside	0.664***	0.667***			0.288***	0.280***		
	(12.269)	(12.174)			(5.218)	(4.963)		
Good Faith × Disperse Inventors			0.146	0.135			0.078	0.071
			(1.605)	(1.544)			(0.827)	(0.755)
Disperse Inventors			0.435***	0.435***			0.075***	0.073***
			(12.947)	(13.028)			(3.319)	(3.241)
Other WDLs & Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
State × Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	44,898	44,803	44,898	44,803	44,898	44,803	44,898	44,803
Adjusted R^2	0.732	0.733	0.731	0.732	0.735	0.735	0.733	0.734

Panel B: Regressions of non-process innovation on Good Faith interacted with Majority Inventors Outside and Disperse Inventors

	Non-Process Claims				C-W Non-Process Patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good Faith	0.027		0.025		0.020		0.018	
	(0.525)		(0.456)		(0.728)		(0.619)	
Good Faith × Majority Inventors Outside	-0.026	-0.026			-0.003	-0.000		
	(-0.286)	(-0.319)			(-0.037)	(-0.005)		
Majority Inventors Outside	0.901***	0.898***			0.658***	0.649***		
	(18.721)	(18.568)			(15.370)	(15.321)		
Good Faith × Disperse Inventors			0.012	-0.004			0.020	0.008
			(0.181)	(-0.066)			(0.256)	(0.107)
Disperse Inventors			0.890***	0.894***			0.515***	0.518***
			(23.760)	(23.904)			(15.690)	(16.183)
Other WDLs & Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
State × Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	44,898	44,803	44,898	44,803	44,898	44,803	44,898	44,803
Adjusted R^2	0.699	0.700	0.702	0.703	0.737	0.738	0.737	0.738

Table 8: Innovation Ability and the Effect of Good Faith on Process vs. Non-Process Innovation

The table reports OLS regressions of process and non-process innovation on *Good Faith,* including an interaction of *Good Faith* with the firm's lagged stock of patents, *Log(1+Patent Stock)* (standardized to a mean of zero and standard deviation of one). The dependent variables are *Log(1+Process Claims)* in columns (1)-(2), *Log(1+C-W Process Patents)* in columns (3)-(4), *Log(1+Non-Process Claims)* in columns (5)-(6), and *Log(1+C-W Non-Process Patents)* in columns (7)-(8). All regressions include *Implied Contract* and *Public Policy* and the lagged controls variables (*Log(1+ Patent Stock)*, *Log(1+R&D Stock)*, *Log(Sales)*, *Log(M/B)*, *State GDP Growth*, and *Political Balance*). All variables are defined in the Appendix. Specifications (1), (3), (5), and (7) include firm fixed effects and year fixed effects. Specifications (2), (4), (6), and (8) include firm fixed effects and state fixed effects interacted with year fixed effects. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Process Innovation				Non-Process Innovation			
	Process Claims		C-W Process Patents		Non-Process Claims		C-W Non-Process Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good Faith	0.065**		0.024		0.028		0.012	
	(2.348)		(0.983)		(0.473)		(0.447)	
Good Faith × Log(1 + Patent Stock)	0.098*	0.081*	0.155**	0.151**	-0.002	-0.023	0.038	0.029
	(1.931)	(1.808)	(2.519)	(2.522)	(-0.034)	(-0.422)	(0.759)	(0.659)
Log(1 + Patent Stock)	0.649***	0.647***	0.405***	0.408***	0.668***	0.661***	0.528***	0.524***
	(16.750)	(15.971)	(12.380)	(12.419)	(12.522)	(11.304)	(14.027)	(12.609)
Other WDLs & Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
State × Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	44,898	44,803	44,898	44,803	44,898	44,803	44,898	44,803
Adjusted R^2	0.728	0.729	0.734	0.734	0.694	0.695	0.733	0.733

Table 9: Innovation Ability and the Effect of Good Faith on Employment and Capital Intensity

The table reports OLS regressions of firm employment and capital intensity on *Good Faith,* including an interaction of *Good Faith* with the firm's lagged stock of patents, *Log(1+Patent Stock)* (standardized to a mean of zero and standard deviation of one). The regressions also include the other Wrongful Discharge Laws indicators (*Implied Contract* and *Public Policy*) and lagged control variables. The dependent variables are a firm's annual employment growth rate (*Employment Growth*) in columns (1)-(2), the logarithm of a firm's employment level (*Log(Employment)*) in columns (3)-(4), the logarithm of a firm's capital-labor ratio defined as property, plant, and equipment divided by employment (*Log(K/L)*) in columns (5)-(6), and the logarithm of a firm's capital expenditures per employee (*Log(Capex/Emp)*) in columns (7)-(8). All other variables are defined in the Appendix. Specifications (1), (3), (5), and (7) include firm fixed effects and year fixed effects. Specifications (2), (4), (6), and (8) include firm fixed effects and state fixed effects interacted with year fixed effects. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Employment Growth		Log(Employment)		Log(K/L)		Log(Capex/Emp)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good Faith	-0.005		-0.022		0.030		0.016	
	(-0.791)		(-0.821)		(1.560)		(0.826)	
Good Faith × Log(1 + Patent Stock)	-0.010**	-0.009***	-0.079***	-0.067***	0.067***	0.074***	0.091***	0.101**
	(-2.083)	(-3.480)	(-6.390)	(-4.411)	(6.091)	(3.824)	(3.764)	(2.553)
Log(1 + Patent Stock)	0.000	-0.000	0.110***	0.109***	0.042***	0.041***	-0.038*	-0.040*
	(0.007)	(-0.095)	(9.668)	(9.004)	(2.907)	(2.825)	(-1.721)	(-1.713)
Implied Contract	-0.004		-0.045**		-0.014		0.002	
	(-0.653)		(-2.259)		(-0.878)		(0.108)	
Public Policy	-0.006		-0.008		-0.035		-0.038	
	(-1.126)		(-0.472)		(-1.638)		(-1.443)	
Log(1 + R&D Stock)	0.087***	0.087***	0.085***	0.082***	0.049***	0.049***	0.385***	0.379***
	(15.139)	(15.028)	(10.455)	(9.978)	(4.209)	(4.056)	(20.882)	(19.584)
Log(Sales)	-0.068***	-0.070***	0.536***	0.529***	0.066***	0.064***	0.106***	0.104***
	(-19.109)	(-19.706)	(22.121)	(21.784)	(6.458)	(6.042)	(6.486)	(6.059)
Log(M/B)	-0.024***	-0.024***	0.041**	0.044***	0.035***	0.037***	-0.024*	-0.020
	(-4.600)	(-4.399)	(2.609)	(2.785)	(3.471)	(3.978)	(-1.879)	(-1.557)
State GDP Growth	0.115*		0.422***		-0.221		0.964***	
	(1.864)		(4.812)		(-1.311)		(3.538)	
State Political Balance	-0.010		-0.032		0.025		0.105**	
	(-0.694)		(-0.869)		(0.503)		(2.255)	
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
State × Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	43,935	43,840	44,216	44,120	44,166	44,070	43,567	43,465
Adjusted R^2	0.175	0.180	0.967	0.967	0.859	0.861	0.697	0.699

Table 10: Innovation Ability and the Effect of Good Faith on Labor Productivity, Profitability, and Equity Value

The table reports OLS regressions of firm labor productivity, profitability, and equity value on *Good Faith,* including an interaction of *Good Faith* with the firm's lagged stock of patents, *Log(1+Patent Stock)* (standardized to a mean of zero and standard deviation of one). The regressions also include the other Wrongful Discharge Laws indicators (*Implied Contract* and *Public Policy*) and lagged control variables. All variables are defined in the Appendix. The dependent variables are the logarithm of sales per employee (*Log(Sales/Emp)*) in columns (1)-(2), operating income before depreciation scaled by assets (*Profit*) in columns (3)-(4), and the logarithm of the market to book equity ratio (*Log(ME/BE)*) in columns (5)-(6). Specifications (1), (3), and (5) include firm fixed effects and year fixed effects. Specifications (2), (4), and (6) include firm fixed effects and state fixed effects interacted with year fixed effects. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Log(Sales/Emp)		Profit		Log(ME/BE)	
	(1)	(2)	(3)	(4)	(5)	(6)
Good Faith	0.022		-0.000		-0.026	
	(1.270)		(-0.071)		(-0.632)	
Good Faith × Log(1 + Patent Stock)	0.069***	0.059***	0.006***	0.006**	0.045**	0.042**
	(7.230)	(4.697)	(2.847)	(2.106)	(2.228)	(2.267)
Log(1 + Patent Stock)	-0.052***	-0.050***	-0.009***	-0.008***	-0.047**	-0.045**
	(-5.201)	(-4.647)	(-3.830)	(-3.602)	(-2.226)	(-2.130)
Implied Contract	0.028*		0.002		0.014	
	(1.754)		(0.568)		(0.441)	
Public Policy	-0.018		0.003		0.014	
	(-1.526)		(1.151)		(0.389)	
Log(Sales)	-0.010	-0.012	-0.017***	-0.016***	-0.076***	-0.073***
	(-0.995)	(-1.140)	(-5.701)	(-5.283)	(-5.835)	(-5.559)
Log(1 + R&D Stock)	0.189***	0.189***	0.024***	0.024***	-0.130***	-0.130***
	(16.979)	(16.411)	(8.838)	(8.850)	(-9.991)	(-9.896)
State GDP Growth	-0.078		0.095**		1.319***	
	(-0.918)		(2.487)		(6.125)	
State Political Balance	0.014		0.010		0.058	
	(0.480)		(1.462)		(0.816)	
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	No	Yes	No
State-Year Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	44,118	44,021	44,744	44,648	43,853	43,761
Adjusted R^2	0.825	0.827	0.669	0.673	0.618	0.627

Online Appendix to

“Shielding Firm Value: Employment Protection and Process Innovation”

Jan Bena, Hernán Ortiz-Molina, and Elena Simintzi

Table A1: Robustness of Main Results to Using Alternative Measures of Innovation

The table reports the results of OLS regressions of process and non-process innovation on *Good Faith* that also include the other Wrongful Discharge Laws indicators (*Implied Contract* and *Public Policy*) and lagged control variables (*Log(1+Patent Stock)*, *Log(1+R&D Stock)*, *Log(Sales)*, *Log(M/B)*, *State GDP Growth*, and *Political Balance*), as well as firm fixed effects and year fixed effects. The dependent variables are *Log(1+Process Patents)* in columns (1)-(2), *Log(1+V-W Process Patents)* in columns (3)-(4), *Log(1+Non-Process Patents)* in columns (5)-(6), and *Log(1+V-W Non-Process Patents)* in columns (7)-(8). *Log(1+Process Patents)* and *Log(1+Non-Process Patents)* are based on (unweighted) counts of process and non-process patents, respectively. *Log(1+V-W Process Patents)* and *Log(1+V-W Non-Process Patents)* are based on value-weighted counts of process and non-process patents, respectively. The value of each patent comes from Kogan et. al. (2017). All other variables are defined in the Appendix. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Process Innovation				Non-Process Innovation			
	Process Patents		V-W Process Patents		Non-Process Patents		V-W Non-Process Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good Faith	0.054***	0.040**	0.087***	0.059**	0.049*	0.032	0.056**	0.026
	(2.752)	(2.074)	(3.099)	(2.310)	(1.945)	(1.354)	(2.172)	(0.997)
Implied Contract	0.001	-0.008	0.004	-0.011	0.002	-0.005	0.003	-0.009
	(0.047)	(-0.559)	(0.131)	(-0.482)	(0.085)	(-0.237)	(0.092)	(-0.318)
Public Policy	-0.016	-0.010	-0.018	-0.007	0.003	0.012	0.038	0.053*
	(-0.875)	(-0.737)	(-0.553)	(-0.287)	(0.117)	(0.548)	(1.001)	(1.933)
Log(1 + Patent Stock)		0.160***		0.250***		0.215***		0.283***
		(8.123)		(5.849)		(10.099)		(8.615)
Log(1 + R&D Stock)		0.045***		0.109***		0.039**		0.113***
		(4.082)		(4.964)		(2.299)		(4.367)
Log(Sales)		0.029***		0.053***		0.084***		0.119***
		(4.953)		(3.794)		(8.259)		(7.057)
Log(M/B)		0.020***		0.089***		0.044***		0.161***
		(3.819)		(8.677)		(4.799)		(9.211)
State GDP Growth		-0.189		-0.247		-0.106		-0.150
		(-1.562)		(-1.166)		(-0.583)		(-0.579)
State Political Balance		-0.032		-0.042		-0.031		-0.073
		(-1.017)		(-0.779)		(-0.733)		(-1.290)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,898	44,898	44,898	44,898	44,898	44,898	44,898	44,898
Adjusted R^2	0.803	0.818	0.788	0.803	0.805	0.820	0.825	0.839

Table A2: Wrongful Discharge Laws and Share of Process Innovation

The table reports the results of OLS regressions of the share of process innovation in total innovation (conditional on a firm's filing at least one patent in that year) on *Good Faith* that also include the other Wrongful Discharge Laws indicators (*Implied Contract* and *Public Policy*) and lagged control variables (*Log(1+Patent Stock)*, *Log(1+R&D Stock)*, *Log(Sales)*, *Log(M/B)*, *State GDP Growth*, and *Political Balance*), as well as firm fixed effects and year fixed effects. In columns (1)-(2), the dependent variable is the share of process claims in the total number of claims contained in all patents filed by a firm in each year (*Process Share in Claims*). In columns (3)-(4), the dependent variable is the ratio of the citation-weighted number of process patents to the citation-weighted number of process and non-process patents filed by a firm in each year (*Process Share in C-W Patents*). In columns (5)-(6), the dependent variable is the share of (unweighted) process patents in the total number of (unweighted) process and non-process patents filed by a firm in each year (*Process Share in Patents*). In columns (7)-(8), the dependent variable is the ratio of the value-weighted number of process patents to the value-weighted number of process and non-process patents filed by a firm in each year (*Process Share in V-W Patents*). The value of each patent comes from Kogan et. al. (2017). All other variables are defined in the Appendix. The standard errors are adjusted for heteroscedasticity and clustering at the state level (t-statistics in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Process Share in Claims		Process Share in C-W Patents		Process Share in Patents		Process Share in V-W Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Good Faith	0.023*	0.021*	0.034**	0.030**	0.028***	0.026**	0.029**	0.026**
	(2.003)	(1.932)	(2.433)	(2.301)	(2.903)	(2.555)	(2.444)	(2.286)
Implied Contract	0.006	0.005	0.011	0.007	0.011	0.010	0.008	0.005
	(1.040)	(0.941)	(1.227)	(0.956)	(1.547)	(1.459)	(1.121)	(0.855)
Public Policy	-0.011	-0.010	-0.009	-0.008	-0.013*	-0.013*	-0.010	-0.009
	(-1.332)	(-1.370)	(-1.076)	(-1.122)	(-1.799)	(-1.863)	(-1.187)	(-1.242)
Log(1 + Patent Stock)		0.005		0.010***		0.011**		0.008**
		(1.419)		(2.924)		(2.648)		(2.569)
Log(1 + R&D Stock)		0.012**		0.018***		0.013**		0.016***
		(2.578)		(3.382)		(2.160)		(3.101)
Log(Sales)		-0.004		-0.006		-0.002		-0.004
		(-0.920)		(-0.992)		(-0.379)		(-0.762)
Log(M/B)		0.001		0.002		0.003		0.004
		(0.122)		(0.387)		(0.666)		(0.829)
State GDP Growth		-0.033		-0.221**		-0.015		-0.173***
		(-0.492)		(-2.608)		(-0.175)		(-2.840)
State Political Balance		-0.017		-0.018		-0.005		-0.020
		(-0.727)		(-0.770)		(-0.208)		(-1.040)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,232	22,232	19,621	19,621	22,002	22,002	19,598	19,598
Adjusted R^2	0.414	0.415	0.411	0.412	0.357	0.358	0.434	0.435