Contingent Employment and Innovation[*]

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Abstract

Using novel indirect employment data and a Supreme Court ruling against subcontracted employment, this paper shows that contingent employment of skilled labor reduces innovation. Innovation increases after establishments convert subcontracted workers into direct hires compared to the establishments that did not use subcontracted workers before the ruling. The finding is without a simultaneous increase in operating leverage, R&D, and capital intensity and conditional on compensation schemes that reward employees for their investment in firm-specific skills and long-term performance. New hires do not innovate more. New inventors, including former subcontracted workers, create more and better patents, yet only through collaboration with existing inventors, who also create more and better non-collaborative patents. Furthermore, a positive spillover follows that innovation-associated voluntary employee departure increases.

JEL classification: J41, J46, L26, O31
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1 Introduction

Contingent employment has rapidly increased worldwide. As of 2015, it accounts for 15.8%[1] of the U.S. labor force, up from 10.7% in 2005 (Bureau of Labor Statistics (BLS), Katz and Krueger (2017), Katz and Krueger (2019a), Katz and Krueger (2019b)). Further, contingent workers make up an average of 43.3% of the labor force of 28 European Union countries (OECD Labor Force Statistics). Despite these trends, the implications of contingent employment on firm outcomes are not well understood. On one hand, contingent employment could afford benefits such as lower cost and greater flexibility in the use and reallocation of labor (Vandlen (2011)), which may help reduce operating leverage (Simintzi et al. (2015), Serfling (2016)) and fuel investment and growth (Bai et al. (2020)). On the other hand, it could incur costs. For example, a contingent contract may discourage employees from engaging in value-enhancing activities such as innovation, which typically require a long-term commitment.

Contingent work is an umbrella term that covers numerous non-permanent arrangements[2]. Contingent workers exist at all skill levels and range from low-skill ones such as janitors to high-skill ones such as lawyers and consultants. However, the present study focuses only on medium-skill workers such as temporary auto engineers[3], who barely fail to secure permanent positions. Such workers enter temporary contracts to effectively work on a permanent basis. They are offered and accept contingent contracts likely because outside options worsen in labor markets while the contracts still pay premiums as high as the cost of switching to other occupations. They may create (incremental) innovations.

This study asks whether contingent employment of skilled labor affects corporate innovation. I find that converting temporary contracts into permanent ones increases innovation output. This could be because contingent workers face excessive termination following short-term failure and have few rewards for long-term success (Manso (2011)); therefore, they are not incentivized to invest in firm-specific hu-

[1] 36% based on a 2015 Federal Reserve survey that uses a more expansive definition of contingent work (Brainard (2016)).

[2] Contingent employment may also be referred as alternative employment, nonstandard employment, atypical employment, shadow workforce, and phantom workforce (Belous (1989), Carré et al. (2000), Delsen (1995), Gleason (2006), Polivka (1996))

[3] For example, the Big Three U.S. automakers have used temps extensively since General Motors (GM) and Chrysler declared bankruptcy in 2009 and, starting in 2020, have been converting temps into permanent employees. The United Auto Workers agreed to the use of temps in 2009 before fighting against it a decade later. These two opposing decisions likely reflect the changes in market conditions and performance.

man capital (Acemoglu (1997), Lazear (2009)) and innovate. Subsequently, I show that the increase in innovation in incumbent businesses has positive spillover effects (Bloom et al. (2013), Babina and Howell (2018)).

Toward this end, I perform a quasi-natural experiment that combines three factors: a work arrangement unique in Korea, a Supreme Court ruling against this arrangement, and novel data on indirect employment. The first factor, i.e., the unique work arrangement, is in-house subcontracting. Studying in-house subcontracted (IS) workers mitigates the concern that the studied contingent workers may differ from regular employees in terms of not only their innovation incentive but also their skills, the tasks they are assigned, and their preference for flexible arrangements. Skills and tasks are likely similar because IS workers perform the same core tasks in the same workplaces as regular employees, hired when labor markets are relatively strong. Flexibility is unlikely a reason for entering into contingent contracts because IS workers work full-time. Such an arrangement is rare. In continental Europe, the equal-pay-for-equal-work principle precludes this arrangement. In the U.S., a similar arrangement exists (e.g., temporary auto engineers hired through staffing agencies). However, a clean shock against it and data on those hired via this arrangement[4] do not[5].

The second factor is the court ruling that provides IS workers with incentives for innovation. An advantage of this ruling is that it has little impact on the operating leverage. Managers might otherwise increase or reallocate the innovation input to reduce the reliance on labor via process innovation (Bena et al. (2021)). This, in turn, would make it challenging to distinguish between whether managers or employees account for changes in the innovation output. The ruling was not costly because it applied to only subcontracted workers who represented 10.6% of manufacturing employment in 2009, and it led firms to convert the IS workers into the lowest-paid regular employees. Moreover, because the court did not enforce immediate conversion, firms could negotiate with the IS workers to perform the conversion gradually as regular employees left or retired.

The third factor is the Workplace Panel Survey (WPS) data, which allows me to overcome two chal-

[4] The BLS does not count workers engaged for more than a year, including many of the auto temps, as contingent workers. Source: `https://www.bls.gov/news.release/conemp.tn.htm`.

[5] Even if they do, the employment-at-will doctrine leaves little variation in the dismissal risk between temporary workers and regular employees.

lenges. The first challenge is that the IS workers are indirect hires and are invisible in their users' data based on disclosure. The WPS makes them visible. It asks each establishment the same set of questions over time, including how many contingent workers it uses. The WPS survey includes different types of contingent workers, including four groups of indirect hires – subcontracted workers, dispatched workers, independent contractors, and day workers – and two groups of direct hires – fixed-term workers and part-timers. The data show that indirect hires (13.2%), including subcontracted workers (10.6%), represent a much greater share of manufacturing employment than direct hires (1.7%) as of 2009, thus demonstrating the worth of using the data for investigating contingent employment.

The second challenge is that businesses that use subcontracted workers may differ from those that do not in terms of other unobservable characteristics that may affect innovation output. The WPS data minimize this difference by randomizing the assignment of firms into treated and control groups. Specifically, the WPS surveys establishments that are randomly selected for each stratum, defined by industry, region, and size, and that are therefore similar in most observable aspects, even after the pre-ruling extent of contingent employment splits the sample. The data also contains information about innovation input (i.e., capitalized R&D) and output (i.e., capitalized patent costs, costs incurred to file for patents), various compensation schemes offered to employees and managers, and employees who join or leave establishments.

Using the difference-in-differences (DiD) method, I compare treated establishments that used subcontracted workers before the ruling with otherwise identical control establishments. I adjust for the treatment intensity, as measured by the share of subcontracted workers before the ruling, in the estimation of treatment effects. However, for supplementary firm-level tests that use patent details, I define the treatment crudely at the industry level[6] and perform propensity-score matching to construct a sample of treated and matched control firms that have similar observable characteristics[7]. Nonetheless, I consider the firm-level evidence to be suggestive at best given the possibility that the industry-specific time trends

[6] Because the WPS data anonymizes establishments, it cannot be merged with other data, and I cannot use the information on indirect hires available in the WPS data to define treatment at the firm level. Alternatively, I define treated firms as firms in four manufacturing industries that heavily used IS workers before the ruling and control firms as firms in 20 other manufacturing industries. Section 4.2 describes the industry-level definition of treatment in greater detail.

[7] Section 4.3 describes the matching procedure.

that I fail to fully control for influence the estimated treatment effects. Patent details are obtained from the Korean Intellectual Property Office (KIPO) and Google Patents.

I first confirm the effect of the ruling on employment and innovation. Subcontracted employment decreases by 1.3 percentage points and regular employment increases by 1.02 percentage points for treated establishments that used 1 percentage point more subcontracted employment before the ruling compared to control establishments after the ruling. Five other classes of contingent employment show little change. I subsequently show that innovation output measured by capitalized patent costs increases both in level (7.31 percentage points or roughly by the amount to file for three patents) and per human capital input measured by wage expenditure. At the firm level, the number of patents increases for treated firms compared to that for control firms after the ruling. The results are robust to alternative treatment definitions, alternative post-ruling periods, and stratum-based fixed effects.

The results support a causal interpretation for several reasons. First, I find no evidence of pre-treatment trends in subcontracted employment and innovation output, thus satisfying the identifying assumption of the DiD estimation. Second, I use a random sample of treated and control establishments with no statistically significant pre-ruling difference in their characteristics other than (more) subcontracted employment, (less) regular employment, and (less) innovation output[8]. The univariate evidence suggests that treated establishments used the IS workers as substitutes for regular employees and simultaneously produced less innovation output than control establishments before the ruling.

Third, I include a battery of fixed effects to control for time-invariant establishment characteristics, time-varying industry characteristics, and time-varying province characteristics that may affect employment and innovation[9]. I also include cohort-specific year fixed effects to compare establishments in the same foundation-year vintage over time. Fourth, for firm-level tests, to alleviate the concern that firm-

[8]Treated establishments were also more likely unionized, a potential reason for IS employment. Thus, I control for unionization in every estimation, although the unionization likelihood evolves no differently between treated and control establishments after the ruling.

[9]The time-invariant establishment characteristics include characteristics of the CEO (Galasso and Simcoe (2011), Hirshleifer et al. (2012), Sunder et al. (2017), Custódio et al. (2019), Custódio et al. (2019)), the board of directors (Balsmeier et al. (2017)), and investors (Aghion et al. (2013), Brav et al. (2018), Guadalupe et al. (2012)). The time-variant industry characteristics include competition (Aghion et al. (2005), Aghion et al. (2018)), investment cycle (Nanda and Rhodes-Kropf (2013), Nanda and Rhodes-Kropf (2017)), and innovation waves (Dicks and Fulghieri (2021)). The time-varying region characteristics include bank distress (Cornaggia et al. (2015)) and taxes (Mukherjee et al. (2017)).

level results are driven by *ex-ante* differences in unobservable characteristics between treated and control firms, I select control firms based on a matching algorithm. I implement the nearest neighbor plus radius matching and construct a sample of treated and matched control firms that are similar across several observable characteristics.

When it comes to channels, I find evidence consistent with the Manso (2011)'s innovation-motivating incentive scheme. I measure the long-term rewards by merit pay, with which employees can negotiate the next year's salary based on their performance this year. I then show that the increase in innovation output is largely conditional on the long-term rewards in place. Further, it is driven by treated establishments that offer basic pay based on skills rather than seniority or function and that therefore reward employees for their investment in firm-specific human capital. In contrast, the increase in innovation output is unassociated with equity-based incentive schemes such as stock options that are more likely to motivate executives (Lerner and Wulf (2007)) and high-skill non-executive employees (Chang et al. (2015), Core and Guay (2001)).

I then show that the costs of the ruling, or lost benefits of contingent employment, are not high. Wage expenditure per employee increases slightly, with a 10%-level statistical significance; however, the total wage expenditure per sale does not increase. Labor flexibility, whose effects are measured by financial leverage (Simintzi et al. (2015)), also shows little change. I do find that the operating leverage increases to crowd out financial leverage. In addition, I do not find a decrease in labor productivity, which may happen if a high risk of termination induced the IS workers to work harder before the ruling. Perhaps because the ruling was not too costly, R&D expenditure and capital intensity do not increase[10]. Overall, the results suggest that contingent employment of skilled labor incurs the cost of less innovation for unclear benefits.

These findings bring into question the reasons why managers use contingent contracts to hire skilled labor in the first place. One testable possibility is managerial myopia (Stein (1988)). Because it takes years to create and operationalize innovations, managers may rationally focus on meeting short-term targets. Edmans (2009) also argues that managers may underinvest in intangible assets because they are invisible

[10] R&D expenditure rather declines, presumably because innovation output is greater per unit expenditure on R&D.

to outsiders and thus do not improve the stock price. I define establishments that have positive foreign ownership or foreign investors as the largest shareholders as those that are less prone to managerial myopia (Bena et al. (2017)). I then show that, after the ruling, innovation increases only for the treated establishments that are more likely to have myopic managers compared to otherwise similar treated establishments and control establishments.

Regarding who innovates, apart from IS workers, three groups of employees may innovate for reasons other than the ruling's impact on innovation incentives: new hires, existing inventor employees, and existing noninventor employees (i.e., inventors who have never invented before the ruling). I do not find that new hires innovate more. New inventors, including former IS workers and existing noninventor employees[11], create more and better patents. The patent quality is measured by the number of citations per patent for three subsequent years. However, the improvement is limited to collaborative patents with existing inventors, who are not newly incentivized but have experience of creating and patenting innovations. Existing inventor employees make more and better non-collaborative patents as well.

Lastly, I find evidence of a spillover effect (Bhide (2000), Burton et al. (2002)). Voluntary employee departure increases for treated establishments compared to control establishments after the ruling. This increase is positively and statistically significantly associated with a change in innovation output. Some employees depart voluntarily to create startups or join other firms including startups. Placebo tests show that involuntary departure does not increase. Further, the change in involuntary departure is not associated with the change in innovation output. The primary reason for involuntary departure is retirement. With regard to who leaves, I show that new inventors leave by only creating patents assigned to startups in subsequent years[12]. However, new inventors leave only after creating collaborative patents with existing inventor employees, who also leave after creating non-collaborative patents.

This study contributes to several strands of the literature. To my knowledge, it is the first paper to examine the effects of contingent employment on innovation or a long-term firm outcome in general[13].

[11] These two groups cannot be distinguished further in the absence of information on how firms connect through subcontracts. However, because existing noninventor employees are neither newly incentivized nor experienced to create and patent innovations, IS workers are likely responsible for changes in innovation quantity and quality.

[12] Section 4.2 defines a startup as a firm that is too small, with annual sales of $1 to $12 million (the threshold varying by sector) or less, not to file audit reports.

[13] Hahn et al. (2020) investigates cash. It shows that contingent employment enhances the bargaining power of firms against

Second, it is the first to empirically establish that Manso (2011)'s innovation motivating incentive scheme also applies to employees. This scheme has been proven to govern managers in different contexts (see, e.g., Ederer and Manso (2013), Tian and Wang (2014), Baranchuk et al. (2014)). This study shows that even the lowest-paid employees innovate as incentivized, compensating for their shortage of experience through collaborations with existing inventor employees.

Third, this study adds to the small literature that examines innovation by rank-and-file employees. Previous studies examine stock options that incentivize a team of employees (Chang et al. (2015), Hsieh et al. (2022)) who are likely at the top of the skill spectrum. In contrast, this study examines employees at the bottom of this spectrum. It shows that the basic pay element that rewards individual employees for their acquisition of firm-specific skills encourages rank-and-file employees to innovate. Many studies have already examined innovation led by managers (e.g., Hirshleifer et al. (2012), Sunder et al. (2017), Custódio et al. (2019), Faleye et al. (2014), Mao and Zhang (2018)).

This paper is also related to environmental, social, and governance literature that views employees as human capital that creates value in the long run rather than a cost center. For example, Chen et al. (2016) shows that firms that treat employees well produce more and better patents. Further, Edmans (2011) shows that employee satisfaction is positively correlated with shareholder returns and need not represent managerial slack.

2 Contingent employment

2.1 Definition and classification

Contingent work is an umbrella term that covers numerous non-permanent arrangements. This term is useful because a wide variety of such arrangements exist, and their definitions and boundaries vary over time across countries. Contingent workers differ broadly in terms of their skill, hirer (as opposed to user), and voluntariness. They include low-skill workers such as cleaners and high-skill workers like lawyers and consultants. They may be hired directly (e.g., fixed-term workers and part-timers) or indirectly through

the union and thereby allows managers to raise cash holdings, of which the union will claim less when it has weaker bargaining power.

staffing agencies. They may voluntarily enter contingent arrangements to maximize income by selling their skills to multiple firms (e.g., freelancers) or are forced into contingent arrangements as labor market condition worsens.

The rise of the contingent workforce is likely an outcome of both increased demand and supply. On the demand side, the cost of contingent employment has declined as technologies advance to standardize tasks, lower the cost of coordinating tasks, and facilitate the monitoring of employees, often in real time. At the same time, the supply of a well-educated workforce has increased, thereby lowering its wage and bargaining power in labor markets. As a result, firms increasingly slide the production process into smaller pieces, have more of them contracted out, and produce end-products by paying closer to the marginal product of labor.

2.2 Contingent employment of skilled labor

This study focuses on medium-skill workers who are forced into temporary contracts to work on a permanent basis. They may be hired directly (e.g., adjunct professors) or indirectly (e.g., auto engineers). They exist by being offered and accepting contingent contracts, likely because outside options worsen in labor markets while contingent contracts still pay premiums as high as the cost of switching to other occupations. Contingent employment of skilled labor is on the rise, particularly in professions that require sector-specific skills and thus incur high switching costs. Importantly, skilled workers are likely able to innovate and, as marginal contingent workers, are the most sensitive to dismissal risk and long-term rewards in their choice of whether to invest in firm-specific human capital and innovate.

As an example, consider the temporary auto engineers of GM. They reportedly perform the same core tasks as the company's regular employees and work for an average of four years. However, they are hired indirectly through staffing agencies and are therefore paid less and receive fewer benefits than regular employees. Because of United Auto Workers's nationwide strike against GM in 2019, GM's temporary workers who had at least three years of service were converted to permanent employees starting in 2020[14]. Ford Motor and Fiat Chrysler Automobiles followed suit. However, BLS does not count them

[14] https://www.usatoday.com/story/money/2020/01/08/gm-workers-temporary-uaw-permanent/

as contingent workers because it defines contingent work as lasting for one year or less. These temporary auto workers who have substituted for permanent hires may innovate. Charles et al. (2019) document trends in the U.S. of both capital and skill deepening within the manufacturing sector. As capital intensity increases, manufacturing industries have shifted toward a higher-skilled workforce, and the share of employees holding a bachelor's degree or higher has increased more in manufacturing industries than in other sectors.

2.3 In-house subcontracted workers

This study focuses on a contingent arrangement called IS employment. Like GM's temporary auto engineers, IS workers allegedly perform the same tasks as regular employees in the same workplace and work on a permanent basis. The average tenure of IS workers in the automobile industry is 4.2 years[15]. However, IS workers differ from the U.S. agency temps in two ways. First, IS workers bear a starkly greater risk of termination than their regular colleagues who barely get fired in Korea. In the U.S., the risk of termination is much less dissimilar between temporary and regular employees because they are both employed at will. The primary difference between the two is pay and benefits. Second, IS workers are hired through in-house subcontractors instead of staffing agencies.

The in-house subcontractors are often created for the sole purpose of hiring IS workers for the main contractor, who demands labor flexibility. In Korea, because a firm cannot fire regular employees unless it goes bankrupt, firms that require labor flexibility extensively use IS workers who can effectively be fired by terminating subcontracts. A common approach is to ask senior employees who are loyal to a firm and close to retirement age to create subcontractors. If the firm terminates subcontracts to reduce labor and consequently shuts down subcontractors, the former senior employees either recreate subcontractors as separate business entities or return to the firm. In 2006, Wonsik Woo, a then lawmaker, discovered that at least 70% of subcontractors of Hyundai Motors Company (HMC) were run by its former employees[16].

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[15] `https://news.joins.com/article/10420656`; this is the lower bound because multiple in-house subcontractors reportedly hire the IS workers while they work for the same main contractor.

[16] Cite the article

3 Research Design

3.1 Supreme Court ruling against contingent employment

On July 22, 2010, the Korean Supreme Court ruled that IS workers were misclassified and must be treated as regular employees of the main contractor[17]. Table 1 lists key developments regarding the HMC case in chronological order. The key legal issue was whether the IS workers were supervised by the main contractor. If supervised and used for more than two years, they are regular employees of the main contractor[18]. If unsupervised, they are employees of subcontractors who independently perform subcontracted tasks in the main contractor's workplaces. The Supreme Court added that the main contractor's supervision was inevitable in workplaces that involved conveyor belts and therefore required close communication between managers of the main contractor and employees, including the IS workers, as Figure 1 illustrates.

Therefore, I define establishments that used IS workers before the ruling as treated establishments and those that did not as control establishments and compare their post-ruling outcomes. In doing so, I adjust for the pre-ruling extent of IS employment, which will determine the intensity of treatment effects. When I use firm-level data that lacks information about IS employment, I inevitably define treated and control firms at the industry level. While I carefully implement a matching algorithm to select control firms and confirm covariate balance and the absence of pre-trends in outcome variables, firm-level results are at best suggestive. To identify treated firms without IS employment data, I rely on the fact that labor experts, data, surveys, and lawsuits all note four manufacturing industries as the ones that were most hit by the ruling.

First, labor experts concluded that the ruling affected not only the firm that was sued, HMC, but also the four manufacturing industries that heavily used both conveyor belts and IS workers. Second, Figure 2, Panel A confirms that these four industries are the heaviest users of IS workers. Third, a 2008 Survey on In-House Subcontracting published by the Ministry of Employment and Labor (MOEL) finds that these

[17] Appendix B provides details of the ruling.

[18] The Korean labor law (i.e., Article 6.2, the Act on the Protection, etc. of Dispatched Workers) forbids firms from using labor under contingent contracts for more than two years. A similar prohibition exists in most OECD member countries, with the threshold length varying from two to three years.

four industries were the heaviest users of IS workers[19]. Fourth, a series of lawsuits followed in the four industries and concentrated on the automobile industry[20]. I define all firms in the four industries as treated firms and all firms in 20 other manufacturing industries as control firms. The control industries include electronics, fabricated metal products, chemicals, rubber and plastic products, and pharmaceuticals.

3.2 Ruling as a shock on innovation incentive of IS workers

The primary advantage of the ruling as a shock on the innovation incentives of employees is that the ruling had a minimal impact on wage expenditure and operating leverage. Otherwise, managers may have increased or reallocated innovative resources to raise the capital intensity. Any change in innovation output can then be due to either managers or employees. The ruling was not costly because only 10.6% (i.e., IS workers' 2009 share of manufacturing employment (see Table 2)) were switched to permanent status, where firms converted the IS workers into the lowest-paid regular employees[21] and negotiated with the IS workers to convert them to direct hires whenever vacancies (e.g., owing to the retirement of regular employees) were available. For example, HMC converted approximately 6,000 IS workers into permanent ones by 2017, with a plan to hire an additional 3,500 by 2021.

The ruling has both an advantage and a disadvantage compared with other shocks that are commonly used in the literature. The advantage is the low monetary cost. Other shocks such as labor law changes and unionization apply to all regular employees (e.g., 85.1% of the 2009 manufacturing employment in Korea), including top innovators who are insensitive to dismissal risk, given their superior outside options, but who add much to the operating leverage. The disadvantage is that conversion was gradual rather than immediate, and so was the treatment effect.

The ruling was unexpected. Such a ruling against contingent employment of skilled labor was the first

[19]The survey reports that the percentage of firms employing IS workers is 100% for the other transport equipment industry represented by shipbuilders, 92.6% for the metal product industry represented by steelmakers, 86.4% for the automobile industry, and 72.5% for the machinery and equipment industry (Eun et al. (2011))

[20]Completed cases are as follows. The Supreme Court ruled against General Motors Korea on February 28, 2013, which is the first criminal case; the Suwon District Court against Ssangyong Motors on November 29, 2013 (`http://www.redian.org/archive/63371`); the Seoul Central District Court against Kia Motors on September 25, 2014; the Gwangju High Court against Kumho Tire on April 24, 2015; and the Gwangju High Court against POSCO on August 17, 2016.

[21]For example, the total cost of conversion is estimated to be 6% of the net income for HMC; `http://www.pressian.com/news/article?no=107847`.

of its kind in the country's modern history. Also, it was against the country's second-largest conglomerate led by HMC, which could allegedly influence the judiciary. Further, the ruling is an outcome following two consecutive losses, as Table 1 shows. As such, any pre-ruling differences between treated and control establishments are unlikely to reflect the ruling's expected effects. Google search records corroborate that the ruling was unexpected. Internet Appendix Figure IA1 shows that they paid little attention to IS employment before the ruling, whereas their attention spiked sharply in July 2010, the month of the ruling. I collected data on Google's search volume index (SVI) for the terms "in-house subcontracting (in Korean)" from January 2010 (year of treatment) to December 2017 (last year of sample period) and plotted the index over months. Google's SVI has been shown to be a useful measure of public attention in several contexts (e.g., Boguth et al. (2019), Da et al. (2011), Hwang et al. (2018)).

3.3 Model specification

By using the DiD framework and establishment-year panel, I estimate the treatment effect of the ruling on outcomes such as employment and innovation. Specifically, I estimate the following specification.

$$Y_{i,t} = \alpha_i + \beta \tilde{Treat}_i \times Post_t + \gamma' \mathbf{X}_{i,t} + \lambda_{j(i),t} + \delta_{r(i),t} + \varphi_{c(i),t} + \eta_{u(i),t} + \epsilon_{i,t} \quad (1)$$

where i indexes establishment, $j(i)$ the industry establishment i belongs to[22], $r(i)$ the province establishment i is located in, $c(i)$ the foundation-year cohort of establishment i, $u(i)$ the business unit of establishment i, and t the number of years after the ruling. The reference year is t = -1, a year before the ruling. $Y_{i,t}$ is an outcome of interest of establishment i in year t.

$Treat_i$ is an indicator of establishment i being treated. It takes the value of one if establishment i uses subcontracted workers before the ruling (i.e., from 2007 to 2009) and zero otherwise. $\tilde{Treat}_i$ is $Treat_i$ multiplied by the average share of subcontracted workers in the employment of establishment i before the ruling (i.e., from 2007 to 2009)[23]. The share proxies for treatment intensity and adds a flavor

[22] Industries follow the Korean Standard Industry Classification that is as granular as the two-digit U.S. Standard Industry Classification (SIC).

[23] I use the 2007-2009 average to mitigate a concern that a 2009 figure may under- or overstate the subcontracted employment, which varies over time. For the pre-ruling period, the percentage of subcontracted workers has a mean of 5.66% and a within-establishment standard deviation of 4.09%.

of a Bartik shock (Goldsmith-Pinkham et al. (2020). $Post_t$ is an indicator of the period starting two years after the ruling. It takes the value of one for $t \geq 2$ and zero otherwise. I choose two years as it takes time for employees to innovate and for the treatment, or the gradual conversion of subcontracted workers to permanent ones, to have an impact on $Y_{i,t}$. $X_{i,t}$ is a vector that collects the characteristics of establishment i in year t, including the establishment size, profitability, capitalized R&D, wage expenditure, per-employee wage, capital intensity, financial leverage, and union (Bradley et al. (2017)). Table A1 defines all variables. β is the coefficient of interest and captures the treatment effect.

α_i is the establishment fixed effect, and it controls for time-invariant establishment characteristics that may affect innovation output. $\lambda_{j(i),t}$ is the industry-specific year fixed effect, and it controls for time-varying industry characteristics that may affect employment and innovation. $\delta_{r(i),t}$ is the province-specific year fixed effect, and it controls for time-varying regional characteristics. $\delta_{r(i),t}$ further controls for changes in local economic conditions and government policies regarding innovation. $\varphi_{c(i),t}$ is the cohort-specific year fixed effect; it ensures that establishments in the same foundation-year vintage are compared over time. The nature, policy, and practice of innovation may be fundamentally different between an old cohort of Microsoft and Apple and a young cohort of Google and Facebook within the same information technology industry. $\eta_{u(i),t}$ ensures that single- and multi-unit establishments are compared over time as separate groups of innovators. Standard errors are clustered by establishment to control for a potential serial correlation in $Y_{i,t}$(Bertrand et al. (2004))[24].

Further, I estimate the leads-and-lags model below, which is introduced by Autor (2003) and recommended by Atanasov et al. (2016). This model allows one to evaluate the identifying assumption of the DiD estimation that outcome variables evolve in parallel between treated and control establishments before the treatment.

$$Y_{i,t} = \alpha_i + \sum_{\tau=-5,\tau\neq-1}^{7} \beta_\tau \tilde{Treat_i} \times \mathbb{1}[t=\tau]_t + \gamma' \mathbf{X}_{i,t} + \lambda_{j(i),t} + \delta_{r(i),t} + \varphi_{c(i),t} + \eta_{u(i),t} + \epsilon_{i,t} \quad (2)$$

[24] A related concern with the grouped error terms is that the unit of observation (i.e., establishment) is more detailed than the level of variation (i.e., industry) (Donald and Lang (2007)). However, in unreported analyses, I find that the main results are robust to standard errors clustered by stratum.

where $\mathbb{1}[t = \tau]_t$ is an indicator of τ years after the ruling; it takes the value of one if $t = \tau$ and zero otherwise. Other variables are defined as above. β_τ are the coefficients of interest. The failure of rejecting $H_0 : \beta_\tau = 0$ for $\tau < 0$ satisfies the identifying assumption of the DiD estimation and permits a causal interpretation of the treatment effect. The rejection of $H_0 : \beta_\tau = 0$ for $\tau \geq 0$ implies the presence of the treatment effect, and the magnitude of β_τ varying in τ indicates the dynamics of the treatment effect.

For the tests that use the firm-year panel instead, I estimate the following. The key difference from the establishment-level DiD estimation is that I define treatment at the industry level. Thus, I do not adjust the estimation of treatment effects for the pre-ruling intensity of subcontracted employment, which I do not observe at the firm level, and do not include industry-specific year fixed effects.

$$Y_{i,t} = \alpha_i + \beta Treat_{j(i)} \times Post_t + \gamma' \mathbf{X}_{i,t} + \delta_{r(i),t} + \varphi_{c(i),t} + \epsilon_{i,t} \tag{3}$$

where i indexes firm, $j(i)$ the industry firm i belongs to, $r(i)$ the province firm i is headquartered in, $c(i)$ the foundation-year cohort of firm i, and t the number of years after the ruling. $Y_{i,t}$ is an outcome of interest for firm i in year t. $Treat_{j(i)}$ is an indicator that takes the value of one if firm i belongs to one (resp. zero) of the four treated (resp. 20 control) manufacturing industries a year before the treatment. $Post_t$ is an indicator of the period starting one year after the ruling; it takes the value of one for $t \geq 1$ and zero otherwise. I pick one year (for firm-level tests) in place of two years (for establishment-level tests) because I use dates of the patent application, which might happen even in a few months after the July 2010 ruling, rather than dates of patent grant[25]. On average, a year and a half are required in Korea for a patent applied to be granted.

$X_{i,t}$ is a vector that collects the characteristics of firm i, including firm size, profitability, expensed R&D, wage expenditure, capital intensity, and financial leverage, in year t. It excludes per-employee wage and the union because they are incomplete and unavailable in the firm-level data. Table A1 defines all variables. β is the coefficient of interest and captures the treatment effect. α_i is the firm fixed effect, $\delta_{r(i),t}$ is the province-specific year fixed effect, and $\varphi_{c(i),t}$ is the cohort-specific year fixed effect. Standard errors

[25]Unreported analyses confirm that the choice of the first treatment year has little impact on the estimated treatment effects on innovation and innovation-associated employee departure because they rise over time and are greater for later years.

are clustered by the firm to control for a potential serial correlation in innovation. I augment Equation 3 with leads and lags, as in Equation 2 compared to Equation 1, and estimate the specification to evaluate the absence of pre-ruling trends in $Y_{i,t}$.

4 Data

4.1 Establishments

The primary dataset is obtained from the Korea Labor Institute (KLI)'s WPS, which biennially surveys a stratified sample of establishments that hire 30 or more regular employees. At the time of this writing, data from 2005 to 2017 is available. A stratum is defined by 12 industries, five regional groups, and four employment size groups from 2005 to 2013. From 2015 to 2017, it is defined by 10 industries and four employment size groups. Internet Appendix Table IA1 lists the 12 and 10 industries. The five regional groups are Seoul, Gyeonggi/Incheon, Gangwon/Chungcheong, Jeolla/Jeju, and Gyeongsang, which span nine provinces and eight special cities in Korea. These four size groups comprise establishments that hire 30-99, 100-299, 300-999, or 1000 or more regular employees, respectively.

The information collected via surveys is used to code a wide range of variables regarding indirect and direct employment, innovation input and output, compensation, human capital inflow and outflow, union, financial performance, etc. Because the KLI surveys a small number (1,905 in the first sampling year of 2005) of establishments that are randomly selected within each stratum, it can ask hundreds of questions. The WPS establishment-year panel is downloadable from the KLI's website[26]. A shortcoming of the data is that it cannot be merged with other datasets at the establishment or firm level because the KLI anonymizes establishments before disclosing the panel. Appendix B describes the WPS data in greater detail.

This study utilizes three broad categories of variables about employment, innovation, pay structure, and human capital flows. The variables on employment include the number of four classes of indirect hires and three classes of direct hires used by each establishment. The direct hires include fixed-term work-

[26] `https://www.kli.re.kr/wps`.

ers, part-timers, and regular employees. The indirect hires include subcontracted workers, dispatched workers, independent contractors, and day workers. The subcontracted workers include both IS workers and outsourced workers such as janitors and cleaners. However, because the ruling has a direct impact only on IS workers and because it is unclear how the ruling may have an indirect impact on the outsourcing of low-skill labor, any changes in subcontracted employment are attributed to changes in IS employment. Notably, variables on indirect employment are unique in this survey-based data from the WPS.

The variables on innovation include capitalized patent costs, which I use to measure the innovation output, and capitalized R&D, which I use to measure the innovation input. The capitalized patent costs are incurred to obtain intellectual properties (IPs), including patents, utility rights, design rights, and trademarks. However, because patents are the largest in number[27] and are the most expensive to obtain and maintain[28], I use the capitalized patent costs as a proxy for the number of patents. The variables on pay structure include indicators for merit pay, basic pay by skill, basic pay by seniority, basic pay by function, ESOP, and stock options. With merit pay in place as a pay component, employees can negotiate their next year's salary based on their performance this year.

The variables on human capital inflow and outflow include the number of new hires with and without relevant experiences, the number of regular employees who leave voluntarily to join other businesses or create ones on their own, and the number of regular employees who leave involuntarily to retire. I use the inflow variables to study potential innovation by new hires and the outflow variables to examine possible spillover effects. In the WPS, reasons other than startup creation for voluntary departure include education, childcare, and health issues; these appear to have little to do with the ruling. As such, I assume that voluntary departure is mainly due to startup creation. A reason for involuntary departure other than retirement is dismissal, which happens only in limited circumstances such as business failure in Korea. Because the WPS surveys continuing businesses only, I attribute involuntary departure to retirement.

[27] As of 2009, patents account for 51% of the IPs in manufacturing, followed by trademarks (28%), design rights (12%), and utility rights (9%) (source: Korean Statistical Information Service).

[28] The KIPO's website provides the cost of filing for each IP.

4.2 Firms

To construct the firm-year panel, I combine financial statement information from TS2000 and patent details from KIPO and Google Patents. TS2000 is a database administered by the Korea Listed Companies Association (KLCA). The KLCA collects information of all publicly traded firms and privately held firms that file audit reports with the Financial Supervisory Service (FSS) through its Data Analysis, Retrieval and Transfer (DART) System[29]. I define firms that are too small not to file annual audit reports as startups[30]. TS2000 is comparable to Compustat in the U.S. The FSS and its DART system are comparable to the U.S. Securities and Exchange Commission and its Electronic Data Gathering, Analysis, and Retrieval system. The sample period is from 2005 to 2017, consistent with the establishment-year panel.

I then merge the firm-year panel with the patent data. In doing so, I use the application date of patents, which is the closest to the actual moment of innovation (Griliches (1998)), application number of patents to combine KIPO and Google Patents data, and unique identifiers (i.e., business registration numbers available from both KIPO and TS2000) of corporate assignees to merge the patent data into the firm-year panel. I use Google Patents to augment the patent data because KIPO is not as comprehensive as Google Patents when it comes to citations. Google Patents keeps track of citations made to and received by patents across more than 100 patent offices worldwide; cross-border citations account for approximately 80% of citations of domestic, or KIPO-filed, patents in the Google Patents data. Internet Appendix Figure IA2 presents the information Google Patents puts together and displays for an arbitrary patent in Panel A and the information Google Patents returns for a search query based on the name of an inventor of the arbitrary patent in Panel B.

To inspect who innovates after the ruling, I also compute patent-based metrics separately for new and existing inventors. I define new inventors as inventors of a firm in a given year who create their first patents assigned to the firm and existing inventors as inventors for whom it has been more than three

[29]Korean commercial law requires that privately held firms that are incorporated in Korea and that satisfy two of the following four conditions file audit reports annually. The four conditions are total assets $\geq$ \$12 million, total liabilities $\geq$ \$7 million, sales $\geq$ \$10 million, and the number of employees $\geq$ 100 at the end of the prior fiscal year. I assume an exchange rate of KRW 1,000 to USD 1 throughout this paper.

[30]It is close to the legal definition of small firms. Article 8.1, Enforcement Decree of the Framework Act on Small and Medium Enterprises defines a small firm as a firm whose annual sales are below a threshold that varies by sector from \$1 million to \$12 million.

years since they created their first patents assigned to the firm. The assumption is that an inventor who assigns a patent to a firm is its employee. There are two limitations. First, without information on sub-contractual relations between firms, I cannot distinguish former IS workers and existing employees who have never invented before in the post-ruling group of new inventors. Second, without unique identifiers of inventors, a distinction between new and existing inventors that relies only on their names is noisy to some extent.

4.3 Propensity score matching

Unlike establishments drawn from each stratum to comprise treated and control groups, firms in treated and control industries can be systematically different. In other words, because I exploit industry-level variation in firm characteristics, unobservable pre-ruling industry differences may generate a differential impact on treated and control firms in their post-ruling choices of employment and innovation. To alleviate this concern, I execute the nearest neighbor and radius matching and construct a sample of treated and matched control firms that are similar across several observable firm characteristics.

First, I estimate the likelihood of treatment (i.e., propensity score) using all dependent variables (i.e., innovation output measures) and control variables as predictors of the treatment a year before the treatment. Second, for each treated firm, I select a control firm whose propensity score is the closest to that of the treated firm within a standard-deviation radius of propensity scores. In doing so, I allow for a control firm to marry more than one treated firm (i.e., matching with replacement). The sample excludes treated firms that fail to find matches. This procedure yields a sample of 2,272 treated and 2,272 control firms, respectively.

4.4 Descriptive evidence and covariate balance

Table 2 exhibits a snapshot of the manufacturing employment in 2009, a year before the ruling. All figures are estimated using the WPS probability weight, in other words, using observations weighted by the inverse of their probabilities of being sampled. There are three notable observations. First, indirect employment accounts for 13.2% of manufacturing employment. The figure may still understate indirect employment if other atypical arrangements exist that do not fall into one of the four indirect hire categories. Second, 13.2% is 7.8 times greater than the value of 1.7% for direct employment of contingent labor. This observation proves the worth of the WPS data in studying the contingent workforce, who are primarily indirect hires. Third, subcontracted workers account for 10.6% and make up the second-largest group following regular employees. The estimated treatment effects will be the effects of converting these 10.6% of workers to permanent employees.

Table 3 shows a comparison of the characteristics of treated and control establishments a year before the ruling. Column (5) reports the difference in means of their attributes computed within each stratum. Because establishments are randomly chosen to comprise each stratum, the treated and control establishments are expected to be similar across most characteristics even though subcontracted employment divides the sample. Column (5) shows that they are indeed similar but have two notable differences. First, on average, treated establishments used 12% more subcontracted employment and 15% less regular employment than control establishments, while differences in other employment categories are insignificant. The observation suggests that subcontracted workers might substitute for regular employees before the ruling.

Second, treated establishments produce significantly fewer innovations than control establishments on average. I measure innovation output by the log of one plus capitalized patent costs or capitalized patent costs divided by wage expenditure. The univariate evidence suggests the possibility that establishments that hire skilled labor under contingent contracts tend to innovate less than otherwise identical establishments that use them under permanent contracts. Internet Appendix Table IA2, Panel A reports the unconditional summary statistics of the establishment characteristics.

Similarly, Table 3 shows a comparison of the characteristics of treated and matched control firms a year before the ruling. The table shows that they are similar across several observable characteristics, which I use as dependent and control variables and predictors of the treatment. Internet Appendix Table IA2, Panel B reports unconditional summary statistics of firm characteristics.

They also differ by unionization rate, which can be a reason for IS employment. Approximately half (49%) of treated establishments have unions, whereas only 14% of control establishments do. The difference in unionization rates is large (29%) and significant at the 1% level. However, I argue the ruling is unlikely to affect unionization and, in turn, innovation output. On the extensive margin, managers cannot readily remove or weaken unions in response to the ruling, even if the ruling leads to a decline in labor flexibility and a rise in operating leverage. Unreported analyses show the difference in unionization likelihoods remains constant between treated and control establishments after the ruling. On the intensive margin, the ruling is unlikely to raise the bargaining power of unions because unions are solely composed of regular employees and, as it turns out, regular employment does not increase after the ruling. Still, in every estimation, I control whether an establishment has a union in a given year.

5 Results

5.1 Employment

Table 4 confirms the effect of the court ruling on employment. The dependent variables are the share of six classes of contingent employment in columns (1)-(6), the share of regular employment in column (7), and the log of one plus total employment in column (8). The six classes of the contingent workforce are subcontracted workers, dispatched workers, independent contractors, day workers, fixed-term workers, and part-timers, respectively. The first four classes are indirect hires. The latter two classes are direct hires. Column (1) shows that subcontracted employment declines by 1.35 percentage points after the ruling for the establishments that used subcontracted employment 1 percentage point more compared to those that did not use subcontracted employment before the ruling.

However, columns (2)-(6) indicate that unaffected classes of contingent employment show little change. These results also hold in the extensive margin as shown in Internet Appendix Table IA3, columns (1)-(6). The scale of subcontracted employment decreases by 15.3%, which is comparable to the average pre-ruling subcontracted employment of 12% in Table 3. The scale of other classes of contingent employment shows little change.

Table 4, column (7) shows that regular employment increases by 1.02 percentage points for seven years following the ruling for the establishments that used subcontracted employment 1 percentage point more compared to those that did not use subcontracted employment before the ruling. However, the scale of regular employment has not increased significantly, as shown in Internet Appendix Table IA3, column (7). The absence of an extensive margin effect is consistent with IS workers replacing regular employees only when the latter retire or leave. Table 4, column (8) indicates that total employment show little change.

Overall, the employment results suggest the following. First, the ruling indeed affected only IS workers and made them replace regular employees. Second, IS workers are substitutes for regular employees, consistent with the univariate evidence presented in Table 3. Third, IS workers are a skilled workforce who could be replaced neither by other classes of low-skill workers nor by machines, in which case total employment might decline.

Figure 3 illustrates the treatment-intensity-adjusted difference in employment over time between treated and control establishments. Panel A shows that, before the ruling, the number of subcontracted workers varies in parallel between treated and control establishments. However, after the ruling, it is significantly smaller for treated establishments than for control establishments. The absence of the pre-ruling trends validates the DiD estimation design and allows for a causal interpretation of the post-ruling difference as the consequence of the ruling. The figure also shows that subcontracted employment declines gradually after the ruling, which is consistent with the gradual conversion of IS workers into direct hires.

Panel B shows that other classes of contingent employment do not exhibit such a pattern. The top-left subpanel shows that the percentage of subcontracted employment decreases only after the ruling, as in the case shown in Panel A. However, other subpanels show that the difference in the percentage of the five other classes of contingent employment is largely constant over time both before and after the ruling between treated and control establishments. Internet Appendix Table IA4, columns (1)-(7) report the coefficient estimates from the leads-and-lags model in Equation 2 that the figure plots.

5.2 Innovation

Table 5 reports the treatment effects on innovation output. Innovation output is measured by the log of one plus capitalized patent costs in column (1) and capitalized patent costs per wage expenditure (i.e., on a per-input basis) in column (2). Capitalized patent costs include the costs incurred to file for patents and the wage expenditure proxies for human capital input. Column (1) shows that innovation output increases after the ruling by 7.31 percentage points for the establishments that used subcontracted employment 1 percentage point more compared to those that did not use subcontracted employment before the ruling. Column (2) shows that innovation output also increases per human capital input, while the coefficient on the interaction term is marginally significant at the 10% level.

Columns (3) and (4) use the firm-year panel, which includes the number of patents a firm creates each year. Because the panel lacks information on indirect employment, I define treated firms based on their affiliation to the manufacturing industries that heavily used subcontracted workers before the ruling, as discussed in Section 3.1, and choose control firms from other manufacturing industries via a combined procedure of the nearest-neighbor and radius matching, as discussed in Section 4.3. Column (3) shows that the number of patents increases after the ruling by 17.21% for treated firms compared to control firms. Column (4) shows that the number of patents also increases on a per-input basis. These results are consistent with the establishment level evidence in columns (1) and (2).

Figure 4 illustrates the treatment-intensity-adjusted difference in innovation output over time between treated and control establishments. It plots coefficient estimates from the leads-and-lags model, presented in Internet Appendix Table IA4, Panel A, column (8). This figure shows that, before the ruling, capitalized patent costs vary in parallel between treated and control establishments. However, after the ruling, they are significantly greater for treated establishments than for control establishments. The absence of the pre-ruling trends validates the DiD estimation design and allows for a causal interpretation of the post-ruling difference as the consequence of the ruling. The figure also shows that the innovation output gradually increases after the ruling, which is consistent with the gradual conversion of IS workers into direct hires. Innovation also requires time. The capitalized patent cost monotonically increases starting three years after the ruling, and this increase becomes statistically significant starting five years after the ruling.

A similar pattern is observed for the number of patents as a proxy for innovation output. Internet Appendix Table IA4, Panel B reports coefficient estimates of the leads-and-lags model. The number of patents increases starting the year of the ruling, and this increase becomes statistically significant starting two years after the ruling. The treatment effect is manifested earlier with the number of patents than with capitalized patent costs as a measure of innovation output, likely because I use the application date of patents.

5.3 Robustness

The baseline results are robust to alternative treatment definitions, an alternative post-ruling period, and alternative sets of fixed effects. Internet Appendix Table IA5, Panel A shows that the employment results in Table 4, column (1) remain if the post-ruling period starts in the year of, rather than two years after, the ruling in column (1) and if the treatment intensity is measured by the 2009 share, rather than the average share, of subcontracted employment in column (2) or the average number of subcontracted workers in columns (3) and (4). Columns (5) and (6) show that the result holds even without treatment intensity adjustment. Column (7) shows that the result holds if I use the industry-level definition of treatment that applies to firm-level tests, although the coefficient is marginally significant at the 10% level. The pre-ruling period over which I examine subcontracted employment to define treatment and treatment intensity is from 2007 to 2009 in columns (3) and (5) and 2009 in columns (4) and (6). Internet Appendix Table IA5, Panel B shows that the innovation result in Table 4, column (1) is robust to the same set of checks. The statistical significance either decreases or disappears; however, the sign of the coefficients is positive in every column.

Internet Appendix Table IA6 shows that the baseline employment result is robust to stratum-specific year fixed effects replacing industry and province-specific fixed effects in column (1) and stratum-industry, stratum-area, and stratum-employment-size-group specific year fixed effects replacing industry and province-specific fixed effects in column (3). Stratum-industry, stratum-area, and stratum-employment-size-group are the industry, area, and size group, respectively, that define each stratum. Columns (2) and (4) show that the baseline innovation result is robust to the same checks.

5.4 Channel I: innovation incentive

Next, I explore channels. The first candidate is an innovation incentive for employees[31]. Because a permanent contract prevents dismissal and rewards long-term performance, IS workers may be newly incentivized to invest in firm-specific human capital (Lazear (2009), Prendergast (1993)) and innovate (Manso (2011))[32]. However, some manufacturing establishments do not have a pay component that remunerates individual rank-and-file employees for their long-term performance. Therefore, I exploit the variation to test whether having such a component is associated with the increase in innovation at treated establishments. I measure the component using merit pay, or the annual salary system, with which employees can negotiate the next year's salary based on their performance this year. It is the only component available from the WPS that rewards individuals instead of teams (e.g., gainsharing). Table 3, Panel A shows that only a quarter of treated establishments had merit pay a year before the ruling.

To examine the innovation incentive of rank-and-file employees as a channel, I interact $\widetilde{Treat} \times Post$ with an indicator for merit pay in place in the regression of the log of one plus capitalized patent costs. Table 6, Panel A, column (1) shows that the triple interaction term is positive and significant at the 5% level, whereas the coefficient on $\widetilde{Treat} \times Post$ is marginally significant at the 10% level and smaller in magnitude. The column suggests that the documented increase in innovation is mostly from treated establishments that offer employees a complete package of the innovation incentive, i.e., both tolerance for short-term failure and rewards for long-term success.

Then, I examine the breakdown of basic pay, which is determined by the skill of employees, the seniority of employees, the function employees serve, or a mix of these factors. Columns (2)-(4) show that the increase in innovation is concentrated at treated establishments that base their basic pay on skills and thereby reward employees for their investment in firm-specific skills. Only the triple interaction term

[31] One may suspect wage plays a role in increasing innovation. However, a higher wage, which raises long-term rewards, alone does not suffice to incentivize IS workers to innovate. Further, IS workers were not lowly paid because, as Figure 2, Panel B shows, establishments used IS workers for flexibility (80.66%), not for cost reduction (17.52%). The MOEL's 2011 Survey on In-House Subcontracting shows that subcontracted workers were paid approximately 80% the salary of their secured colleagues who had the same length of tenure (Park (2012)). Nonetheless, I control for wage expenditure and per-employee wage (not for firm-level tests) in every regression to mitigate the concern.

[32] One may suspect a role of competition. However, it may pressurize employees into performing immediately and is thus likely to discourage innovation (Aghion et al. (2005)). Further, there is no evidence that competition has increased. Internet Appendix Table IA3, column (7) indicates that regular employment shows little change.

is positive and statistically significant in column (2), which considers skill-based basic pay. In columns (3) and (4), which consider seniority and function-based basic pay, only $\tilde{Treat} \times Post$ is positive and statistically significant at the 5% level or above.

Column (5) examines a combination of merit pay and basic pay based on skills and shows that this combination provides the strongest incentive to innovate. The coefficient on the triple interaction term has greater magnitude and statistical significance than those in columns (1) and (2). Internet Appendix Table IA7 examines alternative combinations and confirm that the combination in Table 6, Column (5) is likely to provide the highest-powered incentive to innovate. Basic pay is worth exploring because, unlike top innovators who commit to R&D projects, rank-and-file employees may be more likely to innovate not on purpose but coincidentally while accumulating firm-specific human capital.

Panel B examines innovation incentives for managers. I use equity-based compensation schemes that are disproportionately more likely to reward managers. The schemes are ESOP in column (1), stock options in column (2), and stock options only for executives in column (3). In all three columns, the triple interaction term is negative and statistically insignificant, whereas $\tilde{Treat} \times Post$ is positive and significant at the 5% level or above. The results suggest that managerial innovation incentives are unlikely to be associated with the increase in innovation output. Internet Appendix Table IA8 shows that managerial incentives are also unrelated to changes in innovation input, which managers may control more directly. The table estimates the same set of regression equations using a different dependent variable, namely, the log of one plus capitalized R&D. The triple interaction term is statistically insignificant in all three columns.

5.5 Channel II: managerial responses

The other possibility is that managers find the ruling costly and thus increase innovation input, automate processes, and reduce labor. Table 7, Panel A estimates the costs of the ruling or, equivalently, the lost benefits of IS employment. The costs may materialize in the form of a greater labor cost, lower flexibility, and/or lower productivity.

Column (1) shows that per-employee wage increases by \$ 605.5 or 2.03%[33] for seven years following the ruling for the establishments that used subcontracted employment 1 percentage point more compared to those that did not use subcontracted employment before the ruling. Although the point estimate is only marginally significant at the 10% level, the economic magnitude is not small. However, column (2) shows that total wage expenditure has not increased, implying that the increase in per-employee wage is in part due to the (statistically insignificant) decline in total employment documented in Table 4, column (8).

Columns (3) and (4) show that the ruling did not lead to a significant rise in operating leverage. I use two measures of operating leverage. The first one is selling, general, and administrative (SG&A) expenses divided by earnings before interest, depreciation, and amortization (EBITDA)[34]. Results are similar if I use alternative proxies such as SG&A divided by total assets (Chen et al. (2019)) or COGS plus SG&A divided by total assets (Novy-Marx (2011)). The second measure is financial leverage, which is a proxy for the inverse of operating leverage. If managers anticipate a loss of IS employment would raise operating leverage, they may choose to reduce financial leverage (Simintzi et al. (2015)). In both columns, interaction terms are statistically insignificant, implying operating leverage has not increased significantly.

Columns (5) and (6) show that labor productivity has declined, yet insignificantly. I measure labor productivity by sales divided by the number of employees in column (5) and capital-adjusted sales divided by the number of employees in column (6). The adjustment for capital is through multiplying sales by labor share (i.e., labor / (labor + capital)). I measure labor by total wage and capital by depreciation. The latter is because capital expenditure is unavailable from the WPS. In both columns, interaction terms are negative and statistically insignificant. The insignificant decline in labor productivity is consistent with the removal of dismissal threats faced by IS workers who constituted relatively a small portion (i.e., 10.6%) of the manufacturing employment before the ruling.

Panel B examines managerial responses and shows that innovation input and capital intensity do not increase, probably owing to the low cost of the ruling. Columns (1) and (2) (resp. (4) and (5)) show that expensed (resp. capitalized) R&D does not increase for treated establishments (resp. treated firms)

[33] .6055/29.81 = 2.03%. 29.81 is the 2009 average of the per-employee wage for treated establishments in Table IA2, Panel A.

[34] Because firms do not disclose fixed or variable costs, instead listing the cost of goods sold (COGS) and SG&A expenses, I use a textbook definition of operating leverage to proxy for it: that is, the elasticity of profits to sales (Brealey et al. (2018)), or 1 + fixed cost / profits.

compared to control establishments (resp. control firms) after the ruling. If anything, it rather declines, probably because the enhanced innovation efficiency (i.e., greater output per input) induces managers to cut the innovation input. I use both establishment and firm data because only capitalized (resp. expensed) portion of R&D is available from the establishment (resp. firm) data. Alternatively, managers may reallocate existing innovation resources, rather than increase innovation input, to increase innovation output and thereby lower the reliance on labor. While the reallocation is unobservable in data, its consequence is. The consequence is an increase in capital intensity. Columns (3) and (6) show that capital intensity does not increase, however.

Lastly, Internet Appendix Table IA9 examines whether treated establishments that had relatively greater operating leverage before the ruling find the ruling particularly costly and increase innovation input; the results indicate that they do not. Specifically, I interact $\tilde{Treat} \times Post$ with the pre-ruling level of operating leverage in the regression of the log of one plus capitalized R&D. The triple interaction term is statistically insignificant. I measure operating leverage by sales, general, and administrative expenses (SG&A) divided by earnings before interest, depreciation, and amortization (EBITDA) in column (1), an indicator for union in place in column (2), and financial leverage in column (3).

5.6 Managerial myopia

The results presented above suggest that IS employment bears the cost of less innovation for unclear benefits. As shown below, the newly-created patents are not of lower quality. This poses the question of why firms use IS workers in the first place. One testable possibility is managerial myopia or short-termism. Because it may take years to create and implement innovations, managers may rationally focus on cost reduction. Managers may underinvest in intangible assets because they are invisible to outsiders and thus do not improve the stock price (Edmans (2009)). To test this possibility, I exploit foreign ownership. Bena et al. (2017) shows that foreign investors may exert a disciplinary role on entrenched corporate insiders and foster long-term investment in intangible and human capital.

Table 8 shows that the post-ruling increase in innovation output at treated establishments relative to control firms is not observed among the establishments that had positive foreign ownership in column

(1) and foreign investors as the largest shareholders in column (2) a year before the ruling. The triple interaction term is negative and statistically insignificant, whereas $\tilde{Treat} \times Post$ is positive and significant at the 1% level in both columns. The results suggest that establishments that suffer less from managerial myopia use IS employment such that they do not bear the cost of less innovation.

5.7 Innovation by new hires

Next, I explore who innovates. Other than former IS workers, three more groups of employees may innovate after the ruling: new hires, existing inventor employees, and existing noninventor employees (i.e., existing employees who have never invented before the ruling). As they are all regular employees, their incentives to innovate remain little changed. But new hires may contribute to the increase in innovation if their number significantly increases after the ruling. Existing inventor employees may innovate more if they help IS workers create and patent innovations and thereby create collaborative patents. However, existing noninventor employees may not do so because they are neither newly incentivized nor experienced to help IS workers with innovation.

Table 9, columns (1) and (2) show that the share of new hires does not increase after the ruling for the establishments that used subcontracted employment 1 percentage point more compared those that did not use subcontracted employment before the ruling. The interaction term is insignificant in both columns. Columns (3) and (4) further show that changes in the share of new hires between a year before and three years after the ruling are not associated with the increase in innovation output. The triple interaction term is insignificant, whereas $\tilde{Treat} \times Post$ is positive and significant at the 1% level in both columns. Odd-numbered (resp. even-numbered) columns consider new hires with (resp. without) relevant experience who are more (resp. less) likely to possess industry-specific human capital and innovate. The results are not different. Overall, the results are consistent with anecdotes and Table 4 suggesting that IS workers fill the vacancy of regular employees who leave or retire, and total employment does not increase for treated establishments compared to control establishments after the ruling.

5.8 Innovation by new versus existing inventor employees

Table 10 compares innovation by existing and new inventors. New inventors include former IS workers and existing noninventor employees, who cannot be distinguished further without information on subcontracts between firms[35]. Still, I interpret any changes in innovation attributes as ones due to former IS workers because existing noninventor employees are neither newly incentivized nor experienced. However, the distinction is not of much importance because existing inventors are found to innovate the most. I define a new inventor as one who creates their first patent assigned to a firm and an existing inventor as one for whom more than three years have elapsed since they created their first patent assigned to the firm. I assume that the firm is their employer. The results are robust to thresholds other than three years, such as two and four years.

Panel A examines the number of patents. Columns (1) and (2) show that new inventors innovate more only through collaboration with existing inventors. The number of patents created by new inventors increases by 2.61% for treated firms compared to control firms after the treatment. However, it does not increase if collaborative patents, or patents created jointly by new and existing inventors, are not counted. Columns (3) and (4) show that existing inventors innovate even more with and without new inventors. The number of patents created by existing inventors increases by 4.75%. It increases by 2.8% if collaborative patents are not counted. Point estimates are significant at the 5% level or above.

Panel B examines the quality of patents, measured by the number of citations per patent for the following three years. Columns (1) and (2) show that new inventors create patents of slightly higher quality, and they do so through collaboration with existing inventors. The quality of patents created by new inventors increases by 2.17%, a point estimate being significant at the 10% level. However, it does not if collaborative patents are excluded. Columns (3) and (4) show that existing inventors create patents of greater quality with and without new inventors. The quality of patents created by existing inventors increases by 4.36%. It increases by 2.66% if collaborative patents are not counted. The point estimates are significant at the 5% level or above.

[35] I ignore new hires who have never invented before and thus can enter the group of new inventors because Table 9 suggests that they make an insignificant contribution to the increase in innovation output.

Internet Appendix Table IA10 examines whether process patents (i.e., patents whose first claim is process innovation (Bena et al. (2021))) increase. It shows that neither new nor existing inventors create more process patents. Further, the share of non-collaborative process patents does not increase significantly. I examine the share of process patents because their number would increase mechanically in the total number of patents. The results are consistent with managerial inaction in Table 7, *ex ante* high capital intensity in Korean manufacturing industries, and collaboration between new and existing inventors driving the increase in innovation output. Non-collaborative patents created by IS workers, if they increased, were likely mostly process patents. Internet Appendix Table IA11 examines the originality and generality of patents and finds that they do not increase either[36].

Overall, I interpret the results that compare innovation by new and existing inventors as suggesting that senior inventors innovate more and better when they have junior colleagues who are highly motivated yet have little experience in turning ideas into patentable innovations. This pattern is reminiscent of senior faculty becoming more productive after highly motivated junior faculty join a department. They may then write more and better collaborative and non-collaborative papers.

5.9 Employee departure and entrepreneurship

Lastly, I examine spillover effects. Table 11 shows that voluntary employee departure increases and that this increase is associated with heightened innovative activities. Column (1) shows that the number of employees who voluntarily leave for such reasons as startup creation increases after the ruling for the establishments that used subcontracted employment 1 percentage point more compared to those that did not use subcontracted employment before the ruling. The interaction term is positive and significant

[36] I follow Trajtenberg et al. (1997) to compute the originality of a patent as follows: $Originality_i = 1 - \sum_{j=1}^{n_i} s_{ij}^2$ where s_{ij} is the share of citations made by patent i that belong to patent class j out of n_i patent classes. The sum is the Herfindahl concentration index. The originality takes a high value if a patent cites a diverse class of technologies. I define generality similarly, with one difference being that it uses not citations made but received for the following three years. I use one-digit patent classes throughout this paper. However, the results are robust to three- or four-digit classes. I derive patent classes out of the cooperative patent classification, which assigns each patent publication one or more classification terms that consist of section symbol (a letter), class symbol (two digits), and subclass symbol (a letter). The four-digit (and letter) symbol is often followed by 1- to 3-digit group number, an oblique stroke, and a number with at least two digits representing a main group or subgroup (Source: Wikipedia). Whenever more than one classification term exists, I take the dominant one for each patent. For example, if a patent has the following three terms, G06F 1/1616, G06F 3/03547, and Y10S 345/901, I take G, G06, and G06F as its representative 1-, 3-, and 4-digit terms, respectively.

at the 5% level. However, column (2) shows that the number of employees who leave involuntarily for reasons such as retirement does not increase. The interaction term is negative and insignificant.

To examine a potential link between innovative activities and voluntary employee departure, I interact $\tilde{Treat} \times Post$ with a change in capitalized patent costs per wage expenditure between a year before and three years after the ruling. I use the input-output ratio as I compare establishments of varying scales. Column (3) shows that the voluntary departure is positively associated with the change in innovation output per human capital input. The triple interaction term is statistically significant at the 5% level, whereas other interaction terms are insignificant. Column (4) shows that the involuntary employee departure is unassociated with changes in innovation output per human capital input. The triple interaction term is negative and insignificant. These results are consistent with the possibility that innovative activities elevated by the ruling have resulted in employees leaving to create or join startups.

However, would IS workers quit after securing permanent status? Table 12 examines who leaves between new and existing inventors. I define an outgoing inventor as one who leaves by only creating patents assigned to startups in the following years. Similar to leavers in Bernstein (2015) and mobile inventors in Chemmanur et al. (2019), these outgoing inventors are those who have ever filed two successive patent applications that are assigned to different entities. Because at least two patents detect a move, my analysis excludes inventors who file only one patent throughout their inventor career. Section 4.2 defines a startup as a firm that is too small not to file audit reports.

Columns (1) and (2) show that new inventors leave for startups only after creating collaborative patents with existing inventors. The number of outgoing new inventors increases for treated firms compared to that for control firms after the ruling. The interaction term is positive and significant at the 5% level in column (1). However, the number of outgoing new inventors following non-collaborative patents does not. The interaction term is insignificant in column (2). However, columns (3) and (4) show that existing inventors leave for startups with and without making collaborative patents with new inventors. The number of outgoing existing inventors and that of outgoing existing inventors following non-collaborative patents increase. The interaction terms are significant at the 5% level in both columns.

6 Conclusion

This study investigates the consequences of the contingent employment of skilled labor on innovation. It shows that converting skilled workers from contingent to permanent contracts increases innovation. Cross-sectional evidence attributes the newly created innovations to the innovation incentive that applies to rank-and-file employees. Former contingent workers produce more and better patents; however, this improvement is limited to patents jointly created with existing inventor employees, who also make more non-collaborative patents. The innovation-associated voluntary employee departure follows, suggesting a positive spillover effect. Former contingent workers leave for startups; however, they do so only after creating collaborative patents with existing inventor employees, who also leave after creating non-collaborative patents.

There are several challenges in the causal inference of the treatment effects. First, contingent workers may differ from regular employees not only by their innovation incentive but also by their skills, the tasks they are assigned, and their preference for flexible arrangements. These unobservable employee characteristics may differentially affect the outcomes of treated and control businesses after the treatment. To mitigate this concern, I utilize a work arrangement unique in Korea under which contingent workers perform the same core tasks as their regular colleagues in the same workplace. Skills and tasks are thus likely similar. Also, flexibility is unlikely to be a reason for entering contingent contracts because the contingent workers work full-time.

Second, businesses that use contingent contracts to hire skilled labor may be systematically different from non-users in terms of size, industry, operating leverage, pay structure, etc. Observable and unobservable firm characteristics, other than the conversion of contingent to permanent contracts, may have differential effects on the post-treatment outcomes of treated and control businesses. To mitigate the concern, I use a stratified sample of randomly selected establishments that are similar in most aspects even after contingent employment splits the sample. When using firm data that contains limited information on contingent workers, I perform propensity-score matching to construct a sample of treated and matched control firms that are similar in several observable aspects.

Third, most contingent workers are indirectly hired and invisible in their users' data. To overcome this limitation, I use data from surveys that ask the same establishments about how many indirectly hired contingent workers they employ over time. Fourth, a firm's choice of contingent employment is endogenous. Unobservable forces may jointly influence the choice of contingent employment and innovation output. To alleviate the concern, I exploit a court ruling as a source of exogenous variation in contingent employment which, at the same time, has little to do with innovation output of individual firms. I also include a set of fixed effects in estimating treatment effects to control for the impact of known determinants of innovation that may vary over time.

This study has policy implications because, despite the expected long-term cost of less innovation, firms may keep hiring skilled labor with contingent contracts to meet short-term targets. Further, as long as technologies continue to advance and reduce the cost of using contingent labor and the share of advanced degree holders in the labor force increases, the demand for and supply of contingently hired but permanently used skilled labor may keep rising.

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Figure 1: In-house subcontracted employment

This figure illustrates employment through in-house subcontracting. It portrays a conveyor-belt assembly line where in-house subcontracted (IS) workers, who are regular employees of a subcontractor, work with regular employees of the main contractor.

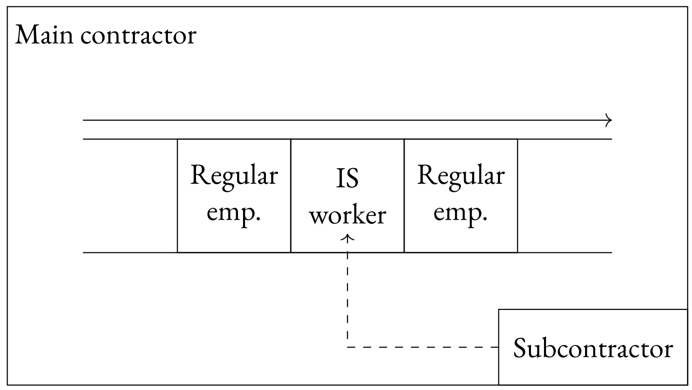
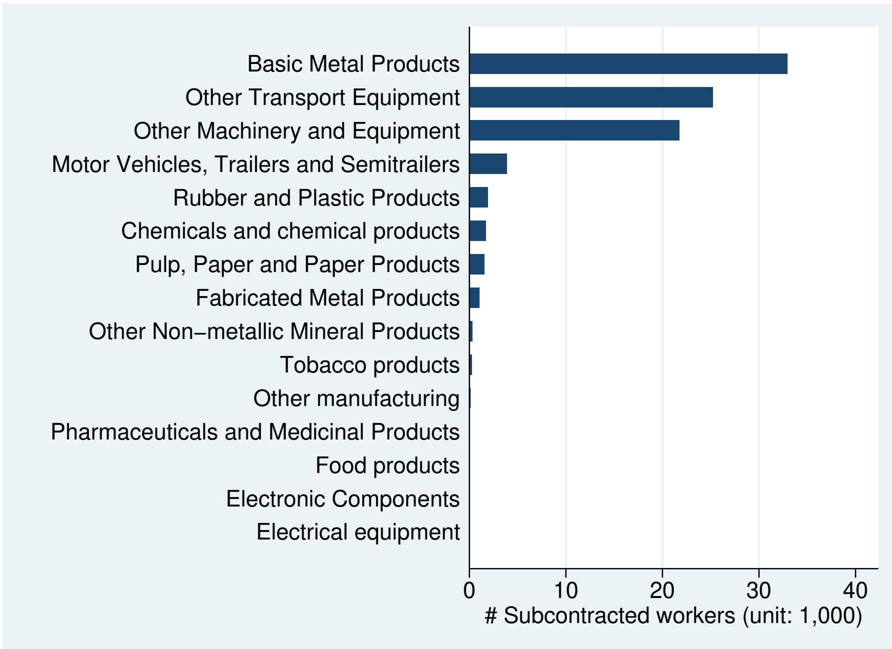


Figure 2: Characteristics of subcontracted employment

This figure exhibits the distribution of subcontracted employment in Panel A and its reasons in Panel B. Panel A reports the number of subcontracted workers for each manufacturing industry. Panel B reports the percent of each reason for subcontracted employment. All figures are as of 2009, a year before the court ruling, from the Korean Labor Institute's Workplace Panel Survey (WPS), and weighted by the WPS probability weight.

Panel A. Distribution across manufacturing industries



Panel B. Reasons

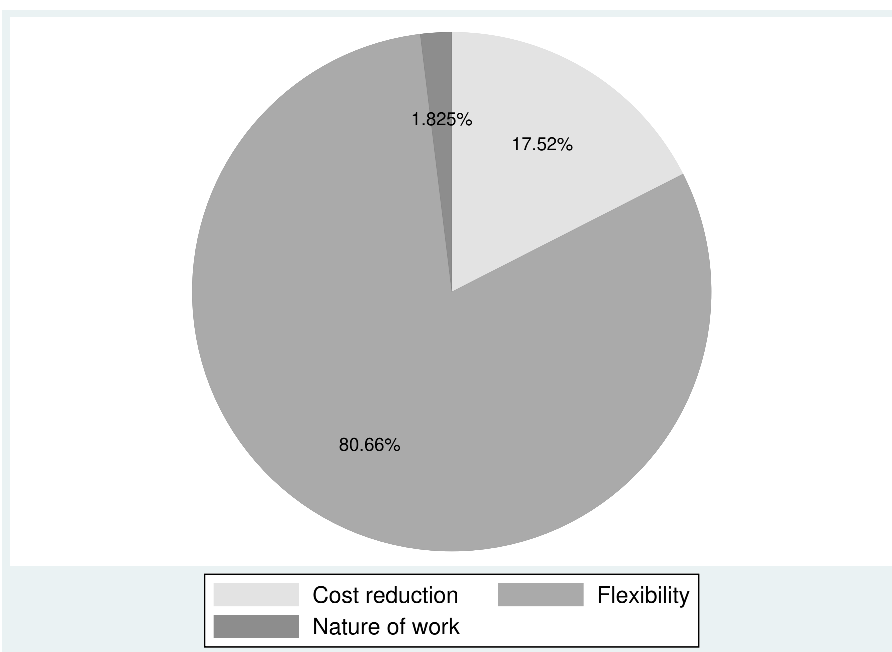
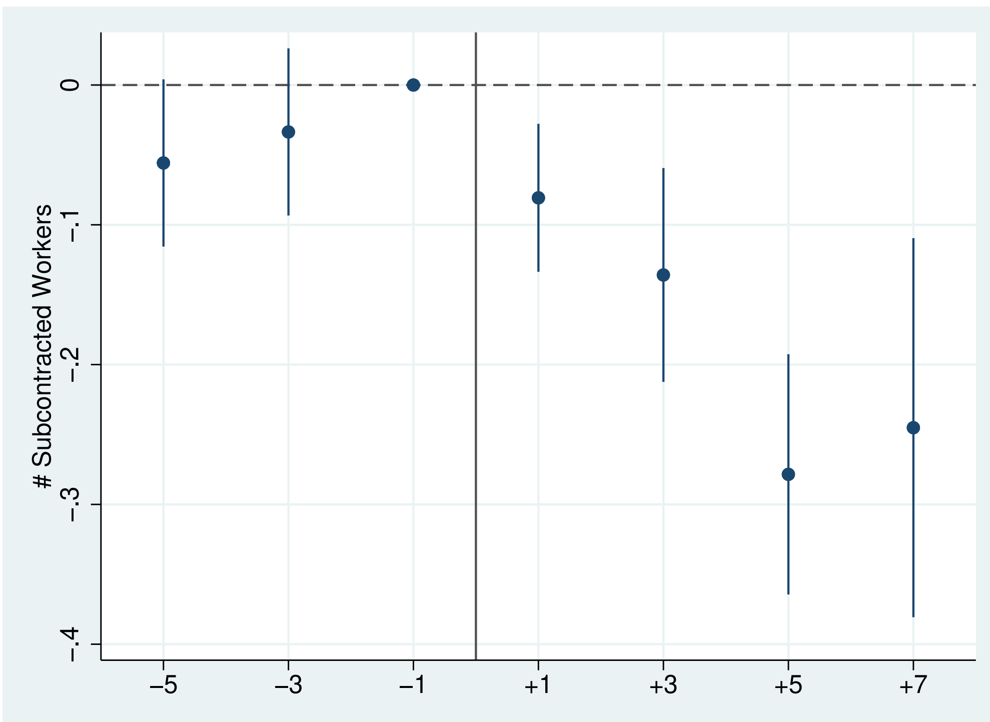


Figure 3: Changes in contingent employment

This figure plots β_τ of Equation 2 estimated in Internet Appendix Table IA4, Panel A, columns (1)-(7). β_τ is a coefficient estimate from the regression on $\tilde{Treat} \times \mathbb{1}[t = \tau]$ and control variables. The dependent variable is the log of one plus the number of subcontracted workers in Panel A and the percent of contingent workers hired under different terms in Panel B. $\tilde{Treat}$ is $Treat$ multiplied by treatment intensity, measured by a mean fraction of subcontracted workers before the ruling (i.e., from 2007 to 2009). $Treat$ is an indicator of an establishment being treated. It takes the value of one if the establishment uses subcontracted workers before the ruling and zero otherwise. $\mathbb{1}[t = \tau]$ is an indicator of τ years after the ruling. It takes the value of one if $t = \tau$ and zero otherwise. Table 5 defines all variables. The vertical line crossing a dot indicates a 95% confidence interval for each coefficient estimate.

Panel A. Subcontracted employment



Panel B. Comparison against other contingent arrangements

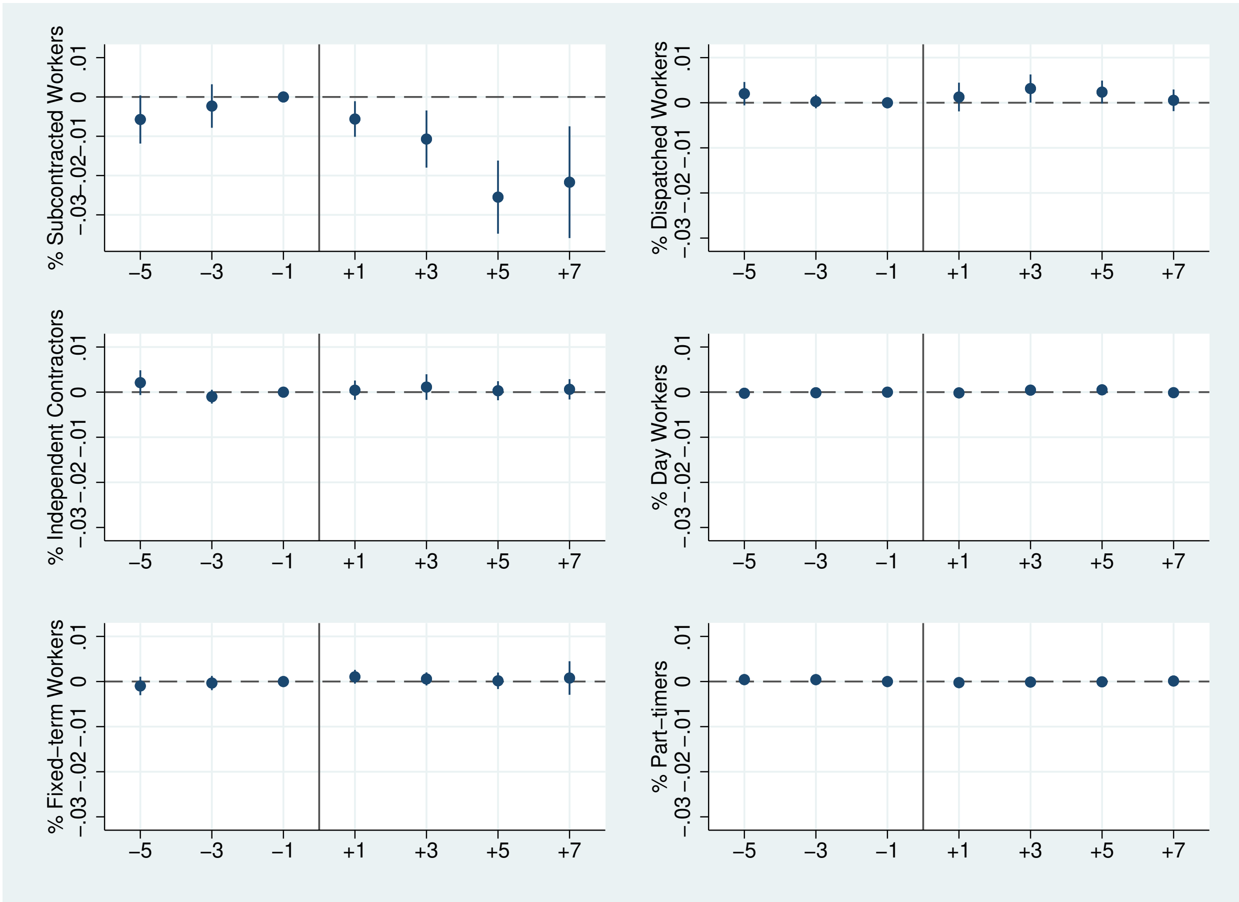


Figure 4: Changes in innovation

This figure plots β_τ of Equation 2 estimated in Internet Appendix Table IA4, Panel A, column (8). β_τ is a coefficient estimate from the regression on $\tilde{Treat} \times \mathbb{1}[t = \tau]$ and control variables, where the dependent variable is the log of one plus capitalized patent costs. $\tilde{Treat}$ is $Treat$ multiplied by treatment intensity, measured by a mean fraction of subcontracted workers before the ruling (i.e., from 2007 to 2009). $Treat$ is an indicator of an establishment being treated. It takes the value of one if the establishment uses subcontracted workers before the ruling and zero otherwise. $\mathbb{1}[t = \tau]$ is an indicator of τ years after the ruling. It takes the value of one if $t = \tau$ and zero otherwise. Table 5 defines all variables. The vertical line crossing a dot indicates a 95% confidence interval for each coefficient estimate.

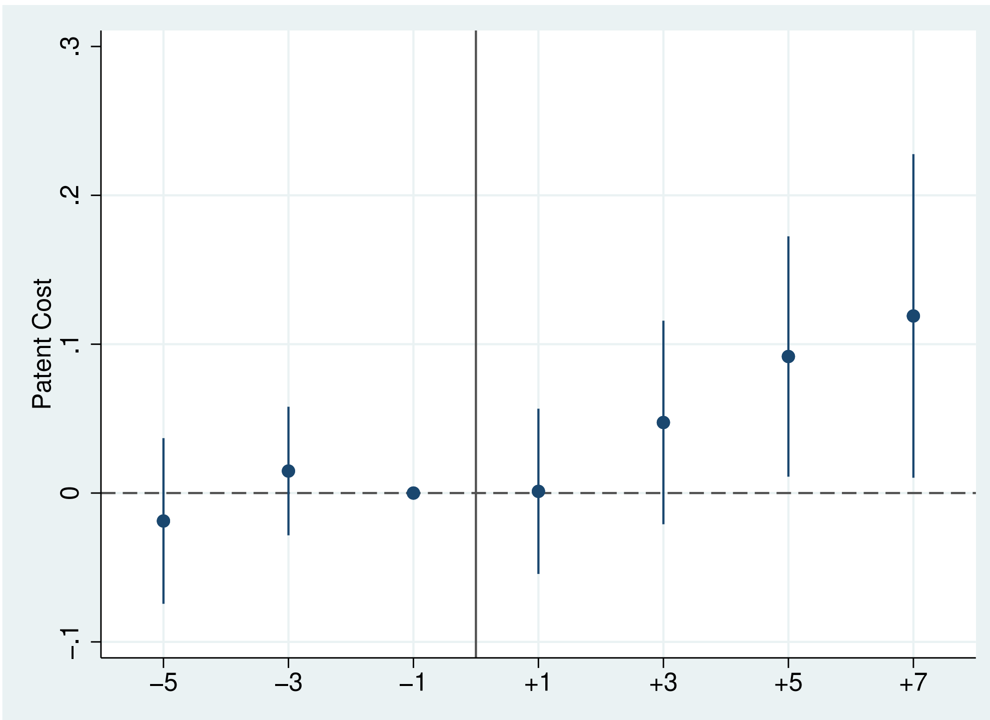


Table 1: Chronology of the Supreme Court ruling
This table lists key developments regarding the Hyundai Motors Company case in a chronological order.

Date	Event
2003	In-house subcontracted (IS) workers of Hyundai Motors Company (HMC) formed a union and petitioned Ministry of Employment and Labor (MOEL) for their being illegally dispatched
December 2004	MOEL confirmed HMC's illegal use of the IS workers
February 2005	Byung-Seung Choi and union leaders were fired by HMC's subcontractors
August 2006	Choi sued HMC asking it to admit him as its employee
July 2007	Seoul Administrative Court dismissed his suit
February 2008	Seoul High Court rejected his appeal
July 2010	**Supreme Court reversed and remanded his case**
February 2011	Seoul High Court ruled in favor of him
February 2012	Supreme Court confirmed the verdict (final ruling)
September 2014	Seoul Central District Court ruled in favor of 1,179 IS workers of HMC

Table 2: Manufacturing employment
This table reports a snapshot of manufacturing employment in 2009, a year before the court ruling. The employment data of establishments is from the Korean Labor Institute's Workplace Panel Survey. All figures are computed using observations weighted by the inverse of their respective probability of being sampled.

	(1) Total	(2) Linearized S.E.	(3) Percent
Indirectly-hired contingent workers	236,060	52,962	13.2%
Subcontracted workers	189,643	51,750	10.6%
Dispatched workers	15,945	4,643	0.9%
Independent contractors	24,607	7,227	1.4%
Day workers	5,866	1,975	0.3%
Directly-hired contingent workers	31,331	8,686	1.7%
Fixed-term workers	26,695	7,733	1.5%
Part-timers	4,636	2,436	0.3%
Regular employees	1,527,446	89,339	85.1%
All Employees	1,794,838	121,169	100.0%

Table 3: Covariate balance

This table compares characteristics in 2009, a year before the ruling, of treated and control establishments in Panel A and treated and matched control firms in Panel B. Column (5) reports the difference in means computed within each stratum, using observations weighted by the inverse of their respective probability of being sampled. The data on manufacturing establishments is from the Korean Labor Institute's Workplace Panel Survey, which biennially surveys a stratified sample of establishments that hire 30 employees or more. The data on manufacturing firms is from TS2000, a database comparable to Compustat, and the Korean Intellectual Property Office. Section 4.3 describes the matching procedure. Table A1 defines all variables.

Panel A. Establishments

	(1)	(2)	(3)	(4)	(5)	(6)
	Treated establishments		Control establishments			
	Mean	Lin-earized S.E.	Mean	Lin-earized S.E.	(1)-(3)	t-stat
% Subcontracted Workers	0.16	0.02	0.00		0.12***	4.61
% Dispatched Workers	0.00	0.00	0.00	0.00	-0.01	-1.50
% Independent Contractors	0.02	0.01	0.00	0.00	0.01	0.86
% Day Workers	0.01	0.01	0.00	0.00	0.01	1.62
% Fixed-Term Workers	0.01	0.01	0.01	0.00	0.01	1.19
% Part-Timers	0.00	0.00	0.00	0.00	0.00	-0.06
% Regular Employees	0.79	0.02	0.99	0.00	-0.15***	-4.48
Patent Costs	1.01	0.16	1.48	0.19	-0.64***	-2.62
Patent Costs / Wage	0.00	0.00	0.01	0.00	-0.01**	-2.13
Capitalized R&D	1.41	0.49	2.13	0.44	-0.62	-1.29
Capitalized R&D / Asset	0.01	0.00	0.01	0.01	0.00	-1.08
Merit Pay	0.15	0.03	0.33	0.05	-0.04	-0.59
Basic Pay by Skill	0.30	0.09	0.47	0.07	-0.09	-1.08
Basic Pay by Seniority	0.50	0.09	0.54	0.07	-0.05	-0.44
Basic Pay by Function	0.36	0.10	0.44	0.07	0.10	1.03
ESOP	0.03	0.00	0.11	0.03	-0.03	-1.49
Stock Option	0.01	0.00	0.04	0.03	0.02	0.59
Stock Option for Executives	0.01	0.00	0.00		0.00	-0.05
Capital Intensity	0.39	0.03	0.40	0.03	0.04	0.97
Financial Leverage	0.50	0.03	0.53	0.03	-0.01	-0.28
Operating Leverage	1.98	0.64	1.60	0.26	-0.80	-1.43
Labor Productivity	711.06	173.15	667.90	315.96	-255.57	-0.94
Capital-Adj. Labor Productivity	5.61	0.71	6.78	2.69	-1.49	-0.49
Union	0.40	0.06	0.18	0.04	0.29***	3.40
Establishment Size	10.34	0.09	9.94	0.13	0.23	1.10
ROA	0.07	0.01	0.07	0.02	-0.01	-0.62
Profit Margin	0.06	0.01	0.06	0.02	0.00	0.11
Wage Expenditure	0.11	0.01	0.16	0.01	-0.02	-0.52
Per-Employee Wage	23.58	2.97	22.52	1.16	3.16	0.81

Panel B. Matched firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Treated Firms (N = 2272)		Control Firms (N = 2272)			
	Mean	S.D.	Mean	S.D.	(1)-(3)	t-stat
# Patent	0.35	0.88	0.32	0.86	0.03	0.98
# Patent / Wage	1.17	3.86	1.15	3.99	0.02	0.24
Expensed R&D	5.13	6.20	5.15	6.17	-0.02	-0.11
Expensed R&D / Asset	0.01	0.01	0.01	0.01	0.00	1.09
Firm Size	17.34	1.06	17.36	1.14	-0.02	-0.82
Return on Assets	0.08	0.10	0.08	0.10	0.00	-0.95
Financial Leverage	0.61	0.26	0.60	0.28	0.01	0.48
Capital Intensity	0.41	0.21	0.41	0.22	0.00	-1.01
Wage Expenditure	0.04	0.04	0.04	0.04	0.00	-0.52

Table 4: Employment

This table reports coefficient estimates from the regression on $\tilde{Treat} \times Post$ and control variables. Dependent variables are the percent of varying classes of contingent workers in columns (1)-(6), the percent of regular employees in column (7), and the log of one plus the number of all employees in column (8). Contingent workers in columns (1)-(4) are indirect hires, i.e., employees hired by other than their users. $\tilde{Treat}$ is $Treat$ multiplied by a measure of treatment intensity, the pre-ruling (i.e., from 2007 to 2009) average of subcontracted employment. $Treat$ is an indicator of an establishment being treated. It takes the value of one if the establishment uses subcontracted workers before the ruling and zero otherwise. $Post$ is an indicator that takes the value of one for years after 2011 and zero otherwise. Control variables are establishment size, return on assets, capitalized R&D divided by total assets, capital intensity, financial leverage, wage expenditure, and per-employee wage. Table A1 defines all variables. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort is composed of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Indirect Employment				Direct Employment		
	% Subcontracted Workers	% Dispatched Workers	% Independent Contractors	% Day Workers	% Fixed-term Workers	% Part-timers	% Regular Employees	# All Employees
$\tilde{\text{Treat}} \times$ Post	-0.0135***	0.0016	0.0005	0.0005	0.0004	-0.0001	0.0102**	-0.0108
	(0.004)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.005)	(0.012)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year							
N	2247	2247	2247	2247	2247	2247	2247	2247
Adjusted R^2	0.719	0.531	0.709	0.484	0.530	0.576	0.728	0.918

Table 5: Innovation

This table reports coefficient estimates from the regression on $\widetilde{Treat} \times Post$ and control variables in columns (1) and (2) and $Treat$, $Treat \times Post$, and control variables in columns (3) and (4). The dependent variable is the log of one plus capitalized patent costs in column (1), capitalized patent costs divided by wage expenditure in column (2), the log of one plus the number of patents in column (3), and the number of patents divided by wage expenditure in column (4). Table 4 defines $\widetilde{Treat}$, $Post$, and control variables. In columns (3) and (4), however, $Treat$ is defined differently as an indicator that takes the value of one (resp. zero) for firms that belong to automobile, shipbuilding, steel, and machinery and equipment (resp. other manufacturing) industries a year before the court ruling. Columns (1) and (2) use a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. Columns (3) and (4) use a sample of treated and matched control firms. Section 4.3 describes the matching procedure. The data on manufacturing firms is from TS2000, a database comparable to Compustat. The data on patents aggregated for each firm year is from Korean Intellectual Property Office. A cohort consists of establishments founded in the same year in columns (1) and (2) and firms in columns (3) and (4). Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. In columns (1) and (2), each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment in columns (1) and (2) and firm in columns (3) and (4). They are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Capitalized Patent Cost	(2) Patent Cost / Wage	(3) # Patent	(4) # Patent / Wage
Sample	Establishments		Firms	
$\widetilde{\text{Treat}} \times$ Post	0.0731**	0.0013*		
	(0.037)	(0.001)		
Treat $\times$ Post			0.0495***	0.1732**
			(0.016)	(0.086)
Controls	Y	Y	Y	Y
Establishment FE	Y	Y	N	N
Firm FE	N	N	Y	Y
Industry-Year FE	Y	Y	N	N
Province-Year FE	Y	Y	Y	Y
Cohort-Year FE	Y	Y	Y	Y
N	2247	1618	44141	44067
Adjusted R^2	0.767	0.382	0.719	0.556

Table 6: Innovation incentives

This table reports coefficient estimates from the regression of the log of one plus capitalized patent costs on interactions between $\widetilde{Treat}$, $Post$, and $Channel_{-1}$ and control variables. Table 4 defines $\widetilde{Treat}$, $Post$, and control variables. $Channel_{-1}$ is an indicator for a pay component in place a year before the ruling. In Panel A, the pay component is merit pay in column (1), skill-based basic pay in column (2), seniority-based basic pay in column (3), and function-based basic pay in column (4), and merit pay plus skill-based basic pay in column (5). In Panel B, the pay component is employee stock ownership plan (ESOP) in column (1), stock option in column (2), and stock option for executives in column (3). This table use a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of businesses founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Employee incentives

	(1)	(2)	(3)	(4)	(5)
	Capitalized Patent Cost				
Channel =	Merit Pay	Basic Pay by Skill	Basic Pay by Seniority	Basic Pay by Function	Merit Pay × Basic Pay by Skill
$\widetilde{\text{Treat}}$ × Post	0.0522*	0.0466	0.1049**	0.0972***	0.0464*
	(0.029)	(0.029)	(0.041)	(0.035)	(0.027)
Post × Channel_{-1}	0.3048	-0.0452	-0.1109	-0.4424*	0.1972
	(0.231)	(0.172)	(0.190)	(0.255)	(0.208)
$\widetilde{\text{Treat}}$ × Post × Channel_{-1}	0.1207**	0.1445***	-0.0082	0.0030	0.1693***
	(0.052)	(0.048)	(0.057)	(0.094)	(0.048)
Controls	Y	Y	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year				
N	1744	1744	1744	1744	1744
Adjusted R^2	0.781	0.780	0.778	0.780	0.781

Panel B. Managerial incentives

	(1)	(2)	(3)
	Capitalized Patent Cost		
Channel =	ESOP	Stock Option	Stock Option for Executives
$\tilde{\text{Treat}} \times$ Post	0.0997***	0.1001***	0.0974**
	(0.038)	(0.038)	(0.038)
Post $\times$ Channel$_{-1}$	-0.4166	0.2962	0.7808
	(0.362)	(0.306)	(0.608)
$\tilde{\text{Treat}} \times$ Post $\times$ Channel$_{-1}$	-0.0866	-0.1297	-0.0790
	(0.122)	(0.164)	(0.147)
Controls	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year		
N	1744	1744	1744
Adjusted R^2	0.779	0.778	0.778

Table 7: Managerial responses

This table reports coefficient estimates from the regression on control variables and $\widetilde{Treat} \times Post$ in Panel A and in Panel B, columns (4)-(6) and $Treat \times Post$ in Panel B, columns (1)-(3). In Panel A, the dependent variable is per-employee wage in column (1), wage expenditure divided by revenue in column (2), operating leverage in column (3), financial leverage in column (4), labor productivity in column (5), and capital-adjusted labor productivity in column (6). In Panel B, the dependent variable is the log of one plus expensed R&D in column (1), expensed R&D divided by total assets in column (2), the log of one plus capitalized R&D in column (4), capitalized R&D divided by total assets in column (5), and capital intensity in columns (3) and (6). Table 4 defines $\widetilde{Treat}$, $Post$, and control variables. The set of control variables excludes a variable used as the dependent variable. Table 5 defines $Treat$. Table A1 defines all other variables. Panel B, columns (1)-(3) use a sample of treated and matched control firms. Section 4.3 describes the matching procedure. The data on manufacturing firms is from TS2000, a database comparable to Compustat. Panel A and Panel B, columns (4)-(6) use a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of firms founded in the same year in columns (1)-(3) and establishments in columns (4)-(6). Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. In columns (4)-(6), each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by firm in columns (1)-(3) and establishment in columns (4)-(6). They are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Lost benefits of subcontracted employment

	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Cost		Flexibility		Productivity	
	Per-Employee Wage	Wage Expenditure	Operating Leverage	Financial Leverage	Labor Productivity	Capital-Adjusted Labor Productivity
$\widetilde{\text{Treat}} \times$ Post	0.6055*	-0.0016	0.0571	0.0017	-1.0673	-0.0183
	(0.318)	(0.002)	(0.076)	(0.004)	(18.071)	(0.172)
Controls	Y	Y	Y	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year					
N	2247	2247	2247	2247	2247	2247
Adjusted R^2	0.797	0.738	0.331	0.783	0.902	0.773

Panel B. Managerial innovation input

	(1) Expensed R&D	(2) Expensed R&D / Asset	(3) Capital Intensity	(4) Capital-ized R&D	(5) Capital-ized R&D / Asset	(6) Capital Intensity
Sample		Firms			Establishments	
Treat × Post	-0.2043*	-0.0004	0.0022			
	(0.121)	(0.000)	(0.004)			
$\tilde{\text{Treat}}$ × Post				-0.0819**	-0.0007**	-0.0013
				(0.036)	(0.000)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Establishment FE	N	N	N	Y	Y	Y
Firm FE	Y	Y	Y	N	N	N
Industry-Year FE	N	N	N	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y	Y
Cohort-Year FE	Y	Y	Y	Y	Y	Y
N	44141	44141	44117	2247	2247	2154
Adjusted R^2	0.791	0.758	0.687	0.796	0.784	0.656

Table 8: Managerial myopia

This table reports coefficient estimates from the regression of the log of one plus capitalized patent costs on interactions between $\widetilde{Treat}$, $Post$, and $Channel_{-1}$ and control variables. $Channel_{-1}$ is an indicator that takes the value of one if an establishment has a year before the ruling foreign investors in column (1) and foreign investors as the largest shareholder in column (2) and zero otherwise. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment. They are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Capitalized Patent Cost	
Channel =	$\mathbb{1}$[Foreign ownership > 0]	$\mathbb{1}$[Largest shareholder = foreign investor]
$\widetilde{\text{Treat}} \times$ Post	0.1053***	0.0990***
	(0.039)	(0.037)
Post $\times$ Channel$_{-1}$	-0.1095	0.5401
	(0.221)	(1.243)
$\widetilde{\text{Treat}} \times$ Post $\times$ Channel$_{-1}$	-0.0662	-0.0837
	(0.069)	(0.536)
Controls	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year	
N	1744	1744
Adjusted R^2	0.778	0.778

Table 9: Innovation by new hires

In this table, columns (1) and (2) report coefficient estimates from the regression on $\tilde{Treat} \times Post$ and control variables. The dependent variable is the percent of experienced new hires in column (1) and inexperienced new hires in column (2). Columns (3) and (4) report coefficient estimates from the regression of the log of one plus capitalized patent costs on interactions between $\tilde{Treat}$, $Post$, and New Hire Change, and control variables. New Hire Change is the change in the percent of new hires, who are experienced in column (3) and inexperienced in column (4), between a year before and three years after the ruling. Table 4 defines $\tilde{Treat}$, $Treat$, $Post$, and control variables. Table A1 defines all other variables. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) % Experienced New Hires	(2) % Inexperienced New Hires	(3) Capitalized Patent Cost	(4) Capitalized Patent Cost
$\tilde{\text{Treat}}$ × Post	0.0000	-0.0005	0.1079***	0.1134***
	(0.002)	(0.003)	(0.031)	(0.033)
Post × $\Delta_{[-1,+3]}$ % Experienced New Hires			0.7198	
			(1.351)	
Treat × Post × $\Delta_{[-1,+3]}$ % Experienced New Hires			0.1965	
			(0.371)	
Post × $\Delta_{[-1,+3]}$ % Inexperienced New Hires				-0.6465
				(0.539)
Treat × Post × $\Delta_{[-1,+3]}$ % Inexperienced New Hires				0.1250
				(0.150)
Controls	Y	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year			
N	1709	1709	1467	1467
Adjusted R^2	0.484	0.504	0.773	0.774

Table 10: Innovation by new versus existing inventor employees

This table reports coefficient estimate from the regression on $Treat \times Post$ and control variables. In Panel A, the dependent variable is the log of one plus the number of patents created by new inventors in column (1), non-collaborative patents created by new inventors in column (2), patents created by existing inventors in column (3), and non-collaborative patents created by existing inventors in column (4). A new inventor is one who creates her first patent assigned to a firm. An existing inventor is one for whom it has been more than three years since he created his first patent assigned to the firm. The firm is assumed their employer. A non-collaborative patent is one that is not jointly created by new and existing inventors. In Panel B, the number of citations per patent for the following three years replaces the number of patents. Table 5 defines $Treat$, $Post$, and control variables. Table A1 defines all other variables. All columns use a sample of treated and matched control firms. Section 4.3 describes the matching procedure. The data on manufacturing firms is from TS2000, a database comparable to Compustat. The data of patents (resp. their citations) aggregated for each firm-year is from Korean Intellectual Property Office (resp. Google Patents). A cohort consists of firms founded in the same year. Standard errors are clustered by firm. They are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Number of patent applications

	(1) # Patents by New Inventors	(2) # Non-Collaborative Patents by New Inventors	(3) # Patents by Existing Inventors	(4) # Non-Collaborative Patents by Existing Inventors
Treat × Post	0.0261**	-0.0097	0.0457***	0.0281**
	(0.011)	(0.009)	(0.013)	(0.011)
Controls	Y	Y	Y	Y
Fixed effects	Firm, province-year, cohort-year			
N	44141	44141	44141	44141
Adjusted R^2	0.602	0.410	0.713	0.665

Panel B. Quality of patent applications

	(1) # Citations per Patent by New Inventors	(2) # Citations per Non-Collaborative Patent by New Inventors	(3) # Citations per Patent by Existing Inventors	(4) # Citations per Non-Collaborative Patent by Existing Inventors
Treat × Post	0.0217*	-0.0099	0.0439***	0.0251**
	(0.012)	(0.009)	(0.014)	(0.012)
Controls	Y	Y	Y	Y
Fixed effects	Firm, province-year, cohort-year			
N	44141	44141	44141	44141
Adjusted R^2	0.479	0.336	0.578	0.544

Table 11: Innovation-associated employee departure

This table reports coefficient estimate from the regression on control variables and $\tilde{Treat} \times Post$ in columns (1) and (2) and interactions between $Treat$, $Post$, and Channel in columns (3) and (4). The dependent variable is the log of one plus the number of voluntarily outgoing employees in columns (1) and (3) and involuntarily outgoing employees in columns (2) and (4). Channel is the change in capitalized patent costs divided by wage expenditure between a year before and three years after the ruling. Table 4 defines $\tilde{Treat}$, $Treat$, $Post$, and control variables. Table A1 defines all other variables. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) # Voluntarily Outgoing Employees	(2) # Involuntarily Outgoing Employees	(3) # Voluntarily Outgoing Employees	(4) # Involuntarily Outgoing Employees
$\tilde{\text{Treat}} \times$ Post	0.0427**	-0.0357	-0.3050	0.2910
	(0.020)	(0.038)	(0.207)	(0.256)
Post $\times\ \Delta_{[-1,3]}$ Cap. Patent Cost / Wage			-2.6885	2.3595
			(2.041)	(2.487)
Treat $\times$ Post $\times\ \Delta_{[-1,3]}$ Cap. Patent Cost / Wage			7.4505**	-2.4920
			(3.624)	(2.956)
Controls	Y	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year			
N	2247	2247	1417	1417
Adj. R^2	0.610	0.365	0.650	0.362

Table 12: Employee departure by new versus existing inventor employees

This table reports coefficient estimate from the regression on $Treat \times Post$ and control variables. The dependent variable is the log of one plus the number of outgoing new inventors in column (1), outgoing new inventors after creating non-collaborative patents in column (2), outgoing existing inventors in column (3), and outgoing existing inventors after creating non-collaborative patents in column (4). Table 10 defines new and existing inventors and non-collaborative patents. An outgoing inventor is one who leave by only creating patents assigned to startups, defined in Section 4.2, in the following years. Table 5 defines $Treat$, $Post$, and control variables. All columns use a sample of treated and matched control firms. Section 4.3 describes the matching procedure. The data on manufacturing firms is from TS2000, a database comparable to Compustat. The data of patents aggregated for each firm-year is from Korean Intellectual Property Office. A cohort consists of firms founded in the same year. Standard errors are clustered by firm and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	# Outgoing New Inventors	# Outgoing Inventors after Non-Collaborative Innovation	# Outgoing Existing Inventors	# Outgoing Existing Inventors after Non-Collaborative Innovation
Treat × Post	0.0182***	0.0035	0.0125**	0.0088**
	(0.005)	(0.002)	(0.005)	(0.004)
Controls	Y	Y	Y	Y
Fixed effects	Firm, province-year, cohort-year			
N	44141	44141	44141	44141
Adjusted R^2	0.341	0.222	0.319	0.300

Table A1: Variable definitions

Establishment characteristics are from the Korean Labor Institute (KLI)'s Workplace Panel Survey (WPS). The financial statement information, which the KLI collects at the firm level, are converted into the establishment level, e.g., based on an establishment's contribution to the firm's sales. Internet Appendix Section A elaborates on the conversion procedure. Firm characteristics are from TS2000, a disclosure-based database comparable to Compustat. Patent and citation information aggregated for each firm year is from Korean Intellectual Property Office and Google Patents. All variables are winsorized at 1% level.

Variable name	Definition
Establishment characteristics	
# Subcontracted Workers	Log of one plus the number of workers hired by subcontractors to work for establishment i under the subcontractors' supervision in year t
# Dispatched Workers	Log of one plus the number of workers hired by third-parties to work for establishment i under the establishment's supervision in year t, for the maximum of two years
# Independent Contractors	Log of one plus the number of independent contractors who work for establishment i in year t
# Day Workers	Log of one plus the number of day workers who work for establishment i in year t
# Fixed-term Workers	Log of one plus the number of employees hired to work for establishment i for a fixed term in year t
# Part-timers	Log of one plus the number of employees hired to work part-time for establishment i in year t
# Regular Employees	Log of one plus the number of employees hired to work full-time, on a permanent basis, for establishment i in year t
# All Employees	Log of one plus the number of all employees either directly or indirectly hired by establishment i in year t
% Subcontracted Workers	Percent of subcontracted workers of establishment i in year t
% Dispatched Workers	Percent of dispatched workers of establishment i in year t
% Independent Contractors	Percent of independent contractors of establishment i in year t
% Day Workers	Percent of day workers of establishment i in year t
% Fixed-term Workers	Percent of fixed-term workers of establishment i in year t
% Part-timers	Percent of part-time employees of establishment i in year t
% Regular Employees	Percent of regular employees of establishment i in year t
# Inexperienced New Hires	Log of one plus the number of new hires of establishment i who lack relevant experience in year t
# Experienced New Hires	Log of one plus the number of new hires of establishment i who have relevant experience in year t
# Voluntarily Outgoing Employees	Log of one plus the number of employees who leave for such reasons as new employment elsewhere, business creation, education, childcare, and health issues for establishment i in year t
# Involuntarily Outgoing Employees	Log of one plus the number of employees who leave for such reasons as retirement, disciplinary dismissal, layoff (due to business failure, for example), advised resignation, and contract revocation for establishment i in year t

Variable name	Definition
Establishment characteristics (continued)	
Capitalized Patent Cost	Log of one plus costs incurred to obtain intellectual properties, which include patents, trademark, utility rights, design right, of establishment i in year t
Capitalized Patent Cost / Wage	Costs incurred to obtain intellectual properties, which include patents, trademarks, utility rights, design rights, divided by total wage, inclusive of welfare and retirement benefits, of establishment i in year t
Capitalized R&D	Log of one plus capitalized expenditure on research and development of establishment i in year t
Capitalized R&D / Asset	Capitalized expenditure on research and development divided by total assets of establishment i in year t
Merit Pay	Indicator that takes the value of one if establishment i has a system in year t with which employees can negotiate the next year's salary based on their performance this year and zero otherwise
Basic Pay by Skill	Indicator that takes the value of one if basic pay is set in part by the the skill of employees for establishment i in year t and zero otherwise
Basic Pay by Seniority	Indicator that takes the value of one if basic pay is set in part by the the tenure of employees for establishment i in year t and zero otherwise
Basic Pay by Function	Indicator that takes the value of one if basic pay is set in part by the the function that employees serve for establishment i in year t and zero otherwise
ESOP	Indicator that takes the value of one if establishment i has employee stock ownership plans in year t and zero otherwise
Stock Option	Indicator that takes the value of one if establishment i offers stock options to employees and zero otherwise
Stock Option for Executives	Indicator that takes the value of one if establishment i offers stock options to only to executives and zero otherwise
Capital Intensity	Property, plant, and equipment (PPE) divided by total assets of establishment i in year t
Financial Leverage	Total book liability divided by total book equity of establishment i in year t
Operating Leverage	Sales, general, and administrative expenses divided by earnings before interest, tax, depreciation, and amortization (EBITDA) of establishment i in year t
Labor Productivity	Sales revenue divided by the number of employees of establishment i in year t
Capital-adjusted Labor Productivity	Sales revenue multiplied by labor share (= L/(L+K)) divided by the number of employees of establishment i in year t, where L is measured by wage and K by depreciation
Union	Indicator that takes the value of one if establishment i has a union in year t and zero otherwise
Establishment Size	Log of one plus total asset of establishment i in year t
Return on Assets	EBITDA divided by total assets of establishment i in year t
Profit Margin	EBITDA divided by sales revenue of establishment i in year t
Wage Expenditure	Total wage, inclusive of welfare and retirement benefits, divided by sales revenue of establishment i in year t
Per-employee Wage	Total wage, inclusive of welfare and retirement benefits, divided by the number of employees of establishment i in year t

Variable name	Definition
Firm characteristics	
# Patents	Log of one plus the number of patents of firm i in year t
# Patents / # Employees	Number of patents divided by the number of directly-hired employees of firm i in year t
Expensed R&D	Log of one plus research and development expenses of firm i in year t
Expensed R&D / Asset	Research and development expenses divided by total asset of firm i in year t
Firm Size	
Return on Assets	EBITDA divided by total assets of firm i in year t
Financial Leverage	Total book liability divided by total book equity of firm i in year t
Capital Intensity	Property, plant, and equipment (PPE) divided by total assets of firm i in year t
Wage Expenditure	Total wage divided by sales revenue of firm i in year t
# Patents by New Inventors	Log of one plus the number of patents created by new inventors of firm i in year t, where new inventors are those who create their first patents assigned to firm i
# Patents by Existing Inventors	Log of one plus the number of patent created by existing inventors of firm i in year t, where existing inventors are those who have been three years or more since they create their first patents assigned to firm i
# Collaborative Patents	Log of one plus the number of collaborative patent, i.e., patents created jointly by new and existing inventors, of firm i in year t
# Non-Collaborative Patents by New Inventors	Log of one plus the number of non-collaborative patents, i.e., patents net of collaborative patents, created by new inventors of firm i in year t
# Non-Collaborative Patents by Existing Inventors	Log of one plus the number of non-collaborative patents, i.e., patents net of collaborative patents, created by existing inventors of firm i in year t
# Citations per Patent	Number of citations divided by the number of patents of firm i in year t
# Citations per Patent by New Inventors	Number of citations divided by the number of patents created by new inventors of firm i in year t
# Citations per Patent by Existing Inventors	Number of citations divided by the number of patents created by existing inventors of firm i in year t
# Citations per Collaborative Patent	Number of citations divided by the number of collaborative patents of firm i in year t
# Citations per Non-Collaborative Patent by New Inventors	Number of citations divided by the number of non-collaborative patents created by new inventors of firm i in year t
# Citations per Non-Collaborative Patent by Existing Inventors	Number of citations divided by the number of non-collaborative patents created by existing inventors of firm i in year t

Variable name	Definition
Firm characteristics (continued)	
% Process Patents	Percent of process patents, i.e., patents whose first claim is process innovation (Bena et al. (2021)), of firm i in year t
% Process Patents by New Inventors	Percent of process patents created by new inventors of firm i in year t
% Process Patents by Existing Inventors	Percent of process patents created by existing inventors of firm i in year t
% Collaborative Process Patents	Percent of collaborative process patents of firm i in year t
% Non-Collaborative Process Patents by New Inventors	Percent of non-collaborative process patents created by new inventors of firm i in year t
% Non-Collaborative Process Patents by Existing Inventors	Percent of non-collaborative process patents created by existing inventors of firm i in year t
# Outgoing Inventors	Log of one plus the number of outgoing inventors, i.e., inventors who create the last patents assigned to firm i in year t and then leave by only creating patents assigned to small firms, defined in Section , in year t+1 or later
# Outgoing New Inventors	Log of one plus the number of outgoing new inventors of firm i in year t
# Outgoing Existing Inventors	Log of one plus the number of outgoing existing inventors of firm i in year t
# Outgoing Inventors after Collaborative Innovation	Log of one plus the number of outgoing inventors who create collaborative patents in year t and leave by only creating patents assigned to small firms in year t+1 or later
# Outgoing New Inventors after Non-Collaborative Innovation	Log of one plus the number of outgoing new inventors who create non-collaborative patents in year t and leave by only creating patents assigned to small firms in year t+1 or later
# Outgoing Existing Inventors after Non-Collaborative Innovation	Log of one plus the number of outgoing existing inventors who create non-collaborative patents in year t and leave by only creating patents assigned to small firms in year t+1 or later

Contingent Employment and Innovation

Sunwoo Hwang

INTERNET APPENDIX

A Workplace Panel Survey (WPS)

The WPS provides a broad set of variables about a stratified sample of establishments that hire 30 employees or more from 2005 to 2017. 2017 is the latest survey year for which the dataset is available at the time of this writing. An establishment, once sampled, remains in the panel unless it goes out of business. Korean Labor Institute (KLI), a government-funded research body, conducts surveys biennially, code variables based on the survey outcome, and releases an updated version of the WPS. The KLI defines a stratum based on 12 industries, five regions, and four size groups and randomly select and contact establishments that represent each stratum. Internet Appendix Table IA1 provides a list of the 12 industries, which later collapses to ten industries in 2015. The five regions are Seoul, Gyeonggi/Incheon, Gangwon/Chungcheong, Jeolla/Jeju, and Gyeongsang. They combine nine provinces and eight special cities in Korea. The four size groups are based on employment. The establishments that hire 30-99, 100-299, 300-999, and 1000 or more regular employees in a sampling year comprise the four respective size groups. WPS User's Guide Version 1.61 details the construction of the data (in Korean). The KLI excludes agricultural, forestry, fishery, and mining industries. I further exclude public-sector establishments and sole proprietors to focus on corporations. Results remain similar with them included in the sample.

In every analysis that uses data from the WPS, observations are weighted by the inverse of their probability of being sampled to enter the panel. The probability weight adjusts for the fact that observations represent a varying number of establishments. For example, a small establishment hiring 50 employees may represent 200 establishments in the same industry, region, and size group, while a large establishment hiring 500 employees may represent only two establishments. In a regression setup, the probability weight corrects for each establishment's contribution to point estimate and standard errors as follows. Consider a linear regression model in matrix form, $y = X\beta + u$, which yields an ordinary least squares estimator for β, $\hat{\beta} = (X'X)^{-1}X'y$. We can implement the weighting-based correction by multiplying each row of X and y by $\sqrt{w_i}$ where w_i is the number of establishments establishment i represents. The greater the weight, the greater the establishment's contribution to the mean and the residual sum of squares in the variance-covariance matrix. Dupraz (2013) illustrates how STATA implements the correction and obtains coefficients and standard errors when one uses survey data and weights. Lastly, the KLI adjusts for the survival likelihood and non-responses in subsequent surveys in the computation of the probability weights.

Also important to note is how financial statement figures, prepared and collected at the firm level, may be converted into establishment-level figures for multi-unit establishments. The WPS provides a variable, named "transr," which can be used for the conversion. The variable is the ratio of sales of a given (multi-unit) establishment to sales of the firm the establishment comprises. If the ratio is unavailable, the conversion variable is defined alternatively as the inverse of the total number of (multi-unit) establishments that constitute the mother firm.

B Summary of the Supreme Court ruling

Below is an excerpt from Supreme Court Decision 2008Du4367 Decided July 22, 2010, titled Revocation of Retrial Decision to Remedy Unfair Dismissal and Unfair Labor Practices. It summarizes the Supreme Court ruling. Its full text is available (in English) from Supreme Court Library of Korea[37].

The ruling addresses three main issues. The first is criteria necessary for a person employed by a primary employer, but working at the business place of a third party and at the third party's business, to be deemed an employee of the third party. The second is the judgment below committed an error in law by misapprehending legal principles when determining the provision on constructive direct employment, as stipulated under the former Act on the Protection, etc. of Dispatched Workers, could not be applied to employees of an in-house subcontractor dispatched to the automobile manufacturer A, who were employed in simple and repetitive work together with regular employees at an automobile assembly-production line using automated conveyor belts system. The third is criteria necessary for applying Article 6 (3) of the former Act on the Protection, etc. of Dispatched Workers (the so-called "provision on deeming direct employment"), and whether this provision can only be applied to cases of "legitimate worker dispatch" (negative).

The decision is summarized below. First, for a person who is employed by a primary employer but

[37] `http://library.scourt.go.kr/SCLIB_data/decision/5.Supreme%20Court%20Decision%202008Du4367%20Decided%20July%2022.htm`

engaged in the business of a third party, and working at the business place of the third party, to be seen as an employee of this third party, the primary employer must be lacking in its identity or independence as a business owner to the extent of it being regarded as a labor agency for the third party, and its existence nothing more than a formality. The employee in question must be in a subordinate relationship to the third party and receive wages from the third party in exchange for providing labor to the third party, thus clearly establishing an implicit labor contract between such employee and the third party.

Second, the judgment below committed an error in law by misapprehending legal principles when determining the provision on deeming direct employment, as stipulated under the former Act on the Protection, etc. of Dispatched Workers (amended by Act No. 8076 of Dec. 21, 2006), could not be applied to employees of an in-house subcontractor dispatched to the automobile manufacturer A, who were employed in simple and repetitive work together with regular employees at an automobile assembly-production line using conveyor belts in an automatic flow method.

Third, Article 6 (3) of the former Act on the Protection, etc. of Dispatched Workers (amended by Act No. 8076 of Dec. 21, 2006) stipulates that "If an employer continues to use a dispatched worker in excess of two years, he/she shall be deemed as directly employing the dispatched worker starting from the day after this two year period has expired" (hereinafter "the provision on deeming direct employment"). The provision on deeming direct employment signifies that in the case where a "worker dispatch" exists as defined in Article 2 subparagraph 1 of the same Act, and the worker dispatch continues more than two years, then this in itself establishes a direct employment relationship between the using employer and the dispatched worker. Thus, a narrow interpretation that the provision on deeming direct employment applies only in the case of a "legitimate worker dispatch" is without basis in light of the wording of the above provision and its legislative intent.

Figure IA1: Supreme Court ruling and attention on in-house subcontracting

This figure plots a monthly search volume index from 2010 to 2016, generated by Google Trends based on a search term, ”in-house subcontracting (in Korean language).” The index displays relative search volume for a selected period using a scale of 0 to 100.

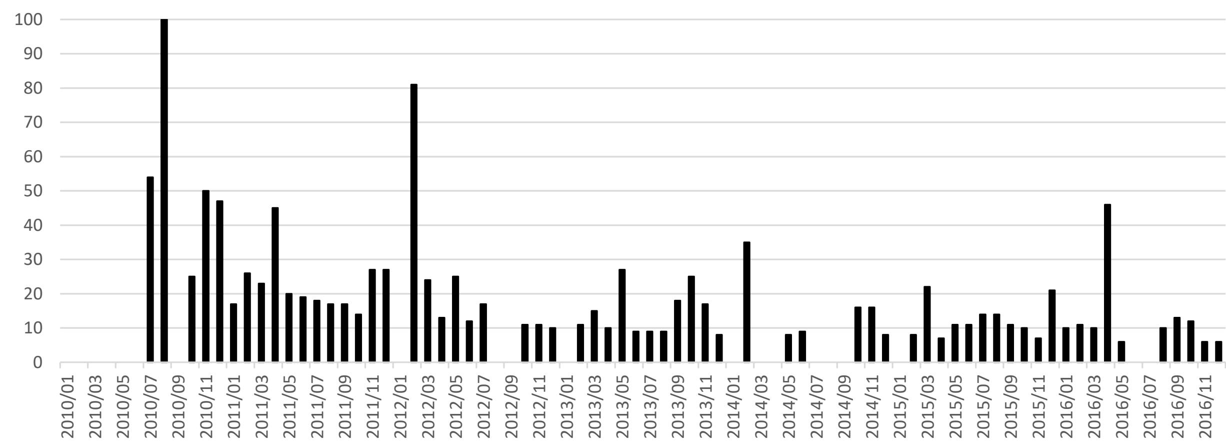
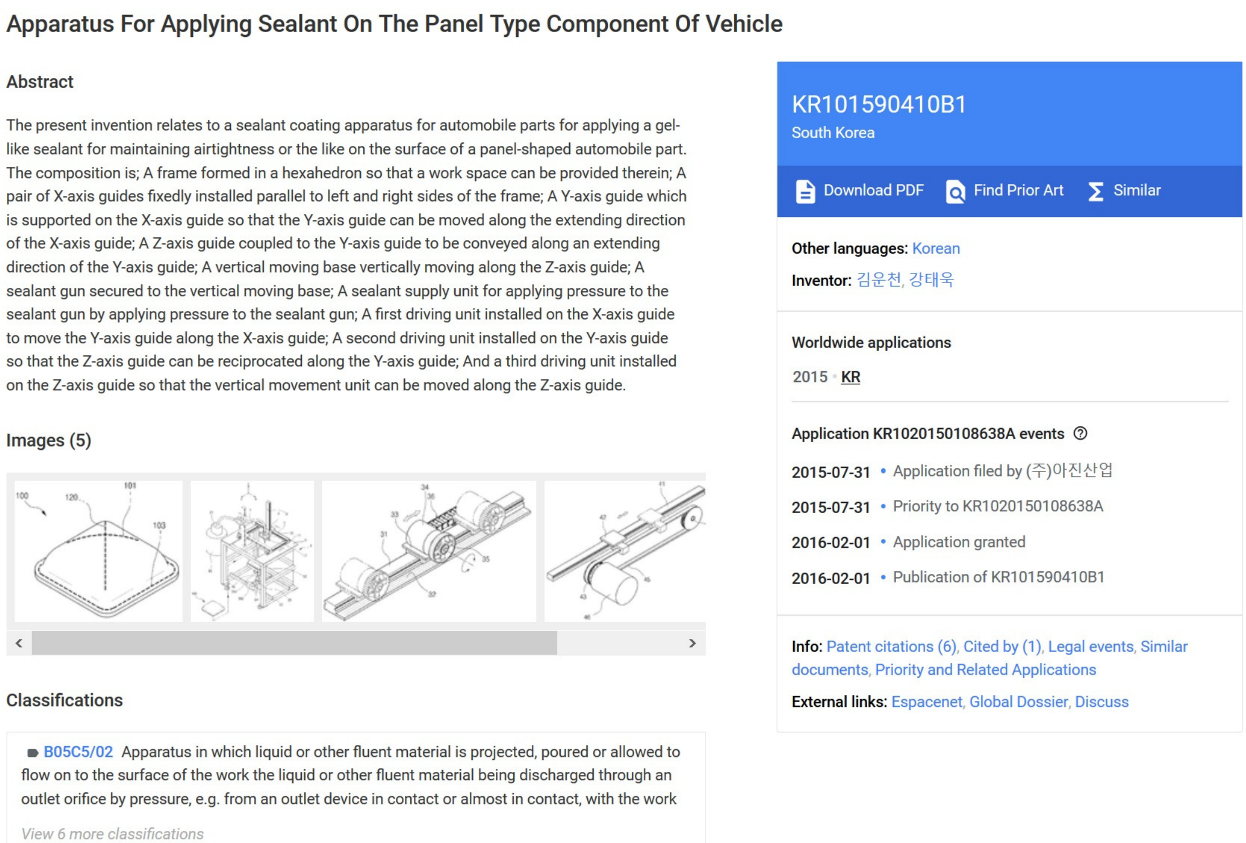


Figure IA2: Examples of Google Patents data

This figure describes the Google Patents data. Panel A is a screenshot of the first page of the description of a patent created in a treated industry (i.e., automobile) after the treatment (i.e., in 2015) and filed at the Korean Intellectual Property Office. The title, abstract, images, and classifications are on the left-hand side. The grant number, starting with a country identifier ("KR"), inventor, dates for application, priority, and grant, and links to citations and legal events are on the right-hand side. Next to the application date, the names of assignees follow "Application filed by." Panel B is a screenshot of the page Google Patents return for a search query based on the name of an inventor (of the patent in Panel A), Woon-Cheon Kim (in Korean language). One can modify search terms on the left-hand side. The list of patents created by the inventor, or his homonyms, is in the middle. The list of assignees are on the right-hand side, with corresponding patent classifications repoted in gray below the names of the assignees.

A. Patent



B. Inventor and firm

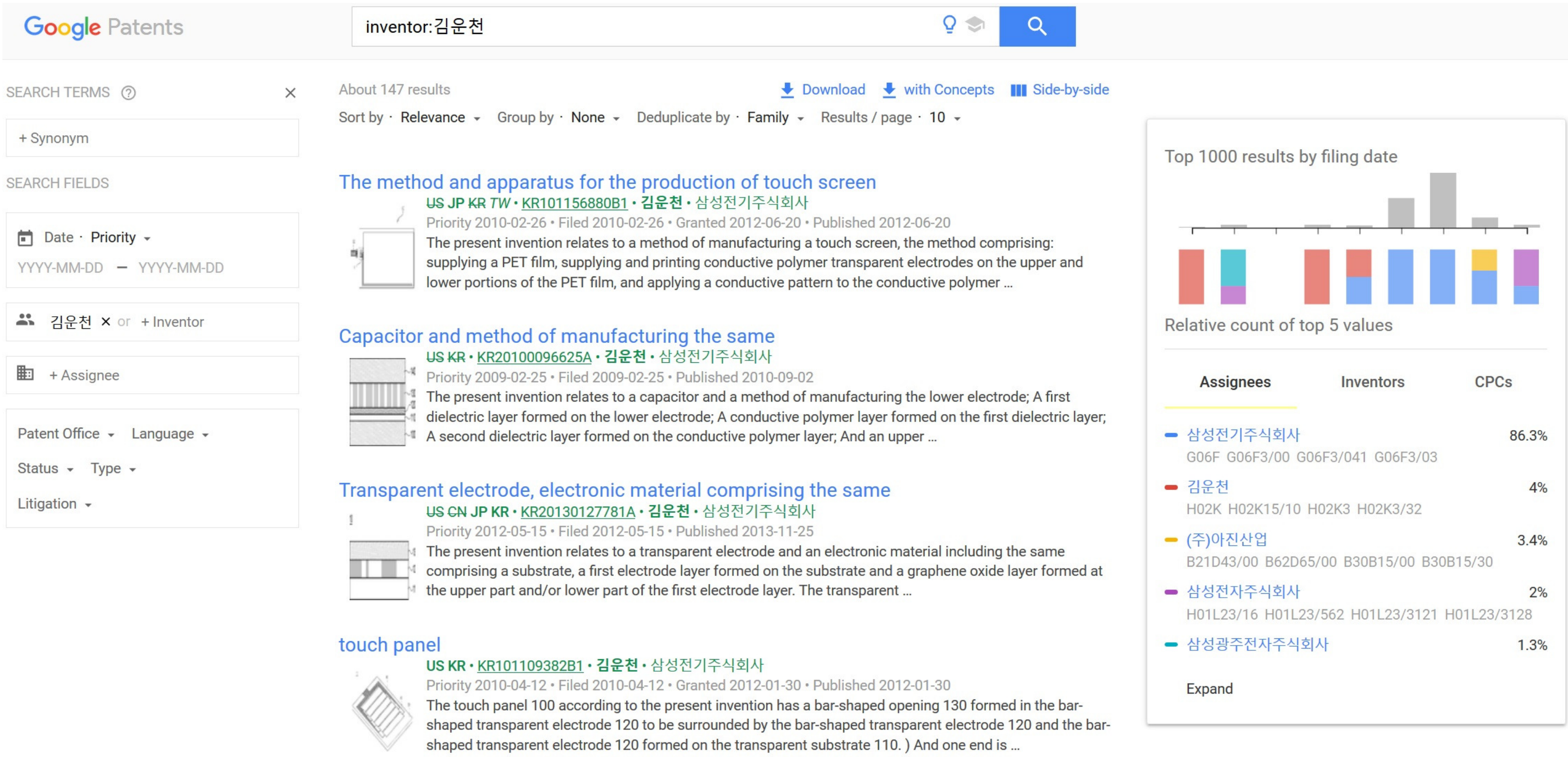


Table IA1: Industry classification

This table lists 12 industries used by Korea Labor Institute to construct strata for 2005-2013 surveys in Panel A and 10 industries for 2015-2017 surveys in Panel B. Two-digit industry codes follow the 9^{th} Korean Standard Industrial Classifications (KSIC). KSIC closely follows International Standard Industrial Classification (ISIC) and is updated periodically to reflect industry boundaries that evolve over time. The transition from 12 to 10 industries is to be consistent with the Organisation for Economic Co-operation and Development and implemented through distribution and communication services in Panel A collapsed to distribution services in Panel B and finance and insurance and other business services in Panel A collapsed to business services in Panel B.

Panel A. 12 industries

Category		Industry code
Manufacturing	Light industry	10-18, 32, 33
	Chemical	19-23
	Metal, automobile, and transport	24, 25, 29-31
	Electrical, electronics, and precision	26-28
Construction		41, 42
Service	Personal	45-47, 55, 56
	Distribution	49-52
	Communication	61
	Finance and insurance	64-66
	Other business	39, 58, 62, 63, 68-75
	Social	37, 38, 59, 60, 84-87, 90, 91, 94-96
Electricity, gas, and water supply		35, 36

Panel B. 10 industries

Category		Industry code
Manufacturing	Light industry	10-18, 32, 33
	Chemical	19-23
	Metal, automobile, and transport	24, 25, 29-31
	Electrical, electronics, and precision	26-28
Non-manufacturing	Construction	41, 42
	Electricity, gas, and water supply	35, 36
	Personal services	37-39, 45-47, 55, 56, 59, 60, 90-98
	Distribution services	49-52, 61
	Business services	58, 62-75
	Social services	84-87, 99

Table IA2: Summary statistics

This table reports summary statistics of characteristics of establishments in Panel A and firms in Panel B. Panel A uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. Panel B uses treated and matched control firms. Section 4.3 describes the matching procedure. The data on these manufacturing firms is from TS2000, a database comparable to Compustat. The data on patents aggregated for each firm year is from Korean Intellectual Property Office. Table A1 defines all variables.

Panel A. Establishment characteristics

	(1) Mean	(2) Linearized S.E.
# Subcontracted Workers	0.576	0.06
# Dispatched Workers	0.342	0.05
# Independent Contractors	0.186	0.04
# Day Workers	0.141	0.03
# Fixed-Term Workers	0.469	0.04
# Part-Timers	0.050	0.01
# Regular Employees	4.486	0.04
# All Employees	4.601	0.04
% Subcontracted Workers	0.036	0.01
% Dispatched Workers	0.014	0.00
% Independent Contractors	0.010	0.00
% Day Workers	0.005	0.00
% Fixed-Term Workers	0.014	0.00
% Part-Timers	0.002	0.00
% Regular Employees	0.914	0.01
# Experienced New Hires	1.989	0.06
# Inexperienced New Hires	1.129	0.06
# Involuntarily Outgoing Employees	0.751	0.04
# Voluntarily Outgoing Employees	2.298	0.06
% New Hires	0.180	0.01
% Experienced New Hires	0.127	0.007
% Inexperienced New Hires	0.053	0.00
% Outgoing Employees	0.191	0.009
% Involuntarily Outgoing Employees	0.032	0.00
% Voluntarily Outgoing Employees	0.157	0.01
Patent Costs	1.280	0.11
Patent Costs / Wage	0.008	0.00
Capitalized R&D	1.744	0.17
Capitalized R&D / Asset	0.012	0.00
Merit Pay	0.367	0.03
Basic Pay by Skill	0.272	0.03
Basic Pay by Seniority	0.541	0.03
Basic Pay by Function	0.362	0.03
ESOP	0.083	0.01
Stock Option	0.048	0.01
Stock Option for Executives	0.013	0.00
Capital Intensity	0.337	0.01
Financial Leverage	0.532	0.01
Operating Leverage	2.398	0.18
Labor Productivity	735.891	145.01
Capital-Adjusted Labor Productivity	9.240	1.15
Union	0.192	0.02
Establishment Size	10.185	0.08
ROA	0.087	0.00
Profit Margin	0.078	0.01
Wage Expenditure	0.155	0.01
Per-Employee Wage	33.485	1.05
Population size = 70,957.269, # Observations = 2,247, # Strata = 118, # Establishments = 700		

Panel B. Matched firm characteristics

	(1) N	(2) Mean	(3) Median	(4) S.D.
# Patents	49013	0.38	0.00	0.93
# Patents / Wage	48938	1.06	0.00	3.63
Expensed R&D	49013	5.55	0.00	6.36
Expensed R&D / Asset	49013	0.01	0.00	0.01
Firm Size	49013	17.55	17.30	1.14
Return on Assets	49013	0.08	0.08	0.09
Financial leverage	49013	0.57	0.58	0.27
Capital intensity	49013	0.40	0.38	0.21
Wage Expenditure	49013	0.04	0.03	0.04
# Patents	49013	0.38	0.00	0.93
# Patents by New Inventors	49013	0.22	0.00	0.65
# Patents by Existing Inventors	49013	0.22	0.00	0.68
# Collaborative Patents	49013	0.17	0.00	0.64
# Non-Collaborative Patents by New Inventors	49013	0.12	0.00	0.44
# Non-Collaborative Patents by Existing Inventors	49013	0.16	0.00	0.56
# Citations per Patent	49013	0.32	0.00	1.00
# Citations per Patent by New Inventors	49013	0.18	0.00	0.70
# Citations per Patent by Existing Inventors	49013	0.20	0.00	0.75
# Citations per Collaborative Patent	49013	0.13	0.00	0.64
# Citations per Non-Collaborative Patent by New Inventors	49013	0.09	0.00	0.45
# Citations per Non-Collaborative Patent by Existing Inventors	49013	0.14	0.00	0.62
Originality of Patents	6312	0.67	0.59	0.60
Originality of Patents by New Inventors	6312	0.25	0.08	0.44
Originality of Patents by Existing Inventors	6312	0.28	0.14	0.42
Originality of Collaborative Patents	6312	0.16	0.00	0.39
Originality of Non-Collaborative Patents by New Inventors	6312	0.16	0.00	0.41
Originality of Non-Collaborative Patents by Existing Inventors	6312	0.21	0.00	0.40
Generality of Patents	5785	0.35	0.14	0.52
Generality of Patents by New Inventors	5785	0.12	0.00	0.30
Generality of Patents by Existing Inventors	5785	0.15	0.00	0.34
Generality of Collaborative Patents	5785	0.09	0.00	0.29
Generality of Non-Collaborative Patents by New Inventors	5785	0.07	0.00	0.27
Generality of Non-Collaborative Patents by Existing Inventors	5785	0.11	0.00	0.31
% Process Patents	49013	0.04	0.00	0.14
% Process Patents by New Inventors	49013	0.03	0.00	0.13
% Process Patents by Existing Inventors	49013	0.02	0.00	0.09
% Collaborative Process Patents	49013	0.01	0.00	0.06
% Non-Collaborative Process Patents by New Inventors	49013	0.01	0.00	0.07
% Non-Collaborative Process Patents by Existing Inventors	49013	0.01	0.00	0.07
# Outgoing Inventors	49013	0.09	0.00	0.36
# Outgoing New Inventors	49013	0.05	0.00	0.24
# Outgoing Existing Inventors	49013	0.04	0.00	0.22
# Outgoing Inventors after Collaborative Innovation	49013	0.04	0.00	0.22
# Outgoing New Inventors after Non-Collaborative Innovation	49013	0.02	0.00	0.10
# Outgoing Existing Inventors after Non-Collaborative Innovation	49013	0.03	0.00	0.17

Table IA3: Employment in scale

This table reports coefficient estimates from the regression on $\tilde{Treat} \times Post$ and control variables. The dependent variable is the log of one plus the number of subcontracted workers in column (1), dispatched workers in column (2), independent contractors in column (3), day workers in column (4), fixed-term workers in column (5), part-timers in column (6), and regular employees in column (7). Table 4 defines $\tilde{Treat}$, $Post$, and control variables. Table A1 defines all other variables. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Indirect employment				Direct employment		
	# Subcontracted Workers	# Dispatched Workers	# Independent Contractors	# Day Workers	# Fixed-term Workers	# Part-timers	# Regular Employees
$\tilde{\text{Treat}} \times$ Post	-0.1528***	0.0288*	0.0066	0.0122	0.0060	-0.0085	0.0047
	(0.035)	(0.017)	(0.015)	(0.015)	(0.015)	(0.007)	(0.008)
Controls	Y	Y	Y	Y	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year						
N	2247	2247	2247	2247	2247	2247	2247
Adjusted R^2	0.705	0.606	0.598	0.449	0.582	0.396	0.920

Table IA4: Changes in employment and innovation

This table reports coefficient estimates from the regression on $\tilde{Treat} \times \mathbb{1}[t = \tau]$ and control variables. The dependent variable is the log of one plus the number of subcontracted workers in column (1), the percent of varying classes of contingent workers in columns (2)-(7), and the log of one plus capitalized patent costs in column (8) in Panel A. It is the log of one plus the number of patents in Panel B. Table 4 defines $\tilde{Treat}$ in Panel A. Table 5 defines $Treat$ in Panel B. Table 4 defines control variables used in Panel A. $\mathbb{1}[t = \tau]$ is an indicator of τ years after the ruling. It takes the value of one if $t = \tau$ and zero otherwise. Panel A uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. Panel B uses a sample of treated and matched control firms. Section 4.3 describes the matching procedure. The data on manufacturing firms is from TS2000, a database comparable to Compustat. The data on patents aggregated for each firm year is from Korean Intellectual Property Office. A cohort consists of establishments founded in the same year in Panel A and firms in Panel B. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. In Panel A, each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment in Panel A and firm in Panel B. They are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Establishments

	(1) # Subcontracted Workers	(2) % Subcontracted Workers	(3) % Dispatched Workers	(4) % Independent Contractors	(5) % Day Workers	(6) % Fixed-term Workers	(7) % Part-timers	(8) Patent Cost
$\tilde{\text{Treat}} \times \mathbb{1}[t = -5]$	-0.0558*	-0.0057*	0.0020	0.0021	-0.0002	-0.0010	0.0004	-0.0188
	(0.030)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.028)
$\tilde{\text{Treat}} \times \mathbb{1}[t = -3]$	-0.0336	-0.0023	0.0003	-0.0010	-0.0001	-0.0003	0.0004	0.0148
	(0.030)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.022)
$\tilde{\text{Treat}} \times \mathbb{1}[t = 1]$	-0.0807***	-0.0056**	0.0013	0.0004	-0.0002	0.0011	-0.0002	0.0012
	(0.027)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.028)
$\tilde{\text{Treat}} \times \mathbb{1}[t = 3]$	-0.1359***	-0.0107***	0.0032**	0.0011	0.0004	0.0006	-0.0001	0.0474
	(0.039)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.035)
$\tilde{\text{Treat}} \times \mathbb{1}[t = 5]$	-0.2785***	-0.0255***	0.0024*	0.0003	0.0005	0.0002	-0.0001	0.0917**
	(0.044)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.041)
$\tilde{\text{Treat}} \times \mathbb{1}[t = 7]$	-0.2451***	-0.0217***	0.0005	0.0006	-0.0001	0.0008	0.0001	0.1190**
	(0.069)	(0.007)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.055)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year							
N	2247	2247	2247	2247	2247	2247	2247	2247
Adjusted R^2	0.716	0.737	0.532	0.710	0.482	0.528	0.577	0.767

Panel B. Firms

	(1) # Patents
Treat × $\mathbb{1}[t = -4]$	0.0209
	(0.028)
Treat × $\mathbb{1}[t = -3]$	-0.0096
	(0.024)
Treat × $\mathbb{1}[t = -2]$	-0.0053
	(0.021)
Treat × $\mathbb{1}[t = 0]$	0.0203
	(0.019)
Treat × $\mathbb{1}[t = 1]$	0.0267
	(0.021)
Treat × $\mathbb{1}[t = 2]$	0.0574**
	(0.023)
Treat × $\mathbb{1}[t = 3]$	0.0488**
	(0.024)
Treat × $\mathbb{1}[t = 4]$	0.0669***
	(0.025)
Treat × $\mathbb{1}[t = 5]$	0.0720***
	(0.026)
Treat × $\mathbb{1}[t = 6]$	0.0642**
	(0.027)
Treat × $\mathbb{1}[t = 7]$	0.0582**
	(0.029)
Controls	Y
Fixed effects	Firm, province-year, cohort-year
N	44141
Adjusted R^2	0.719

Table IA5: Alternative definitions for treatment and post-ruling period

This table reports coefficient estimates from the regression on $\tilde{Treat}$ (and its variants) times $Post$ (and its variants) and control variables. The dependent variable is the log of one plus the number of subcontracted workers in Panel A and the log of one plus capitalized patent costs in Panel B. Table 4 defines $\tilde{Treat}$, $Post$, and control variables. $Post2009$ is an indicator that takes the value of one for years after 2009 and zero otherwise. The pre-ruling period that defines variants of Treat is from 2007 to 2009. The variants take an average value computed over the period. The four most treated industries are automobile, shipbuilding, steel, and machinery and equipment industries. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Contingent employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				# Subcontracted Workers			
$\tilde{\text{Treat}}$ × Post 2009	-0.0111***						
	(0.003)						
% Subcontracted Workers in 2009 × Post		-0.0043***					
		(0.001)					
ln(1 + # Subcontracted Workers Pre-Ruling) × Post			-0.0889***				
			(0.025)				
ln(1 + # Subcontracted Workers in 2009) × Post				-0.0288***			
				(0.007)			
1(Has Subcontracted Workers Pre-Ruling) × Post					-0.0544***		
					(0.017)		
1(Has Subcontracted Workers in 2009) × Post						-0.0707***	
						(0.021)	
1(Belongs to 4 Most-Treated Industries) × Post							-0.0279*
							(0.015)
Controls	Y	Y	Y	Y	Y	Y	Y
Fixed effects				Establishment, industry-year, province-year, cohort-year, unit-year			
N	2247	2247	2247	2247	2247	2247	1916
Adjusted R^2	0.711	0.722	0.711	0.715	0.699	0.704	0.688

Panel B. Innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Capitalized Patent Cost			
$\tilde{\text{Treat}} \times$ Post 2009	0.0481*						
	(0.025)						
% Subcontracted Workers in 2009 $\times$ Post		0.0171					
		(0.012)					
ln(1 + # Subcontracted Workers Pre-Ruling) $\times$ Post			0.3843				
			(0.269)				
ln(1 + # Subcontracted Workers in 2009) $\times$ Post				0.0601			
				(0.086)			
1(Has Subcontracted Workers Pre-Ruling) $\times$ Post					0.2074		
					(0.201)		
1(Has Subcontracted Workers in 2009) $\times$ Post						0.0047	
						(0.222)	
1(Belongs to 4 Most-Treated Industries) $\times$ Post							0.1257
							(0.223)
Controls	Y	Y	Y	Y	Y	Y	Y
Fixed effects				Establishment, industry-year, province-year, cohort-year, unit-year			
N	2247	2247	2247	2247	2247	2247	1916
Adjusted R^2	0.765	0.766	0.765	0.764	0.764	0.764	0.750

Table IA6: Stratum fixed effects

This table reports coefficient estimates from the regression on $\tilde{Treat} \times Post$ and control variables. The dependent variable is the log of one plus the number of subcontracted workers in columns (1) and (3) and the log of one plus capitalized patent costs in columns (2) and (4). Table 4 defines $\tilde{Treat}$, $Post$, and control variables. Stratum industries are 12 industries in Internet Appendix Table IA1, Panel A. Stratum regions are five regional groups of Seoul, Gyeonggi/Incheon, Gangwon/Chungcheong, Jeolla/Jeju, and Gyeongsang, which span nine provinces and eight special cities of Korea. Stratum employment size is based on the number of regular employees. Establishments hiring 30-99, 100-299, 300-999, and 1000 or more regular employees form four respective size groups. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) # Subcontracted Workers	(2) Capitalized Patent Cost	(3) # Subcontracted Workers	(4) Capitalized Patent Cost
$\tilde{\text{Treat}} \times$ Post	-0.0136***	0.1111***	-0.0128***	0.0694*
	(0.003)	(0.024)	(0.002)	(0.035)
Controls	Y	Y	Y	Y
Establishment FE	Y	Y	Y	Y
Stratum-Year FE	Y	Y	N	N
Stratum Industry-Year FE	N	N	Y	Y
Stratum Area-Year FE	N	N	Y	Y
Stratum Employment Size-Year FE	N	N	Y	Y
Cohort-Year FE	Y	Y	Y	Y
Unit-Year FE	Y	Y	Y	Y
N	2232	2232	2232	2232
Adjusted R^2	0.727	0.750	0.719	0.755

Table IA7: Alternative combinations of merit pay and basic pay components

This table reports coefficient estimates from the regression of the log of one plus capitalized patent costs on interactions between $Treat$, $Post$, and $Channel_{-1}$ and control variables. Table 4 defines $Treat$, $Post$, and control variables. $Channel_{-1}$ is an indicator for a pay component in place a year before the ruling. The pay component is merit pay plus basic pay based on skill and seniority in column (1), skill and function in column (2), seniority and function in column (3), skill, seniority, and function in column (4) and zero otherwise. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Capitalized Patent Cost			
Channel =	Merit Pay × Basic Pay by Skill & Seniority	Merit Pay × Basic Pay by Skill & Function	Merit Pay × Basic Pay by Seniority & Function	Merit Pay × Basic Pay by Skill & Seniority & Function
$\widetilde{\text{Treat}}$ × Post	0.0554*	0.0975**	0.0974**	0.0976***
	(0.029)	(0.038)	(0.038)	(0.037)
Post × Channel_{-1}	0.1361	-0.0111	0.0272	0.6881
	(0.276)	(0.400)	(0.369)	(0.815)
$\widetilde{\text{Treat}}$ × Post × Channel_{-1}	0.1539***	-1.2644	-1.5631	-1.7498
	(0.053)	(1.306)	(1.288)	(1.451)
Controls	Y	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year			
N	1744	1744	1744	1744
Adjusted R^2	0.780	0.778	0.778	0.778

Table IA8: Managerial innovation incentive

This table reports coefficient estimates from the regression of the log of one plus capitalized R&D on interactions between $\tilde{Treat}$, $Post$, and $Channel_{-1}$ and control variables. Table 4 defines $\tilde{Treat}$, $Post$, and control variables. $Channel_{-1}$ is an indicator for a pay component in place a year before the ruling. The pay component is employee stock ownership plan (ESOP) in column (1), stock option in column (2), and stock option for executives in column (3). This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
		Capitalized R&D	
Channel =	ESOP	Stock Option	Stock Option for Executives
$\tilde{\text{Treat}}$ × Post	-0.0725*	-0.0830**	-0.0734*
	(0.040)	(0.040)	(0.040)
Post × Channel_{-1}	0.9573	-1.6026*	-2.5889
	(0.799)	(0.840)	(2.121)
$\tilde{\text{Treat}}$ × Post × Channel_{-1}	-0.1020	0.3286	0.4451
	(0.163)	(0.295)	(0.428)
Controls	Y	Y	Y
Fixed effects		Establishment, industry-year, province-year, cohort-year, unit-year	
N	1744	1744	1744
Adjusted R^2	0.805	0.807	0.806

Table IA9: Sensitivity of managerial response to operating leverage

This table reports coefficient estimates from the regression on interactions between $\tilde{Treat}$, $Post$, and $Channel_{-1}$ and control variables. Table 4 defines $\tilde{Treat}$, $Post$, and control variables. The dependent variable is the log of one plus capitalized R&D. $Channel_{-1}$ is operating leverage a year before the ruling. The operating leverage is measured by operating leverage in column (1), union in place in column (2), and financial leverage in column (3). Table A1 defines all other variables. This table uses a stratified sample of manufacturing establishments that hire 30 employees or more. The data on these establishments is from the Korean Labor Institute's Workplace Panel Survey and available from 2005 to 2017. A cohort consists of establishments founded in the same year. Unit distinguishes single-unit, multi-unit headquarter, and multi-unit non-headquarter establishments. Each observation is weighted by the inverse of its probability of being sampled in the estimation of coefficients and standard errors. Standard errors are clustered by establishment and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
		Capitalized R&D	
Channel =	Operating Leverage	Union	Financial Leverage
Channel_{-1}	0.0067	-0.5435	-0.4386
	(0.016)	(0.403)	(0.730)
$\tilde{\text{Treat}} \times$ Post	-0.0783*	-0.0616	-0.0233
	(0.042)	(0.043)	(0.079)
Post $\times$ Channel_{-1}	0.0062	0.0590	0.4198
	(0.028)	(0.331)	(0.687)
$\tilde{\text{Treat}} \times \text{Channel}_{-1}$	0.0006	0.1058	0.2393
	(0.004)	(0.087)	(0.209)
$\tilde{\text{Treat}} \times$ Post $\times$ x Channel_{-1}	0.0001	-0.0294	-0.0867
	(0.011)	(0.069)	(0.120)
Controls	Y	Y	Y
Fixed effects	Establishment, industry-year, province-year, cohort-year, unit-year		
N	2247	2247	2247
Adjusted R^2	0.789	0.789	0.790

Table IA10: Process versus non-process innovation

This table reports coefficient estimate from the regression on $Treat \times Post$ and control variables. The dependent variable is the share of process patents created by new inventors in column (1), non-collaborative process patents created by new inventors in column (2), process patents created by existing inventors in column (3), and non-collaborative process patents created by existing inventors in column (4). A process patent is one whose firm claim is process innovation (Bena et al. (2021)). Table 10 defines new and existing inventors. A non-collaborative patent is one that is not jointly created by new and existing inventors. Table 5 defines $Treat$, $Post$, and control variables. Table A1 defines all other variables. All columns use a sample of treated and matched control firms. Section 4.3 describes the matching procedure. The data on manufacturing firms is from TS2000, a database comparable to Compustat. The data of patents (resp. their citations) aggregated for each firm-year is from Korean Intellectual Property Office (resp. Google Patents). A cohort consists of firms founded in the same year. Standard errors are clustered by firm. They are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) % Process Patents by New Inventors	(2) % Non-Collaborative Process Patents by New Inventors	(3) % Process Patents by Existing Inventors	(4) % Non-Collaborative Process Patents by Existing Inventors
Treat $\times$ Post	0.0013	-0.0071*	0.0058	-0.0032
	(0.006)	(0.004)	(0.006)	(0.005)
Controls	Y	Y	Y	Y
Fixed effects	Firm, province-year, cohort-year			
N	44141	44141	44141	44141
Adjusted R^2	0.455	0.311	0.592	0.572

Table IA11: Originality and generality of innovation

This table reports coefficient estimate from the regression on $Treat \times Post$ and control variables. The dependent variable is the average originality of patents created by new inventors in column (1), non-collaborative patents created by new inventors in column (2), patents created by existing inventors in column (3), and non-collaborative patents created by existing inventors in column (4). Table 10 defines new and existing inventors. A non-collaborative patent is one that is not jointly created by new and existing inventors. In Panel B, generality replace the originality. The originality and generality is computed as in Trajtenberg et al. (1997) and described in Section 5.8. Table 5 defines $Treat$, $Post$, and control variables. Table A1 defines all other variables. All columns use a sample of treated and matched control firms. Section 4.3 describes the matching procedure. The data on manufacturing firms is from TS2000, a database comparable to Compustat. The data of patents (resp. their citations) aggregated for each firm-year is from Korean Intellectual Property Office (resp. Google Patents). A cohort consists of firms founded in the same year. Standard errors are clustered by firm. They are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Originality of patent applications

	(1) Originality of Patents by New Inventors	(2) Originality of Non-Collaborative Patents by New Inventors	(3) Originality of Patents by Existing Inventors	(4) Originality of Non-Collaborative Patents by Existing Inventors
Treat × Post	0.0229	0.0076	-0.0241	-0.0394
	(0.030)	(0.028)	(0.027)	(0.026)
Controls	Y	Y	Y	Y
Fixed effects	Firm, province-year, cohort-year			
N	5834	5834	5834	5834
Adjusted R^2	0.146	0.147	0.185	0.185

Panel B. Generality of patent applications

	(1) Generality of Patents by New Inventors	(2) Generality of Non-Collaborative Patents by New Inventors	(3) Generality of Patents by Existing Inventors	(4) Generality of Non-Collaborative Patents by Existing Inventors
Treat × Post	0.0214	0.0133	-0.0040	-0.0144
	(0.021)	(0.018)	(0.025)	(0.024)
Controls	Y	Y	Y	Y
Fixed effects	Firm, province-year, cohort-year			
N	5289	5289	5289	5289
Adjusted R^2	0.0872	0.0998	0.146	0.109