Time to Innovate*

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Abstract

We leverage Korea's 52-hour workweek law and a regression discontinuity design to examine how reduced working hours affect corporate innovation. Effective July 2018, the law leads to an immediate fall in working hours and a subsequent rise in innovation output by the end of 2019, only in light manufacturing, a sector heavily reliant on employee-driven innovation. This effect is attributed to suboptimal pre-law time allocation, as evidenced by the absence of significant changes in output, labor inputs, and capital inputs. The impact is more pronounced in establishments where innovation incentives complement increased non-labor time and is weaker where other forms of slack act as substitutes. The pre-law suboptimality is explained by structural inertia (proxied by a higher average employee age) and not by agency conflicts.

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1 Introduction

"We encourage our employees, in addition to their regular projects, to spend 20 percent of their time working on what they think will most benefit Google," co-founders Larry Page and Sergey Brin wrote in their 2004 IPO letter. "This empowers them to be more creative and innovative. Many of our significant advances have happened in this manner."[1] Companies such as Google, 3M, Linkedin, Apple, and Atlassian operate "discretionary time" programs, such as 20% time, 15% rule, InCubator, Blue Sky, and ShipIt Days, respectively, to foster creativity and innovation. Yet these examples remain exceptions, and there is little systematic evidence that extra non-work time drives innovation. This paper aims to address that gap by examining how a law change that imposes a stricter upper bound on working hours - in effect forcing an increase in employees' leisure time, a part of which may be used to increase innovation productivity during working hours - affect innovation outcomes.

We begin by extending the classic labor–leisure choice model (Hicks, 1932; Becker, 1965; Mincer, 1962) to incorporate the possibility that additional leisure not only raises workers' utility but can also boost their creative capacity. This, in turn, can increase firms' profitability and employees' utility through bonuses tied to profit increments. This idea, which builds on the psychology literature, implies that if a firm's innovation process heavily relies on rank-and-file employees, then increasing non-work time for the entire workforce can raise inventive output by allowing employees to rest and recover (Sonnentag and Fritz, 2015) and pursue "off-hours" idea generation (Baird et al., 2012). The model thus predicts that any exogenous rise in leisure time - particularly in an economy where pre-law working hours likely exceed the optimal level - should lead to higher innovation in firms where employee-driven innovation plays a crucial role.

We test this prediction using Korea's 52-hour workweek law, enacted in 2018 to reduce the maximum allowable hours from 68 to 52. This reform, introduced for reasons unrelated to innovation, such as improving work-life balance, provides a quasi-natural experiment for analyzing innovation effects. Leveraging a regression discontinuity design (RDD) around the 300-employee threshold, above which the law took effect earlier, we examine whether establishments just above the threshold differ in innovation outcomes from otherwise similar establishments below it. We

[1] https://abc.xyz/investor/founders-letters/ipo-letter/

draw on establishment-level data from the Korean Labor Institute (KLI)'s Workplace Panel Survey (WPS), which offers rich detail on work hours, staffing, and financials, including capitalized intellectual properties (IPs) as a measure of innovation output.

Our findings reveal that the law reduces weekly work hours by about three hours for treated establishments, primarily through a decline in regular weekend work. However, we find no significant economy-wide surge in innovation. Instead, the gains concentrate in *light manufacturing*, where evidence suggests that a broad base of employees plays a pivotal role in the innovation production. In this sector, treated establishments show a significant rise in capitalized IPs by the end of fiscal year 2019, relative to control establishments just below the 300-employee threshold[2]. Further analysis shows that establishments that do not penalize short-term failures and reward skill-based achievements (Manso, 2011) - incentivizing employees to use some of their leisure time to enhance their innovation productivity during working hours[3] - experience pronounced gains in innovation. Conversely, when establishments offer flexible working hours or days as an alternative form of slack, the extra leisure time yields smaller innovation gains.

We interpret the law's effects as causal for the following reasons. First, in survey years predating the law's proposal, there is no observed discontinuity in weekly work hours or innovation outcomes near the 300-employee threshold. Second, the discontinuity appears immediately after the law's July 2018 implementation and gradually fades as coverage extends to smaller establishments. Third, the pre-law characteristics of treated and control groups are statistically indistinguishable except for size-related attributes, such as employment, total assets, and ownership structure. Finally, the distribution of establishments close to the 300-employee cutoff is reasonably smooth to ensure comparability between treated and control establishments.

We find no evidence that reducing hours lowered firms' productivity or profitability. Rather,

[2] No comparable increase emerges in medium manufacturing, heavy manufacturing, and non-manufacturing, where innovation tends to rely on a smaller set of inventors (e.g., heavy manufacturing) or where employee size rarely reaches 300 (e.g., tech industries). See Section 8.4 for further discussion.

[3] The precise off-hours activities remain unobserved at the establishment level in the WPS data and observed from time use data from Statistics Korea without employee counts, our forcing variable. However, the 2019 National Leisure Activity Survey, conducted by the Ministry of Culture, Sports, and Tourism and the Korea Culture and Tourism Institute, sheds light on how employees in reduced-hour systems use their additional leisure time (multiple responses allowed): "emotional and physical stability through rest" (23.3%), "increased time spent with family" (22.0%), "greater personal enjoyment and self-satisfaction through leisure activities" (22.0%), "more time for social interactions and relationships" (18.0%), "improved work efficiency" (14.0%), "enhanced health through physical activities" (12.8%), "reduced income" (7.9%), and "increased work pressure and intensity due to tasks within limited hours" (4.7%). These responses suggest rest, recovery, and enhanced work efficiency may underlie the innovation boost, rather than second jobs or other economic activities.

the results are consistent with the premise that pre-law working hours were longer than optimal[4], so capping hours did not require adding labor or augmenting capital (to replace labor). Indeed, we observe no systematic increase in fixed assets, R&D expenditures, or employment, encompassing broad categories of direct and indirect employment observable from the WPS data[5]. At the same time, we do detect an uptick in labor-augmenting capital, such as software investments, possibly helping sustain output despite fewer hours.

Additional evidence points to structural inertia, particularly among older workforces, as a factor behind previously suboptimal time allocations. The law's effect on innovation is significantly larger in establishments employing a greater share of older workers (Hannan and Freeman, 1984; Damanpour and Evan, 1984), suggesting that entrenched routines and norms can slow adaptation to more efficient work–leisure splits. In contrast, classic agency conflicts, where managers lack incentives to dismantle entrenched norms for uncertain long-term benefits, appear less relevant. The increase in innovation output is not significantly weaker in establishments run by owner–managers (Berle and Means, 1932; Fama and Jensen, 1983), those whose managers are also the largest shareholders (Shleifer and Vishny, 1986), those with concentrated ownership (Demsetz and Lehn, 1985; Jensen and Meckling, 2019), or those affiliated with business groups (Claessens et al., 2000) or featuring higher foreign ownership (Aggarwal et al., 2011; Ferreira and Matos, 2008)[6].

While pinpointing the exact mechanism awaits further research, these findings suggest that long-term shareholders did not recognize or correct pre-law excess in labor hours, likely due to the absence of theoretical or empirical support linking leisure time to innovation. Indeed, current economics and management textbooks rarely treat discretionary time as a critical innovation driver. Absent its endorsement in academic research or widely consulted materials, both corporate managers and policymakers may have lacked a compelling basis to reform time-allocation practices.

This study contributes to the literature on the determinants of corporate innovation (see He and

[4]Labor productivity in Korea, measured as GDP per hour worked, is lower than the OECD average in 2015, while it was among the highest at the time Korea joined the OECD in 1996 (Source: OECD statistics). Real wage per hour worked barely increased during the period, while the education level markedly increased.

[5]We also examine compositional changes and non-permanent arrangements, which include fixed-term workers, part-timers, independent contractors, day workers, dispatched workers, and subcontract workers. The latter mitigates concerns that establishments might respond to the law by increasing indirect employment of skilled workers (i.e., dispatched or subcontract workers).

[6]While these foreign-ownership findings help alleviate external-validity concerns, they do not rule out the possibility that foreign institutional investors overlook widespread long-hours norms, focusing instead on readily addressable, firm-specific issues.

Tian (2018) for a survey) by offering, to our knowledge, the first evidence that firms' innovation output can be a function of employees' discretionary time. More broadly, it connects with several strands of endogenous growth theory (Romer (1990); Aghion and Howitt, 1992), which examine how innovation is influenced by R&D investment (Arrow, 1962; Hall and Lerner, 2010), legal institutions (North, 1990; Acemoglu et al., 2005), and human capital (Lucas Jr, 1988; Benhabib and Spiegel, 1994; Becker, 2009). By highlighting discretionary time as another key driver, our findings suggest that legal frameworks and work-hour policies, which vary across countries, may help explain cross-country differences in innovation rates (Barro, 1991) and that allowing workers more time away from routine tasks can raise the effective use of human capital.

Furthermore, this study enriches the nascent literature on how rank-and-file employees contribute to corporate innovation in manufacturing sectors that increasingly rely on higher-skilled labor (Charles et al., 2019). While previous research has explored how equity-based incentives (Chang et al., 2015; Hsieh et al., 2022) or hiring arrangements (Hwang, 2024) promote innovation among skilled workers, our evidence suggests that discretionary time is a necessary input for innovation-motivating incentive schemes (Manso, 2011) to increase innovation output.

The findings also speak to the literature on the potential limitations of corporate governance mechanisms (Shleifer and Vishny, 1997; Tirole, 2001), including the board of directors (Adams et al., 2010), executive compensation (Bebchuk and Fried, 2003), and internal control systems (Jensen, 1993). This paper shows that the effectiveness of governance mechanisms in mitigating principal-agent conflicts (or those between short- and long-term shareholders) can be limited by the absence of economic theories and evidence that guide the principal (or long-term shareholders).

Lastly, our findings contribute to the literature on time use (Becker, 1965; Aguiar and Hurst, 2007) by illuminating how leisure time outside working hours, including rest periods, may foster creativity and knowledge production during working hours. Traditional frameworks treat leisure as a source of utility that substitutes for consumption (Hicks, 1932) or stimulates it indirectly through leisure-related spending (Gronau, 1977). In contrast, our results suggest that off-hours leisure can generate spillover benefits for firms by enhancing workers' inventive capacity. This perspective expands wage–leisure choice models to incorporate the innovation gains that discretionary time away from work can engender, thereby underscoring the potential of balanced work–leisure arrangements to stimulate broader economic growth beyond leisure-intensive industries.

2 Theoretical motivation

2.1 Canonical labor-leisure choice (Hicks, 1932)

The framework for analyzing labor supply and demand is traced to the work of Hicks (1932) and later formalizations by Becker (1965) and others. On the supply side, each individual decides how many hours to devote to labor versus leisure out of a fixed total time endowment t. Earning a wage rate $w > 0$ for each unit of labor time, employees face a trade-off between the consumption goods purchased with labor income and the enjoyment derived from leisure hours. Specifically, if an individual chooses $l > 0$ hours of leisure, then labor hours are $t - l$ and consumption is $c = w(t - l)$. The worker selects l to maximize her utility $u(l \mid w)$, balancing the marginal utility of leisure against the marginal benefits of labor income. On the demand side, firms hire labor to maximize profits π. Let the firm's production quantity be q, sold at price p, with labor n and capital K. If the capital rental rate is r, then profits can be expressed as

$$\pi(n \mid w) = pq - wn(t - l) - rK. \tag{1}$$

In equilibrium, the wage w^* is determined by the intersection of labor demand and supply. The model yields an interior solution (l^*, n^*) where the marginal utility of leisure equals the marginal product of labor, capturing an optimal split of each worker's available time.

2.2 Labor supply with leisure-driven innovation

A key assumption in the canonical model is that devoting time to leisure generates utility only in the sense of personal well-being, without affecting labor productivity or innovative output. However, if a portion of leisure time can enhance creativity and problem-solving - ultimately benefiting both the worker and the firm - then standard conclusions about the optimal division of hours may change. To allow for this possibility, suppose that a fraction δ of an employee's leisure time l can be spent in rest, mental recovery, or self-directed creative work that yields an innovation benefit during working hours. Let each employee gain additional expected compensation b for their creative output, so that utility depends not just on labor income $w(t - l)$ but also on the innovation income $b\delta l$. Formally, each worker's utility may be written as

$$u(c, l) \quad \text{where} \quad c = w(t - l) + b\delta l. \tag{2}$$

In such a scenario, employees have an incentive to request additional leisure time if the innovation payoffs and corresponding utility gains are sufficiently large. This channel goes beyond classical wage–leisure trade-offs highlighting that longer rest or discretionary time can boost workers' creativity and income (at the rate of $b\delta$), rather than merely lowering their pay from routine tasks (at the rate of w).

Proposition 1. *The optimal leisure time for employees l_e^* is longer when leisure-driven innovation is considered than when it is not, provided that rewards for inventive outputs are in place ($b > 0$).*

Proof. Assume, without loss of generality, a log utility for employees: $u = \alpha \ln c + (1 - \alpha) \ln l$, where $\alpha \in [0, 1]$ represents the relative weight placed on consumption versus leisure. Then, Equation 2 implies $u = \alpha \ln(w(t - l) + b\delta l) + (1 - \alpha) \ln(l - \delta l)$. The first-order condition $\partial u/\partial l = 0$ gives the optimal leisure time:

$$l^* = \frac{1 - \alpha}{1 - b\delta/w} t. \tag{3}$$

Note that the optimal leisure time is $l_1^* = (1 - \alpha)t$ when leisure-driven innovation is not considered ($\delta = 0$) and is $l_2^* = l^*$ when leisure-driven innovation is considered ($\delta > 0$). Since $b\delta < w$, which is required by $l > 0$, it follows that $l_1^* < l_2^*$. □

2.3 Labor demand with leisure-driven innovation

From the firm's perspective, extending leisure may at first appear to reduce labor input, risking a drop in output. However, if non-work time enhances employees' creative capacity - particularly in environments heavily reliant on rank-and-file innovation - overall profits may rise if new ideas more than offset any foregone labor hours. Formally, suppose profits increase by $\lambda n \delta l$, capturing the possibility that each worker's leisure δl can spark innovations valuable to the firm, where $\lambda \geq 0$ parameterizes the sensitivity of innovations to these off-hour efforts. The firm pays an innovation bonus $b\delta l$ per employee but may earn higher profits from improved products or processes. Profits can be written as

$$\pi = \big(1 + \lambda n \delta l\big) \big[pq - wn(t-l) - rK\big] - nb\delta l, \tag{4}$$

where q is a decreasing function of leisure time l (i.e., $q'(l) < 0$). Note that innovation $\lambda n \delta l$, which determines the profit increment in Equation 4, is modeled as a non-decreasing function of leisure time l following prior research (Romer, 1990; Aghion and Howitt, 1992, among others).

Proposition 2. *Holding employee count n fixed, if the innovation to labor sensitivity λ exceeds a threshold value $\underline{\lambda}$, the profit-maximizing leisure time l_f^* is greater than in a benchmark model with no leisure-driven innovation in Equation 1.*

Proof. The firm maximizes profits in Equation 4, and the first order condition is:

$$q'(l) = -wn/p - \frac{\lambda \pi(l) - b}{(1/(\delta n) + \lambda l)p}$$

Let π_1 and l_1 be profits and leisure time when leisure-driven innovation is not considered ($\lambda = 0$ and $b = 0$) and π_2 and l_2 be profits and leisure time when leisure-driven innovation is considered ($\lambda > 0$ and $b > 0$). Then, the first order conditions for π_1 and π_2 are, respectively:

$$q'(l_1) = -wn/p \qquad\qquad q'(l_2) = -wn/p - \frac{\lambda \pi_1(l_2) - b}{(1/(\delta n) + \lambda l_2)p}$$

Since $q'(l) < 0$, it follows that $l_1^* < l_2^*$ when $\lambda > \underline{\lambda} \equiv b/\pi_1(l_2^*)$. $\square$

$\underline{\lambda}$ represents the critical threshold level of innovation sensitivity. It is defined as the ratio of the additional compensation b provided to employees for their innovation efforts to the firm's baseline profit $\pi_1(l_2^*)$ without considering innovation. The proposition implies that once λ crosses a threshold (large enough reliance on employees' inventive ideas), offering more leisure can be profitable.

In typical settings, firms fear that shorter labor hours might reduce production. However, if preexisting work hours $t-l$ are already above the *effective* level required to maintain output — i.e., there are diminishing returns or significant fatigue beyond some point - then cutting back on hours need not diminish output at all (Pencavel, 2015, Collewet and Sauermann, 2017). In that case, the firm might discover that additional leisure yields real innovation benefits while not harming current production levels. As we discuss further below, this possibility is especially pertinent when cultural or routine-based norms keep hours longer than necessary for standard productivity.

Corollary 1. *In equilibrium, if the economy has historically operated at $t - l_1^*$ that are longer than effective working hours, then a shift toward more non-work time can boost innovation while leaving output unchanged or even enhanced, so long as λ exceeds a certain threshold $\underline{\lambda}$.*

Proof. This corollary directly follows from Propositions 1 and 2. They together suggest that the equilibrium leisure time l^* determined in the labor market is longer with leisure-driven innovation than without when $\lambda > \underline{\lambda}$. □

2.4 Labor market equilibrium in the 21st century: leisure-innovation tradeoffs

Evidence suggests that many modern economies operate on the *long-hours* side of the optimal leisure–innovation curve. While human capital's role in growth is well established (Romer, 1990; Aghion and Howitt, 1992), cross-country data reveal a negative correlation between average annual hours worked and innovation indicators such as R&D spending and patenting rates. For example, Figure 1 shows that across OECD countries in 2014, the last year before Korea's 52-hour workweek law proposal, those with shorter work hours exhibit higher R&D intensity and more patents per capita.

One explanation is that many workers worldwide – especially in countries with historically long workweeks – already exceed *effective* working hours. In other words, adding more hours yields minimal or even negative marginal returns, whereas reducing hours can maintain or even increase output through improved efficiency and creative engagement. Consequently, if current working hours surpass the productivity-maximizing level, imposing stricter workweek limits could increase innovation without harming baseline production.

Figure 1 provides preliminary evidence that in the early 21^{st} century, labor time and innovation are inversely related. This figure covers all OECD member countries in 2014, the last year with complete data before Korea's workweek law was proposed. It shows a negative relationship between labor time – measured as average annual hours worked per worker – and two innovation metrics: R&D expenditure as a share of GDP (innovation input) and patent counts per working-age population (innovation output).

This negative association yields several insights. First, work hours may be suboptimally long worldwide, possibly due to policies or practices rooted in models ignoring leisure-driven innovations. Second, it implies a positive relationship between leisure time and innovation. Lastly, it suggests that OECD countries lie on the left-hand side of the inverted–U curve in Figure 2 relating leisure time (x-axis) to innovation output (y-axis) – in other words, current leisure time is below its innovation-maximizing level[7].

Figure 2 further illustrates the law's hypothetical impact on leisure and innovation, holding other factors constant. In 2014, Korea had the OECD's second-longest working hours (and thus second-shortest leisure), behind Mexico, suggesting its leisure was far to the left of the optimal point, though still above the old 68-hour weekly cap. The 52-hour law raises this lower bound on leisure from $\underline{l_0}$ to $\underline{l_1}$, effectively expanding non-work time. By increasing leisure from l_0 to l_1, the law could in turn raise innovation output from i_0 to i_1, but only if λ, the innovation-to-labor sensitivity, exceeds a critical threshold $\underline{\lambda}$. We aim to test this prediction in the remainder of the paper.

3 Institutional details

3.1 Regulations on working hours worldwide

In the 1990s, some European civil law countries introduced regulations to limit working hours, aiming to protect workers while maintaining flexibility. For instance, since 1994, **Germany**'s Working Time Act (Arbeitszeitgesetz) has capped average weekly working hours at 48, including overtime, calculated over a six-month period. Similarly, since 1996, the **Netherlands**'s Working Hours Act (Arbeidstijdenwet) has allowed a maximum of 60 hours per week, provided that the four-week average does not exceed 48 hours. **Belgium**'s Labour Act of 1971 sets the standard at 38 hours per week but permits flexible arrangements, allowing work hours to exceed this limit based on a longer reference period. These European regulations reflect a balance between worker protection and the need for flexibility, with average weekly working hours capped between 38 and 48 while allowing for adjustments over extended periods.

[7] We assume that the leisure time l^* maximizing firm profits $\pi(l^*)$ also maximizes innovation output $i(l^*)$. Here i represents the incremental value of innovation to firm profits and could be measured more cleanly by stock market reactions (Kogan et al., 2017) than by patent counts. Since q exhibits diminishing returns to labor time, i is likely concave for reasonable parameter values.

In June 2018, **Japan** enacted similar reforms, capping overtime to combat excessive work and "karoshi" (death from overwork). The legal limit was set at 45 hours of overtime per month and 360 hours per year, translating to a weekly cap of approximately 50 to 51 hours (including 40 statutory hours), which is comparable to Korea's 52-hour limit. In both Korea and Japan, penalties for violations include fines and, in severe or repeated violation cases, criminal charges. Additionally, these countries impose public shaming by publishing the names of non-compliant companies, adding a cultural layer of accountability.

3.2 52-hour workweek law in Korea

On February 28, 2018, Korea's National Assembly passed the 52-hour workweek law (bill no. 2000028) as part of an amendment to the Labor Standards Act. The law was implemented in phases: it first applied to establishments with over 300 employees on July 1, 2018, then to those with 50 to 299 employees on January 1, 2018, and finally to those with 5 to 49 employees on July 1, 2021. See Table 1 for the legislative timelines. The law caps weekly working hours at 52, consisting of 40 statutory hours and a maximum of 12 overtime hours. This legislation marked a significant reduction from the previous maximum of 68 hours per week, which included 16 hours of weekend work that were excluded from the computation of statutory hours. The law was intended to address the issue of overwork, a persistent problem in Korea, which had the second longest working hours among OECD member states in 2014, just behind Mexico, as shown in Figure 1.

Despite the law's well-intended objectives, its implementation has sparked mixed reactions. On one hand, it has successfully reduced the number of people working excessively long hours. On the other hand, critics argue that it lacks the necessary flexibility for industries with variable work demands, such as those driven by project-based schedules or seasonal peaks. This has led to ongoing discussions about revising the law to allow for more flexible calculations, such as monthly averages, similar to the system in some European countries. Concerns have also been raised about the potential negative impact of the 52-hour workweek on innovation. Some worry that reduced working hours could lead to lower innovation, particularly in sectors that depend heavily on continuous R&D. They argue that the strict limitations may not align with the fast-paced, iterative nature of innovative projects, potentially stifling their dynamic processes. However, proponents counter that increased leisure time could lead to more focused and productive work hours, ultimately enhancing creativity and efficiency.

4 Research design

4.1 52-hour workweek law as a shock

The 2018 reform of Korea's Labor Standards Act imposed a 52-hour weekly work cap on firms with 300 or more employees, down from the previous maximum of 68 hours. Under the old law, firms could legally schedule 40 standard hours plus 12 overtime hours each week, and also use up to 16 hours of extended time (often on weekends) without penalty. The new rule effectively removed this extra allowance, making any work beyond 52 hours subject to penalties. Violations incur strict penalties (up to two years' imprisonment or fines of roughly KRW 20 million) and can be detected by labor inspections or employee complaints. Importantly, employers remain liable even if employees voluntarily offer to work longer.

This reform provides a quasi-experimental shock for studying innovation. First, the law was motivated by work-life balance rather than innovation promotion, making the cutoff plausibly exogenous to firms' innovation activities (i.e., addressing reverse causality concerns). Second, implementation was staggered by firm size, creating a discontinuity at 300 employees: establishments just below this threshold faced no change, while those just above had to cut hours. Firms near the cutoff are thus comparable except for treatment status (i.e., mitigating omitted variable bias concerns). Third, this is a rare contemporary episode of national work-hour regulation. The previous comparable case was the Netherlands' 1996 law (Section 3.1). Innovations and production processes have evolved greatly since then, so this context provides new insight. Finally, Korea's economy is balanced between manufacturing and services. Many European economies are services-heavy while many Asian economies are manufacturing-heavy, but Korea spans both. Studying its cross-sector impacts can thus shed light on how such a reform might play out in diverse economies.

At the same time, we address identification concerns related to early compliance and strategic defiance. The law was proposed in May 2016, nearly two years before enactment, with support from 122 of 300 National Assembly members (Table 1), giving firms ample time to anticipate its passage. Public interest, proxied by Google searches for "52 hours workweek," surged at enactment but was already elevated in 2017 (Figure B1), suggesting early awareness. In an unreported analysis, we observe that during June 2016 to March 2017, establishments above the 300-employee threshold (and those just below) start trimming weekly hours, and light-manufacturing establishments above the threshold show a modest rise in capitalized IPs by the 2017 fiscal year-end, after years of no relative growth. These patterns indicate some pre-trends in compliance following the law's proposal. To safeguard the validity of RDD, we verify continuity of key outcomes at the threshold using the most recent pre-proposal data: 2014 for weekly hours and 2015 for innovation. This approach avoids bias from anticipatory adjustments.

We also examine potential non-compliance, or strategic defiance, of two forms. First, some treated establishments may continue exceeding the 52-hour weekly limit post-reform, weakening the estimated treatment effect by dampening reductions in labor time and associated gains in innovation. Second, control establishments may deliberately limit their workforce to remain below the 300-employee threshold and avoid regulation. While this endogenous sorting raises interpretive concerns, it does not bias identification within the RD framework, as such firms remain untreated and should exhibit no policy-driven changes in labor or innovation outcomes. To assess potential manipulation of the running variable, we implement the McCrary density test (McCrary, 2008) using 2017 end-of-year employment data (Figure 3). We find no significant discontinuity at the 300-employee threshold, either in the full sample (Panel A) or within sector-specific subsamples (Panel B).

4.2 Rationale for cross-sectoral analysis

We measure innovation-to-labor sensitivity λ at the sector level and compare the law's effects on establishment outcomes across sectors. This approach minimizes omitted variable bias, which could be more severe at the industry or establishment level. Also, the small number of observations makes it impractical to compute λ at the industry or establishment level[8]. We categorize establishments into four sectors: light manufacturing (North American Industry Classification System (NAICS) 31), medium manufacturing (NAICS 32), heavy manufacturing (NAICS 33), and non-manufacturing (NAICS 42 to 81). Table 2, Panel A compares these sectors with other classification systems, including two-digit Standard Industrial Classification (SIC) codes. We opt to use NAICS

[8]For example, computing establishment-level λ would require time-series data, but only four data points are available during our sample period from 2015 to 2021 in the biennial WPS data.

over SIC for several reasons. First, it is less prone to confounding factors as Korea follows SIC. Second, this newer classification system likely better reflects the current innovation landscape. Third, NAICS provides better distributional balance across sectors and bandwidths near the threshold, as discussed below. However, an unreported analysis shows that the main results remain similar when using SIC-based sectors. We aggregate non-manufacturing industries due to the sparse distribution of establishments with over 300 employees, including potentially high-λ industries like IT.

4.3 Innovation-to-labor sensitivity in data

Figure 4 illustrates how the innovation-to-labor sensitivity parameter, λ, manifests in the data by relating employment size (x-axis) to innovation output (y-axis) in 2015, one year before the law's proposal. Panel A presents unconditional relationships using scatter plots with fitted lines. The slope, which proxies for λ, is steepest in light manufacturing, moderate in medium manufacturing, and shallow in heavy manufacturing. In non-manufacturing, the slope is near zero. Panel B shows conditional estimates from regressions of innovation output on labor and controls – capital (proxied by PPE) and innovation input (capitalized R&D expenditure). All variables are log-transformed after adding one. The estimated λ values follow the same sectoral gradient as in Panel A: highest in light manufacturing, declining through medium and heavy manufacturing, and slightly negative in non-manufacturing.

Further evidence of labor-dependence in light manufacturing comes from Figure B2, which shows that innovation capital—measured by capitalized R&D (Panel A) and capitalized IPs (Panel B) as a share of total assets—is lowest in light manufacturing and highest in heavy manufacturing, with medium manufacturing in between. Figure 5 offers additional support: darker dots and fitted lines show a strong positive association between innovation output (y-axis) and employee-driven innovation input (x-axis, proxied by wage expenditure) across all sectors. In contrast, brighter dots and fitted lines indicate a strong link between innovation output and manager-driven inputs (R&D expenditure) in all sectors except light manufacturing, where the slope is positive but nearly flat—suggesting a weaker marginal role for managerial innovation investment.

4.4 Bandwidth choice

We use the bandwidth of ± 100, ± 200, and ± 300 to ensure at least 30 observations in total, with a minimum of 15 observations on each side of the cutoff, for each sector when using the tightest bandwidth. Table 2, Panel B displays the distribution of establishments across sectors by employment range as of the 2017 calendar year, confirming that every sector meets this criterion. For example, light manufacturing includes 16 establishments in the [200, 299) range and 18 establishments in the [300,399) range.

4.5 Estimation models

To estimate the law's effect on innovation output and other outcomes using RDD, we employ the following specification. While we assume a linear (first-degree polynomial) relationship between the dependent and independent variables, our main results are robust to higher-degree polynomial specifications, as shown in Figure B3, Panel A.

$$Y_i = \alpha_{j(i)} + \beta_0 + \beta_1 \mathbb{1}[E_i \geq 300] + \gamma' X_i + \epsilon_i. \tag{5}$$

Here, i denotes the establishment, and $j(i)$ indicates the industry, based on the two-digit SIC code to which establishment i belongs. Y_i represents an outcome of interest for establishment i, such as weekly work hours or innovation output, measured by capitalized IPs. The term $\alpha_{j(i)}$ represents industry fixed effects, controlling for the influence of time-invariant industry characteristics. Our main results remain similar when sector fixed effects are used instead. $\mathbb{1}[E_i \geq 300]$ is an indicator that equals one if establishment i has 300 or more employees at the end of the 2017 calendar year and zero otherwise. X_i is a vector of observable characteristics of establishment i that may influence the outcome, including size (total assets), R&D (capitalized or expensed R&D expenditure), other intangible assets (intangible assets excluding capitalized IPs and capitalized R&D spending as a percentage of total assets), capital intensity (PPE over total assets), and union presence. The coefficient β_1 captures the law's causal impact on Y_i, provided that the RDD's identifying assumptions are satisfied.

To explore potential heterogeneous treatment effects in light manufacturing compared to other sectors, we extend Equation 5 as follows.

$$
\begin{aligned}
Y_i = \alpha_{j(i)} + \beta_0 + \beta_1 \mathbb{1}[E_i \geq 300] + \beta_2 \mathbb{1}[E_i \geq 300] \times \mathbb{1}[s(i) = L] \\
+ \beta_3 E_i + \delta E_i \times \eta_{s(i)} + \gamma' X_i + \epsilon_i.
\end{aligned}
\tag{6}
$$

Here, $\mathbb{1}[s(i) = L]$ is an indicator variable for the light manufacturing sector. Each establishment i belongs to one of four sectors: $s(i) \in \{L, M, H, N\}$, representing light manufacturing, medium manufacturing, heavy manufacturing, and non-manufacturing, respectively. The vector $\eta_{s(i)}$ consists of sector-specific indicators, and their interactions with employee count (E_i) control for the differential impact of E_i on Y_i across sectors. The terms $\mathbb{1}[s(i) = L]_i$ and $\eta_{s(i)}$ are not included as separate terms on the right-hand side because their variations are absorbed by $\alpha_{j(i)}$ and thus, they are effectively omitted. All other variables are as previously defined. Given the weak evidence of non-compliance in medium manufacturing discussed in Section 4.1, we present results both for the light manufacturing sample using Equation 5 and for the entire sample using Equation 6.

5 Data

5.1 Workplace Panel Survey

Our data comes from the KLI's WPS[9]. Since 2005, the KLI has conducted biennial surveys on a stratified sample of establishments with 30 or more regular employees. Our sample period spans from 2015 to 2021, with 2021 being the most recent survey year available at the time of this writing. In 2015, the KLI nearly doubled the sample size to improve representativeness. The KLI constructs strata based on industry and employment size. Table 2 lists the ten industry groups used to define these strata. Employment size groups are categorized as 30-99, 100-299, 300-499, or 500 or more regular employees. The WPS collects a wide range of variables related to labor relations, unions, compensation, job training, human capital flows, and the financial status and performance of establishments. The financial statement data available at the firm level are converted to establishment-level figures using the procedure outlined in Internet Appendix A. Summary statistics for all establishment characteristics examined in this paper are provided in Table B1.

[9]This longitudinal data is available for download from the KLI's website (`https://www.kli.re.kr/wps`).

The data includes three innovation-related variables: capitalized IPs, expensed R&D, and capitalized R&D. Capitalized IPs represent the total costs associated with creating, purchasing, or renewing IPs, including patents, utility models, design rights, and trademarks. Patents dominate both in quantity and in cost[10]. This cost-based measure may better capture grassroots innovation, which is the focus of this study, than measures based on stock market reactions (Kogan et al. (2017)). It may also more accurately reflect the long-term economic value of patents than patent counts, as it accounts for renewal fees. Expensed and capitalized R&D tend to represent early- and late-stage R&D spendings, respectively.

With a relatively small sample of randomly selected establishments (3,431 in 2015) surveyed through their representatives, the KLI can ask hundreds of questions. However, to ensure confidentiality, establishments are anonymized, making it impossible to merge WPS data with other establishment or firm-level datasets. The lack of cash holdings data also limits the exploration of liquidity-related research questions (Matsa, 2010), which are increasingly important in labor finance (Nishesh et al., 2022) and corporate finance more broadly (Denis and Wang, 2023). Nonetheless, the WPS data is gaining recognition in academic research for its unique advantages. One such advantage is that it reveals previously invisible aspects such as indirectly hired non-permanent workers (Hwang, 2024) and the relational quality perceived by employees relative to management (Hwang and Lee, 2023). Further details on the WPS data can be found in Internet Appendix Section A.

5.2 Timing of data collection

A clear understanding of the data collection timeline, as illustrated in Figure 6, is crucial to appreciate the experimental setting of this study. The law's application is based on the average number of employees in a prior month, which for the first cohort of establishments subject to the law starting July 1, 2018, is June 2018. However, because the WPS data only provides the end-of-calendar-year employee count, we use the 2017 year-end workforce size as the forcing variable. Second, information on work hours is collected at the time of the surveys, which for the 2017 WPS takes

[10] In the manufacturing sector, as of 2009, patents constituted 51% of IPs, followed by trademarks (28%), design rights (12%), and utility rights (9%) (Source: Korean Statistical Information Service). A detailed fee structure for each IP type is available on the KIPO's website. The correlation between capitalized IPs and patent counts, aggregated at the two-digit industry and year level, is about 70%.

place between June and November 2018. This period follows the law's passage in February 2018 but includes one month - June 2018 - before the law's implementation. For simplicity, we include establishments surveyed in June 2018 in our analysis and report robustness tests excluding these observations reported in the Internet Appendix, even though excluding them slightly strengthens the results. Third, innovation output is measured as of the end of the 2019 fiscal year, since the end of the 2017 fiscal year precedes the law's passage for most establishments. In our sample, 95.82% of establishments have a fiscal year ending on December 31, 2017, 1.56% on March 31, 2018, and 0.22% on June 30, 2018.

5.3 Sample selection

The WPS data comprises 20,592 observations from 4,985 establishments surveyed between 2005 and 2019. Our final sample is derived through a series of selection criteria. First, we limit the sample to for-profit corporations, excluding sole proprietors and various non-profit entities, reducing the sample to 16,524 observations from 4,048 establishments. Next, we restrict the data to the 2015-2021 period, further reducing the sample to 9,631 observations from 2,983 establishments. We then exclude observations with missing financial statement figures, narrowing the sample to 7,680 observations from 2,683 establishments. Finally, we exclude any observations with missing control variables as of 2017, resulting in a sample 7,649 observations from 2,680 establishments. However, to assess the continuity of potential outcomes near the threshold, which requires data from the 2013 WPS, we use the 2013 sample comprising 1,393 for-profit corporations in Section 6.1.

6 Main results

6.1 Continuity of potential outcomes near the threshold

Figure 7 validates the RDD's identifying assumption - the continuity of potential outcomes near the cutoff - using pre-law data. This includes weekly work hours collected in 2014 through the WPS and innovation output measured by capitalized IPs from the end of the 2015 fiscal year. These years represent the most recent data available for these metrics before the law's proposal, as detailed in Section 4.1. The forcing variables are employee counts from the end of the 2013 calendar year for weekly work hours and from the end of the 2015 calendar year for innovation output. The year

2015 data is chosen to include establishments newly sampled that year, as explained in Section 5.1, but results are similar when using 2013 employment counts, as shown in Figure B3, Panel B

This figure presents binned scatter plots with regression lines fitted separately for establishments above and below the 300-employee threshold. Panel A examines weekly work hours across the entire sample, showing a slight but insignificant reduction in work hours for treated establishments. Within the $\pm$ 300 employee bandwidth, average work hours remain approximately 48 hours on both sides of the threshold, indicating no significant discontinuity. Panel B examines the innovation output, revealing no significant breaks in continuity. The slope of the fitted lines is consistent on both sides of the threshold within each sector, though cross-sectoral differences are evident, as shown in Figure 4. In addition, Figure 3 confirms the continuity in the distribution of establishments at the 300-employee cutoff, both across and within sectors, as depicted in Panels A and B, respectively.

6.2 Covariate balance

Table 3 assesses covariate balance as of the end of the 2017 fiscal year and reveals that treated and control establishments are similar across many observable characteristics before the law's passage, with exceptions related to size. Specifically, treated establishments tend to have fewer employees (the forcing variable), smaller amounts of capitalized software, and fewer assets compared to control establishments. They also show differences in ownership structure, with a smaller ownership stake held by the largest shareholders and a lower likelihood that the CEO is also the largest shareholder - typical of larger firms where ownership is more diluted. Although this table focuses on establishments within the bandwidth of $\pm$ 200 employees, similar patterns are observed with the other bandwidths of $\pm$ 300 and $\pm$ 100 employees.

6.3 Law's effect on weekly work hours

Table 4, Panel A confirms the law's impact on weekly work hours, based on surveys conducted from June through November 2018. The analysis includes establishments with 600 or fewer employees (columns 1 and 4), those with 100 to 500 employees (columns 2 and 5), and those with 200 to 400 employees (columns 3 and 6). Coefficient estimates are derived from Equation 5, excluding control variables and fixed effects in columns 1 to 3 and including them in columns 4 to 6. The results indicate that establishments with 300 or more employees report weekly work hours that are two to three hours shorter than those with fewer than 300 employees. The coefficients on $\mathbb{1}[E \geq 300]$ are similar in magnitude and statistical significance across bandwidths, with significance levels at 5% or 1%. This suggests that the reduction in weekly work hours is driven by the law rather than by observable establishment characteristics or industry-specific factors.

Figure 8 visually illustrates the discontinuity in weekly work hours around the 300-employee threshold. This RD plot shows weekly work hours on the y-axis against employee count on the x-axis, with each dot representing the average weekly work hours of establishments within each 50-employee bin. Fitted lines are separately estimated for establishments above and below the threshold. The figure reveals that weekly work hours average around 46 for establishments not yet subject to the law and around 43 for those subject to the law, consistent with the two to three-hour gap reported in Table 4. All dots to the right of the threshold are lower than those to the left.

Figure 9 displays the distributional shift in weekly work hours beyond the local average treatment effects presented in Table 4 and Figure 8. Using histograms with normal density curves, the top subplot shows the shift from 2016 to 2018, while the bottom subplot shows the shift from 2016 to 2020. The normal density curves indicate a decrease in mean hours and an increase in variance, reflecting the law's impact. The shift is more pronounced by 2020 when the law applies to establishments with 50 or more employees. A smaller fraction of establishments remain above the 52-hour mark, likely those with fewer than 50 employees. Figure B4 shows that the top subplot remains similar when excluding observations surveyed in June 2018, just before the law's implementation.

Table B2, Panel A shows that the results become slightly stronger, with greater magnitude and significance, when excluding establishments surveyed in June 2018. However, for simplicity, we include these establishments in our main analysis, as explained in Section 5.2. Also, some establishments may have proactively reduced hours before July 2018 to minimize disruptions, anticipating the enforcement of the law passed in February.

6.4 Law's effect on overtime and weekend work

Table 4, Panel B examines the law's impact on overtime and weekend work and reveals a significant reduction in regular weekend work, which aligns with the law's objectives. The table estimates Equation 5, using different dependent variables: an indicator for weekday overtime in columns 1 to 3, occasional weekend work in columns 4 to 6, and regular weekend work (defined as more than

23 regular workdays per month) in columns 7 to 9. Columns 1 to 3 show an insignificant decline in weekday overtime, with the coefficient on $\mathbb{1}[E \geq 300]$ being negative and marginally significant at the 10% level only in column 2. Columns 4 to 6 indicate no change in occasional weekend work. In contrast, columns 7 to 9 show a significant decrease in regular weekend work. The coefficient on $\mathbb{1}[E \geq 300]$ is negative and significant at the 10% level in column 7 and at the 1% level in columns 8 and 9, where tighter bandwidths of ± 200 and ± 100 employees are applied.

Table B2, Panel C further explores intensive margin effects by interacting the model's regressors from Equation 5 with the three extensive margin indicators considered in Table 4, Panel B. Columns 1 to 3 show no significant decline in overtime hours per day, conditional on weekday overtime work, with the interaction term being negative but insignificant. Columns 4 to 6 provide weak evidence of a decline in weekend work hours per day, conditional on occasional weekend work, with the interaction term being negative and significant at the 1% level in column 4, at the 5% level in column 5, and insignificant in column 6. Columns 7 to 9 offer moderate evidence of decreased weekend work hours per day, conditional on regular weekend work, with the interaction term significant at the 5% level in columns 7 and 9, but insignificant in column 8.

6.5 Law's effect on innovation output

Table 5 investigates the law's potential effect on innovation output. It reveals a significant impact only within the light manufacturing sector, which is most heavily reliant on labor for innovation, as discussed in Section 4.2. Innovation output is measured by capitalized IPs as of the end of fiscal year 2019, the most recent fiscal year-end since the law's implementation. The definition of capitalized IPs and the rationale for using this cost-based measure, rather than patent counts (which are unavailable in the WPS data), are provided in Section 5.1. To assess the law's potential influence on employees-driven innovation, the analysis focuses on innovation output rather than input measures like R&D, which are primarily determined by managers and examined separately in Table 9, Panel E. Panel A (of Table 5) uses the same bandwidths, control variables, and fixed effects as in Table 4. Panel A estimates Equation 5 using the entire sample. In Panel B, columns 1 to 3 estimate Equation 5 using the sample of light manufacturing establishments, while columns 4 to 6 estimate Equation 6 using the entire sample.

Panel A first examines the law's overall impact on innovation across the economy and finds no significant effect. The coefficient on $\mathbb{1}[E \geq 300]$ is positive (except in column 4) but insignificant across all columns, indicating an observable treatment effect on innovation output, as is also confirmed visually in Figure B3, Panel C.

Panel B then explores the heterogeneous treatment effects across sectors, which are shown to have varying innovation-to-labor sensitivity in Section 4.2. The analysis reveals significantly higher innovation output in treated establishments within the light manufacturing sector. In columns 1 to 3, where the sample is limited to light manufacturing, the coefficient on $\mathbb{1}[E \geq 300]$ is positive and significant at the 1% or 5% level. In columns 4 to 6, where light manufacturing is compared to three other sectors, the interaction term between $\mathbb{1}[s = L]$ and $\mathbb{1}[E \geq 300]$ is positive and significant at the 1% level, while $\mathbb{1}[E \geq 300]$ remains insignificant across all columns. Table B8 examines the three other sectors individually and finds no significant increase in innovation output at treated establishments compared to control establishments. None of the coefficients on $\mathbb{1}[E \geq 300]$ is significant, except in column 3, where it is negative and significant at the 10% level. Overall, the results suggest that the law significantly boosted innovation output in treated establishments within the light manufacturing sector, with no comparable effects observed in other sectors.

Figure 10 visually supports these findings using RD plots. The discontinuity is prominent in light manufacturing, where innovation output on the y-axis shows a strong positive association with employee count on the x-axis. This positive treatment effect, characterized by a clear discontinuity, is not seen in other sectors, where the relationship between innovation output and employee count is weaker or absent.

6.6 Robustness checks

Table 6 examines whether our main innovation results (from the sharp RDD) hold under two alternative identification strategies: a fuzzy RDD and a DiD approach. These methods can help address certain limitations of the sharp RDD - such as its reliance on post-proposal employee counts as the forcing variable - by using pre-proposal counts as an exogenous source of variation. However, they also suffer from reduced sample sizes (fewer than 30 observations within the tightest $\pm$ 100 bandwidth), so we do not adopt them as our primary design. Instead, they serve as complementary tests that reinforce the causal interpretation of our core findings.

6.6.1 Alternative design I: Fuzzy RDD

Panel A implements a fuzzy RDD in which the law's enforcement status, $T_{i1} = \mathbf{1}\big[E_{i1} \geq 300\big]$, is treated as endogenous, with pre-proposal employee counts (E_{i0}, T_{i0}, $E_{i0} \times T_{i0}$) serving as instruments. Specifically, we estimate the following pair of equations:

- First stage:

$$T_{i1} = \zeta_{j(i)} + \alpha_0 + \alpha_1 T_{i0} + \alpha_2 \widetilde{E}_{i0} + \alpha_3 T_{i0}\widetilde{E}_{i0} + \xi_i \tag{7}$$

- Second stage:

$$Y_{i2} = \zeta_{j(i)} + \beta_0 + \beta_1 T_{i1} + \beta_2 \widetilde{E}_{i0} + \beta_3 T_{i1}\widetilde{E}_{i0} + \xi_i \tag{8}$$

where i indexes establishments and $j(i)$ denotes the two-digit SIC industry. Y_{i2} is capitalized IPs at the end of fiscal year 2019. We let E_{it} be the employee count at the end of calendar year t, and define $T_{it} = \mathbf{1}[\,E_{it} \geq 300]$, $t \in \{0, 1, 2\}$, with $t = 0$ corresponding to 2015 (pre-proposal), $t = 1$ to 2017 (post-proposal, pre-enforcement), and $t = 2$ to 2019 (post-enforcement). We further set $\widetilde{E}_{it} = E_{it}$ - 300 to center the running variable at the cutoff, enabling more direct interpretation of the main coefficients. The same first stage is set up for $T_{i1}\widetilde{E}_{i0}$. Because including all sectors and introduce interactions among T_{i1}, $\widetilde{E}_{i1}$, and the sector dummy (as in Equation 6) would increase the number of endogenous variables from two to five, which could lead to multicollinearity and overfitting. To avoid this issue, we limit the analysis to light manufacturing. Columns 1 to 3 apply a $\pm$ 300 bandwidth and columns 4 to 6 apply a $\pm$ 200 bandwidth.

Columns 1, 2, 4, and 5 report the first-stage results. Columns 1 and 4 show that T_{i0} strongly predicts T_{i1}. The coefficient on T_{i0} is large (0.66 and 0.55, respectively) and significant (1% and 5% levels), while the interaction $T_{i0} \times \widetilde{E}_{i0}$ is insignificant. Similarly, columns 2 and 5 show that $T_{i0} \times \widetilde{E}_{i0}$ strongly predicts $T_{i1} \times \widetilde{E}_{i1}$, with coefficients around 1.03 and 1.08, significant at the 1% level, and the F-statistics exceed 10, except in column 4, where it is 4.16. Columns 3 and 6 present the second-stage estimates, showing strong treatment effects on capitalized IPs: β_1 is large (around 4.89 and 5.75) and significant (1% and 5% levels), while the other coefficients remain insignificant, except one on $T_1 \times \widetilde{E_0}$ in column 3 that is marginally significant at the 10% level.

These estimates align well with the sharp RDD results in Table 5, though they tend to be larger. A standard explanation is that IV estimates capture a local average treatment effect among compliers, which can exceed the reduced-form effect. Indeed, once we multiply 4.89 and 5.75 by the partial compliance rates (0.66 and 0.55) from the first stage, we obtain approximately 3.23 and 3.16, comparable to the sharp RDD magnitudes. Whether crossing the 300-employee threshold is intentional or inadvertent remains untestable, but our fuzzy RDD evidence further corroborates the conclusion that reduced work hours spurred innovation in light manufacturing establishments.

6.6.2 Alternative design II: DiD

Panel B implements a DiD design, using pre-proposal employee counts (E_{i0}, T_{i0}) to define treatment and comparing outcomes before and after the law's enactment. Specifically, we estimate:

- Light manufacturing:

$$Y_{it} = \alpha_{j(i)} \times \theta_t + \beta_0 T_{i0} \times Post_t + \epsilon_{it} \tag{9}$$

- All sectors:

$$Y_{it} = \alpha_{j(i)} \times \theta_t + \beta_0 T_{i0} \times Post_t + T_{i0} \times Post_t \times \mathbb{1}[s(i) = L] + \epsilon_{it} \tag{10}$$

where θ_t are year fixed effects for the survey years 2015, 2017, and 2019, and Post_t is an indicator for the law's post-enforcement period (2019). Other terms are as defined in Equations 7 and 8. Industry-year fixed effects $\alpha_{j(i)} \times \theta_t$ control for time-varying industry-specific trends in Y_{it}. Because three survey years are used in a single estimation, the total number of observations increases, but the number of unique establishments (i.e., panel units present in all years) does not and remains under 30 within the tightest bandwidth. Columns 1 and 2 restrict the sample to light manufacturing using bandwidths ± 300 and ± 200, respectively; columns 3 and 4 do the same for the full sample (all four sectors).

The DiD estimates confirm that establishments above the 300-employee threshold (as of 2015) exhibit significantly higher capitalized IPs after the law takes effect relative to before. In columns 1 and 2 (light manufacturing), β_0 is positive and significant at the 10% and 1% levels. In columns 3 and 4 (all sectors), the triple interaction $T_{i0} \times \text{Post}_t \times \mathbb{1}[s(i) = L]$ is positive and significant at the 5% and 1% levels, while β_0 on $T_{i0} \times \text{Post}_t$ alone is insignificant. The sizes of the estimated treatment effect - on the order of a 200–400% increase in IPs - are comparable to our earlier results in Table 5, reinforcing the robustness of the law's positive impact on innovation output in light manufacturing establishments.

Unreported analysis confirms the absence of pre-law trends, wherein industry-year fixed effects are replaced by industry fixed effects and Post_t by two indicators for 2015 and 2019, with the base year of 2017 omitted. The coefficients on $T_{i0} \times \text{Year=2015}$ in columns 1 and 2 and $T_{i0} \times \text{Year=2015} \times \mathbb{1}[s(i) = L]$ in columns 3 and 4 are insignificant, while those on $T_{i0} \times \text{Year=2019}$ in columns 1 and 2 and $T_{i0} \times \text{Year=2019} \times \mathbb{1}[s(i) = L]$ in columns 3 and 4 are significant. The absence of pre-law trends in innovation output aligns with Figure 7, Panel B and Figure B3, Panel D, which display minimal differences in innovation output between establishments above and below the 300-employee cutoff before the law's proposal, including 2015.

6.6.3 Patent applications across sectors

A final concern is that our narrow sample near the 300-employee cutoff—although randomly selected—may not adequately represent the broader population. Figure 11 helps assess external validity by plotting population-level patent applications (sourced from the Korea Intellectual Property Office) across four major sectors over 2000–2020, spanning both the pre-proposal and post-enforcement periods. Because the anonymized WPS data do not link each patent application directly back to a specific establishment, we compare sector averages[11].

The figure shows that in light manufacturing, the average number of patent applications was relatively stable (around 10) prior to the 2016 proposal but rose substantially after 2016, peaking above 20 in 2019. No comparable pattern emerges in other sectors. Although heavy and medium manufacturing started with higher and more volatile levels of patenting, their averages generally trended downward or stayed flat post-proposal. Non-manufacturing shows only a minimal increase. Thus, the macro-level patterns in patent filings reinforce our micro-level conclusion that the law's enforcement had a differential impact on innovation in light manufacturing, consistent with our RDD and DiD estimates.

[11] More specifically, patents cannot be directly linked to the establishments that produce them because patent documents lack information on which constituent establishment was responsible for their creation. Therefore, even if we identify some of the establishments anonymized as explained in Section 5.1 using financial statement figures, attributing firm-level patents to innovating establishments is not feasible. Note that in Korea, financial statements are available for tends of thousands of privately held firms, because those exceeding a certain size threshold must undergo external audits and prepare audit reports, which include detailed financial statements similar to those in annual reports.

Overall, while these fuzzy RDD and DiD analyses are limited by sample size, and the patent-application patterns are measured at the aggregate sector level, each corroborates our main finding: a binding cap on working hours stimulated innovation specifically in labor-reliant environments such as light manufacturing.

7 Cross-sectional analyses

7.1 Innovation incentives as a complement of leisure time

Table 7 examines how increased leisure time may enhance innovation output by considering the role of innovation incentives as a complement to leisure time, which is unobservable in the WPS data. The analysis focuses on two key components of the innovation-motivating incentive scheme (Manso, 2011): tolerance for short-term failure in Panel A and rewards for long-term success in Panel B. Columns 1 and 2 estimate Equation 5 using the sample of light manufacturing establishments, while columns 3 and 4 estimate Equation 6 using the entire sample. The outcome is innovation output measured by capitalized IPs as of the end of the 2019 fiscal year. The regressors further interact with mediator variables. In Panel A, the mediator represents whether an establishment does not penalize low performers through programs such as wage reductions, promotion restrictions, and warnings, rather than support low performers with mentor-mentee relationships, training, or position changes better suited to employee skills, as of the end of the 2017 calendar year. In Panel B, the mediator indicates whether an establishment raises salaries based on employee skill improvements as of the end of the 2017 calendar year. Due to limited data availability on mediators, including the two considered in this table, the analysis is confined to wider bandwidths of ± 300 and $\pm$ 200 for the cross-section tests hereafter.

Panel A shows that the law's impact on innovation output, as observed in Table 5, is more pronounced in light manufacturing establishments that do not penalize low performers. The coefficients on the interaction term in columns 1 and 2 are positive and significant at the 5% or 10% level. The triple interaction term in columns 3 and 4 is positive although insignificant. The positive and significant (at the 1% or 5% level) coefficient on $\mathbb{1}[E \geq 300]$ in columns 1 and 2 confirm the law's effect on innovation output. In columns 3 and 4, the interaction between $\mathbb{1}[E \geq 300]$ and $\mathbb{1}[s = L]$ is positive and significant at the 10% level in column 3, while $\mathbb{1}[E \geq 300]$ remain insignificant in both columns.

Panel B further demonstrates that the law's effect on innovation output is more pronounced in light manufacturing establishments that reward skill improvements with base salary increases. The interaction term in columns 1 and 2 and the triple interaction term in columns 3 and 4 are both positive and significant at the 1% or 5% level. The law's impact on innovation output, as observed in Table 5, is also reaffirmed by the positive and significant (at the 1% or 5% level) coefficient on $\mathbb{1}[E \geq 300]$ in columns 1 and 2 and on its interaction with $\mathbb{1}[s = L]$ in columns 3 and 4. However, $\mathbb{1}[E \geq 300]$ remains insignificant in columns 3 and 4.

7.2 Other forms of slack as a substitute for leisure time

Table 8 examines whether flexible hours or days serve as substitutes for leisure time. It shows that innovation increases to a lesser extent when other forms of slack are in place. Columns 1 and 2 estimate Equation 5 using the sample of light manufacturing establishments, while columns 3 and 4 estimate Equation 6 using the entire sample. The outcome is innovation output measured by capitalized IPs as of the end of the 2019 fiscal year. The regressors further interact with an indicator for whether employees have the flexibility to adjust working hours or days at the end of the 2017 calendar year. The table shows the law's impact on innovation output, as observed in Table 5, is less pronounced in light manufacturing treated establishments that allow employees to adjust their working hours or days. The coefficient on the interaction term in columns 1 and 2 is negative, increasing in magnitude as the bandwidth narrows, and significant at the 1% level. Similarly, the coefficient on the triple interaction term in columns 3 and 4 is negative although insignificant. The positive and significant (at the 1% level) coefficient on $\mathbb{1}[E \geq 300]$ in columns 1 and 2 and on its interaction with $\mathbb{1}[s = L]$, along with an insignificant coefficient on $\mathbb{1}[E \geq 300]$, in columns 3 and 4 confirms the law's effect on innovation output.

7.3 Law's effect on production output

Table 9, Panel A investigates the potential impact of reduced labor time on production output and finds no evidence of a decline. If pre-law hours matched effective working hours, a reduction in hours could have decreased output, offsetting the innovation gains seen in light manufacturing. However, if pre-law hours exceeded effective working hours, the reduction may not harm output.

Output is measured by the ratio of sales to total hours worked, with sales figures from the end of the 2019 fiscal year and total hours worked calculated by multiplying the average number of employees in 2018 by weekly work hours (collected from June to November 2018) and then annualizing this figure by multiplying by 52. Columns 1 and 2 estimate Equation 5 using the sample of light manufacturing establishments, while columns 3 and 4 estimate Equation 6 using the entire sample. The coefficients on $\mathbb{1}[E \geq 300]$ in columns 1 and 2 and the interaction term in columns 3 and 4 are positive (except in column 1) and insignificant in all columns.

7.4 Law's effect on labor and capital input

Panels B and E (of Table 9) examine the law's effects on employee count (as a component of labor input) and capital input and show insignificant changes in both. If firms faced a labor shortage due to the law reducing hours, they might respond by increasing employment n in Equation 4 or augmenting capital K to maintain output q. However, the table shows no significant increase in employment, capital intensity, or R&D expenditure. Employment is assessed across all categories - permanent, directly-hired non-permanent, or indirectly-hired non-permanent workers - to account for potential shifts within the workforce toward indirect employment of skilled labor. We also examine the inflow and outflow of skilled employees, although cross-establishment moves are less likely following the law that induces nationwide changes in hours. Capital intensity is measured as the ratio of PPE to total assets, while R&D expenditure is evaluated using both expensed and capitalized R&D. The latter may increase if firms opt to augment capital internally rather than through acquisitions. Columns 1, 2, 5, and 6 estimate Equation 5 using the sample of light manufacturing establishments, while columns 3, 4, 7, and 8 estimate Equation 6 using the entire sample. Odd-numbered columns use the bandwidth of $\pm$ 300, whereas even-numbered columns use the bandwidth of $\pm$ 200.

In Panel B, columns 1 to 4 report the estimated effect of the reduced working hours law on overall employment, showing no significant changes in total headcount. The coefficients on $\mathbb{1}[E \geq 300]$ in columns 1 and 2 and those on $\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$ in columns 3 and 4 are insignificant. Further, unreported analyses confirm no significant increases in permanent or direct non-permanent employment. Similarly, columns 5 to 8 indicate that establishments did not expand their indirect workforce (e.g., dispatched or subcontracted workers); coefficients on $\mathbb{1}[E \geq 300]$ in columns 5 and

6 and those on $\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$ in column 8 remain insignificant here as well. Although the interaction term in column 7 is marginally significant at the 10% level, its sign is negative, and it becomes insignificant under the tighter ± 200 bandwidth in column 8. Turning to Panel C, which examines skilled labor inflows (columns 1 to 4) and outflows (columns 5 to 8), there is little evidence of changes in either hiring or separations: coefficients on $\mathbb{1}[E \geq 300]$ in columns 1, 2, 5, and 6 and those on the interaction term in columns 3, 4, 7, and 8 remain insignificant. Taken together, these findings suggest that, because the shorter workweek was implemented nationwide, it did not shift employees' relative outside options across establishments, resulting in no discernible adjustment along direct or indirect employment margins.

Panels D and E present evidence on whether establishments responded to the shortened workweek by investing in capital, either to replace labor or to augment existing labor, and on whether they increased R&D expenditures to adjust their capital base in-house. In Panel D, columns 1 to 4 examine labor-replacing capital (PPE), while columns 5 to 8 focus on labor-augmenting capital (software). Overall, the coefficients remain statistically insignificant, suggesting minimal shifts in PPE or software acquisition. However, the coefficient on $\mathbb{1}[E \geq 300]$ in column 8 is significant (at the 5% level), indicating that managers increased software acquisitions in all sectors, likely aiming to make existing employees more effective rather than replacing them outright. This increase in labor-augmenting capital may help explain why production output does not decline, as reported in Table 9. Meanwhile, Panel E reports no significant changes in expensed or capitalized R&D, implying that establishments did not invest more heavily in in-house research or development activities to adapt to the reduced workweek.

7.5 Law's effect on profitability

Panel F (of Table 9) explores the law's impact on profitability and shows a marginal increase in return on assets in light manufacturing but no significant changes in profit margins across all sectors. Profitability is measured by the ratio of earnings before interest and taxes (EBIT) to total assets in Panel A and EBIT to sales in Panel B. Columns 1 to 3 estimate Equation 5 using the sample of light manufacturing establishments, while columns 4 to 6 estimate Equation 6 using the entire sample. Unreported analyses yield similar results when using alternative numerators such as net income or earnings before interest, taxes, depreciation, and amortization. In Panel A, the coefficient on $\mathbb{1}[E \geq 300]$ in columns 1 to 3 and the interaction term in columns 4 to 6 are positive and significant (at the 5% or 10% level) with wider bandwidths but become insignificant with the narrowest bandwidth of ± 100. In Panel B, however, none of the coefficients are significant, suggesting that the observed increase in profits (output) relative to total assets (input) is not primarily driven by cost reduction efforts. The absence of a significant decline in profitability, despite reduced labor time, supports the notion that pre-law labor time may have been longer than optimal.

7.6 Cultural explanation for suboptimal pre-law time allocation

Table 10 explores structural inertia as a potential reason for the seemingly suboptimal pre-law allocation of employee time between labor and leisure and provides supporting evidence. Structural inertia, or slow adaptation to new practices, is measured using the pre-law percentage of employees under 35 and, conversely, the percentage of employees aged 55 and above. These measures, which involve the age thresholds set by KLI, serve as proxies for organizational flexibility, with a greater share of a younger workforce indicating greater adaptability. To align with other cross-sectional tests that use binary indicators, these continuous variables are dichotomized at their sample medians and interacted with the regressors. Columns 1 and 2 estimate Equation 5 using the sample of light manufacturing establishments, while columns 3 and 4 estimate Equation 6 using the entire sample. The outcome is innovation output measured by capitalized IPs as of the end of the 2019 fiscal year.

Panel A shows that the law's effect on innovation output, as observed in Table 5, is less pronounced at light manufacturing treated establishments with a greater share of employees under 35. The coefficients on the interaction term in columns 1 and 2 and the triple interaction term in columns 3 and 4 are negative, similar in magnitude, and significant at the 5% or 10% level in columns 1, 3, and 4. The law's effect on innovation output is confirmed by the positive and significant (at the 1% level) coefficient on $\mathbb{1}[E \geq 300]$ in columns 1 and 2 and on its interaction with $\mathbb{1}[s = L]$ in all columns, along with an insignificant coefficient on $\mathbb{1}[E \geq 300]$ in columns 3 and 4. It is also shown that establishments with a greater share of employees below 35 tend to innovate more on average. The coefficient on the mediator in columns 3 and 4 is positive and significant at the 5% or 10% level.

Panel B presents weak evidence that the law's effect on innovation output is more pronounced at light manufacturing treated establishments with a greater share of employees aged 55 and above. The coefficients on the interaction term in columns 1 and 2 and the triple interaction in columns 3 and 4 are positive although significant at the 5% level only in column 4. The law's effect on innovation output is confirmed by the positive and significant (at the 1% or 5% level) coefficient on $\mathbb{1}[E \geq 300]$ in columns 1 and 2 and its interaction with $\mathbb{1}[s = L]$ in columns 3 and 4 in most columns (except column 4), along with an insignificant coefficient on $\mathbb{1}[E \geq 300]$ in columns 3 and 4.

7.7 Agency explanations for suboptimal pre-law time allocation

Table B9 investigates whether agency conflicts could explain the seemingly suboptimal pre-law allocation of employee time, but the analysis finds no supporting evidence for this hypothesis. The table examines two types of conflicts: principal-agent conflicts and conflicts between long-term and short-term shareholders. Principal-agent conflicts are assessed using two metrics: whether the CEO is not a professional manager in Panel A, and whether the CEO is also the largest shareholder in Panel B. Conflicts between long-term and short-term shareholders are analyzed using three measures: whether the largest shareholder's ownership exceeds the sample median in Panel C, whether the establishment is affiliated with a business group in Panel D, and whether foreign ownership exceeds the sample median in Panel E. These five indicators interact with the regressor in the model from Equation 5, estimated in columns 1 and 2 using the sample of light manufacturing establishments, and regressors in the model from Equation 6, estimated in columns 3 and 4 using the entire sample. The outcome variable is innovation output, measured by capitalized IPs as of the end of the 2019 fiscal year.

This table shows that the law's effect on innovation output, as observed in Table 5, is not less pronounced at light manufacturing treated establishments with less severe conflicts of interest between principals and agents or between long-term and short-term shareholders. The coefficients on the interaction term in columns 1 and 2 and the triple interaction term in columns 3 and 4 are insignificant in all columns in Panels A through E. The positive effect of the law on innovation is confirmed by the positive and significant (at the 1% or 5% level) coefficient on $\mathbb{1}[E \geq 300]$ in columns 1 and 2 and on its interaction with $\mathbb{1}[s = L]$ in columns 3 and 4, except Panel A, column 2, where the coefficient on $\mathbb{1}[E \geq 300]$ is significant at the 10% level.

8 Discussions

8.1 Year-by-year trends in innovation output

The increase in innovation output in light manufacturing, as depicted in Figure 10 and Table 5, becomes evident nearly two years after the law's passage in February 2018. This timeframe aligns with the average duration required for a patent application to be granted, typically about a year and a half. However, capitalized IPs - a balance sheet item - could reflect the capitalized portion of patent filing costs earlier, during fiscal year 2018. Moreover, as discussed in Section 4.1, the law's enactment might be anticipated as early as May 2016, when the law was proposed with strong support from the National Assembly. Some establishments may have proactively reduced working hours shortly after the proposal, especially if managers recognized that actual hours exceeded effective working hours. In such cases, the increase in capitalized IPs may have started even earlier. To address concerns about the timing of the observed increase in innovation output, Figure B3, Panels C and D examine annual trends in light manufacturing innovation output from 2014 to 2021. This analysis uses beginning-of-period values from the WPS data, which are only available for financial statement figures, to measure end-of-period values for the previous fiscal year.

Panel C presents a series of RD plots for light manufacturing innovation output from 2014 through 2021. The data shows no significant increase in innovation output from 2014 to 2016, followed by a slight and noisy increase beginning in 2017, with the most substantial gains observed in 2018 and 2019. This trend suggests that the rise in innovation output may have begun earlier than 2018, possibly due to establishments anticipating the law's enactment as early as 2016. The plots for 2020 and 2021 indicate a continued but less pronounced increase. Panel D displays the coefficients on $\mathbb{1}[E \geq 300]$ from Equation 5, estimated using the sample of light manufacturing establishments for capitalized IPs recorded at the end of fiscal years 2014 through 2021. The bars are small from 2014 to 2016, indicating little to no impact on innovation output. Starting in 2017, the bars increase, peaking in 2019, suggesting a significant positive impact of the law, potentially stemming from an anticipatory reduction in working hours. The effects continue into 2020 but decline in 2021. Red error bars, representing 95% level confidence intervals, accompany each bar and are above zero only in 2019.

8.2 Placebo test

The pre-law increase in innovation output observed in 2017 from Figure B3, Panel E proves to be insignificant in a placebo test, where the employee count (the forcing variable) is measured using data from 2015 rather than 2017. Specifically, we re-estimate the regressions from Table 4, Panel A, columns 4 to 6, which examine weekly working hours, and Table 5, Panel B, columns 4 to 6, which assess innovation output. This analysis uses weekly work hours from 2016 and innovation output measured by capitalized IPs at the end of fiscal year 2017. The results, presented in Table B4, indicate that none of the coefficients on $\mathbb{1}[E \geq 300]$ in columns 1 to 3 and the interaction term in columns 4 to 6 are statistically significant. This suggests no significant pre-law differences in weekly work hours or innovation output between treated and control establishments. Similarly, we find no significant extensive margin effects on overtime or weekend work using data from the previous survey year. We re-estimate the regressions from Table 4, which analyzes overtime work, occasional weekend work, and regular weekend work, using 2016 data. The results, presented in Table B2, Panel B, show that the coefficient on $\mathbb{1}[E \geq 300]$ is insignificant across all columns.

8.3 Heterogeneous total available hours

An alternative interpretation of the results in Table 10, which shows a less pronounced increase in innovation output among establishments with a higher proportion of employees under 35, could be that these younger employees have more total available hours t rather than being more effective at overcoming structural inertia or customs that sustain suboptimally long labor time $t - l$. In other words, younger employees may have enjoyed longer effective leisure time before the law's passage, for example, because they are more likely to be childless. Even if labor time $t - l(t)$ is the same for all employees, those with children may experience less effective leisure time $l(t_1) < l(t_2)$ if $t_1 < t_2$. Although the WPS does not provide data on marital status or parenthood, it does include the percentage of employees under 35. Given that the average age at first marriage in Korea is 32.6 for men and 30.0 for women, as reported by Statistics Korea, most employees under 35 are likely childless. However, this interpretation remains speculative, as the percentage of younger employees may also reflect factors like ability or wealth. Further research is needed to better understand the influence of available hours and effective leisure time on innovation.

8.4 Implications for heavy manufacturing and technology sectors

While the observed increase in innovation output associated with longer discretionary time is most pronounced in light manufacturing, where innovation-to-labor sensitivity λ is highest, similar outcomes might also be seen in heavy manufacturing if the number of lab scientists could be used as the forcing variable. This alternative experiment would involve a shock on the number of lab scientists, with a smaller cutoff value. The λ for lab scientists is likely much larger than for rank-and-file employees in light manufacturing. The intensity of the treatment effect would then depend on the discretionary time available to lab scientists relative to its optimal level l^*, which is likely longer than that for light manufacturing employees.

Similarly, comparable results might be observed in technology industries if a smaller threshold value were used. The 300-employee threshold left almost no tech companies in the WPS data above the threshold, making it difficult to draw causal inferences using the 52-hour workweek law. For tech companies, total employment may still be an appropriate metric for computing λ, as many of their employees are directly involved in innovation. This may explain why four of the five firms that have implemented company-wide policies allowing discretionary time for employees - Google, 3M, Linkedin, Apple, and Atlassian - are tech companies. It is noteworthy that 3M, although part of heavy manufacturing, follows a similar approach.

8.5 Policy implications

This study provides implications for various stakeholders. Firstly, companies with high innovation-to-labor sensitivity but longer or similar working hours compared to their peers should consider reducing working hours or implementing "XX% rules" to enhance innovation. This approach could also benefit firms reliant on labor-driven innovation, such as those in the IT sector, though their smaller employment sizes made them untestable in this study. Secondly, investors might consider acquiring shares in firms with high innovation-to-labor sensitivity and shorter working hours, since they might possess greater innovation potential, and investors should advocate for their portfolio companies to adopt reduced or more flexible working hours. Thirdly, lawmakers in countries with longer working hours might consider introducing a working-hour cap to boost innovations. Lawmakers in Korea may consider tightening the cap on working hours, potentially aligning it with other civil law countries where the cap is 40 hours or less. This study finds no apparent costs with the 52-hour cap. Fourthly, government bodies should enforce existing caps and reform work-hour policies and incentive schemes to foster innovation, thereby promoting both employee well-being and corporate innovation.

Lastly, the findings contribute to the ongoing debate on the 4-day workweek by showing that reduced working hours can enhance innovation without compromising productivity. This study suggests that a shorter workweek, like a 4-day schedule, could benefit industries heavily reliant on labor-driven innovation. The maintained output despite reduced hours - achieved mainly through a reduction in regular weekend work - indicates that more condensed work schedules might not only sustain productivity but also boost innovation. However, these results are based on data from Korea, where working hours are among the longest in the OECD, as discussed in Section 3.2, so the implications may differ in other contexts.

9 Conclusion

This study explores the impact of discretionary time on corporate innovation, utilizing the 2018 Korean law that capped the workweek at 52 hours. Our findings reveal that the law effectively reduced weekly work hours, primarily by reducing regular weekend work, creating a more conducive environment for innovation. While no significant economy-wide increase in innovation output is observed, the light manufacturing sector, where innovation heavily relies on labor, shows a notable rise in innovation output for treated establishments compared to control establishments near the threshold that determines the law's application. The study also highlights the role of innovation incentives, showing that establishments offering employees mentorship programs and skill-based wage increases see more substantial innovation gains. Despite the reduction in labor time, there is no observed decline in output, suggesting that pre-law labor time was suboptimally long. This is supported by the absence of significant changes in labor or capital inputs and R&D expenditure. However, an increase in labor-augmenting capital, such as capitalized software, is observed across sectors, which may partly explain the absence of a decline in output levels. The analysis also explores cultural and agency-based explanations for the pre-law allocation of employee time, finding that structural inertia or entrenched customs may have played a role in maintaining long working hours. However, the study finds that the law's impact on innovation output is not significantly weaker in establishments with owner-managers, concentrated ownership, business group affiliations, or foreign institutional ownership, indicating that suboptimal employee time allocation is not primarily driven by agency issues.

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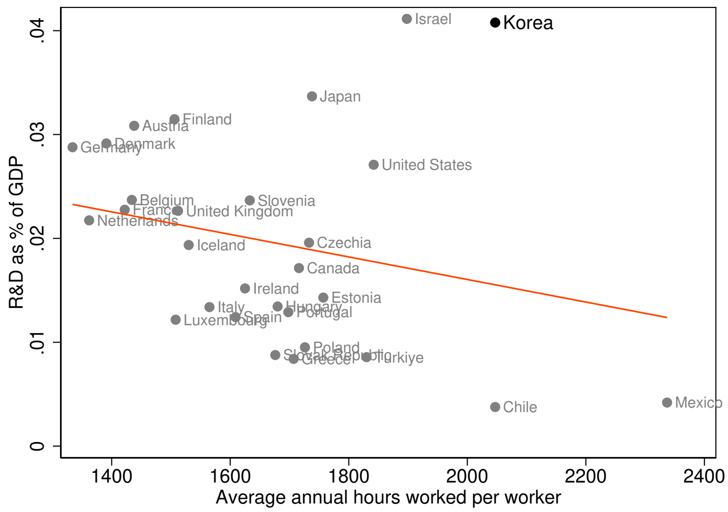
Figure 1: Relationship between work hours and innovation among OECD member states
This figure presents scatter plots illustrating the relationship between annual average hours actually worked per worker (x-axis) and measures of innovation (y-axis) across OECD member states. Innovation measured by R&D expenditure as a percentage of GDP at the top and patent counts normalized by the working-age population at the bottom. The data is sourced from OECD Statistics and is from 2014, the most recent year with available data for all variables before the law was proposed in 2016. Australia, New Zealand, Sweden, and Switzerland are not included in Panel A due to insufficient data on R&D expenditure.

Panel A. Innovation input



Panel B. Innovation output

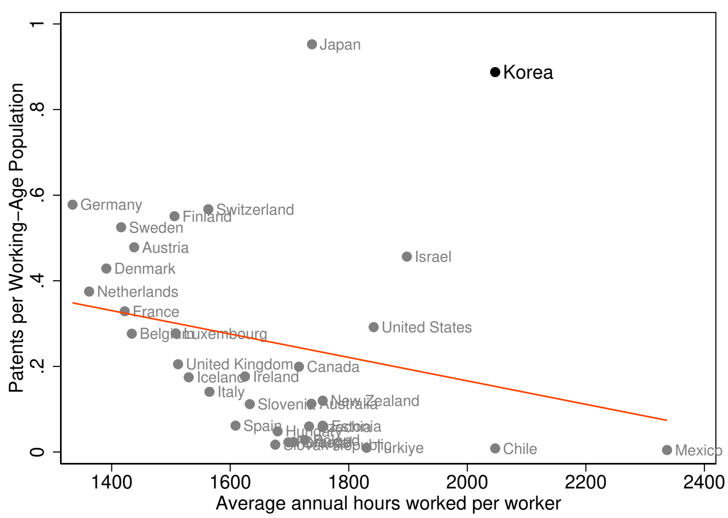


Figure 2: 52-hour workweek law and leisure-innovation relationship

This figure illustrates the inverted U-shaped relationship between leisure time (x-axis) and innovation (y-axis) in an economy with leisure below its optimum. The 52-hour workweek law, indicated by a shift from $\underline{l_0}$ to $\underline{l_1}$, increases leisure time from l_0 to l_1, resulting in a shift in innovation levels from i_0 to i_1. The points before and after the law's implementation are marked by blue dots, positioned just above the legal lower bounds on leisure time indicated by red vertical lines.

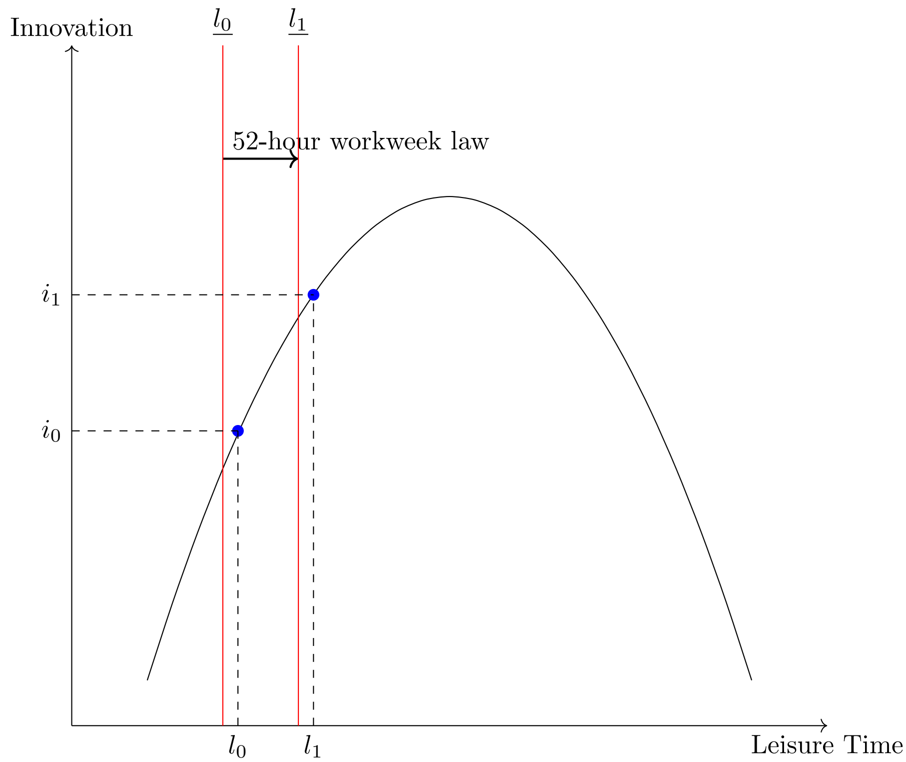
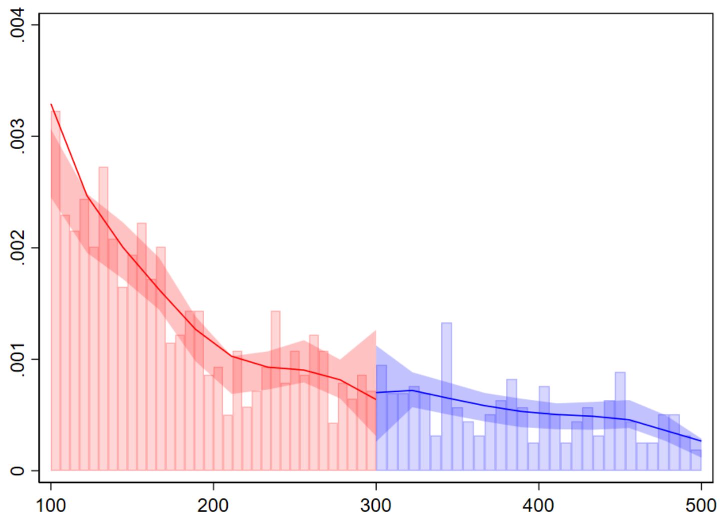


Figure 3: Distribution of establishments by pre-law employment size

This figure presents McCrary (2008) density test results, which assess potential manipulation of the running variable around the 300-employee threshold. It shows the distribution of establishments by employment size at the end of 2017, with the vertical red line marking the 300 threshold. Panel A uses the full sample. Panel B splits it into four North American Industry Classification System (NAICS)-based sectors: light manufacturing (31), medium manufacturing (32), and heavy manufacturing (33), and non-manufacturing (42–81, excluding agriculture, mining, and public administration). The data are drawn from the Korea Labor Institute's Workplace Panel Survey and weighted using cross-sectional sampling weights. While the default range of employment size varies by sector - 100-5– for the full sample, 0-1000 for light manufacturing, 0-800 for medium and heavy manufacturing, and 0-600 for non-manufacturing - we use the 100-500 range consistently when reporting the McCrary test results. This choice reflects both the regression bandwidths focused around the 300-employee threshold and the WPS survey design, which includes only establishments with 30 or more employees.

Panel A. Full sample



Panel B. By sector

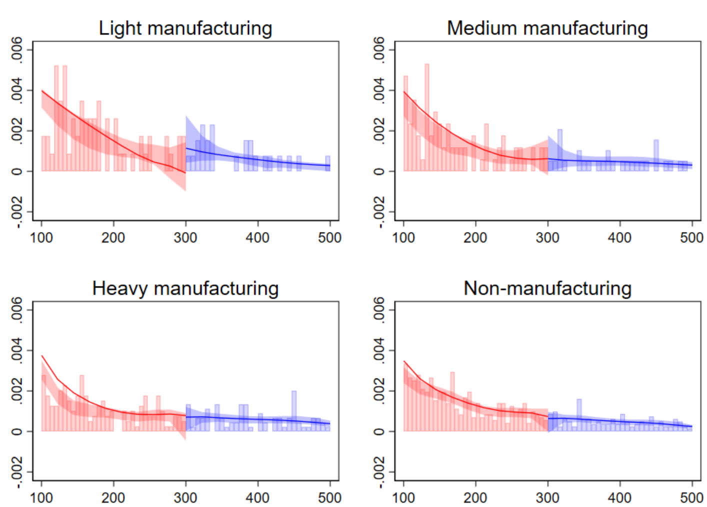
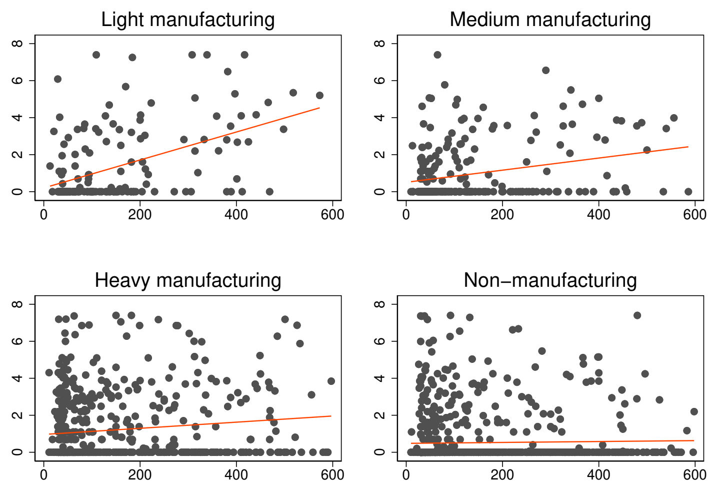


Figure 4: Heterogeneous labor-innovation relationship across sectors
This figure displays the observed relationship between labor input and innovation output across four sectors, as defined in Figure 3, in 2015, one year before the law was proposed. Panel A presents binned scatter plots with fitted lines, separately estimated for establishments above and below the 300-employee threshold. Panel B presents bar charts showing the coefficients on labor input from sector-specific regressions of innovation output on labor input, with capital input and innovation input included as control variables to estimate the conditional relationship. Innovation output is measured by capitalized intellectual properties, labor input by employee count, capital input by property, plant, and equipment, and innovation input by capitalized R&D expenditure. All variables are log-transformed after adding one. The data is described in Figure 3.

Panel A. Unconditional relationship



Panel B. Conditional relationship

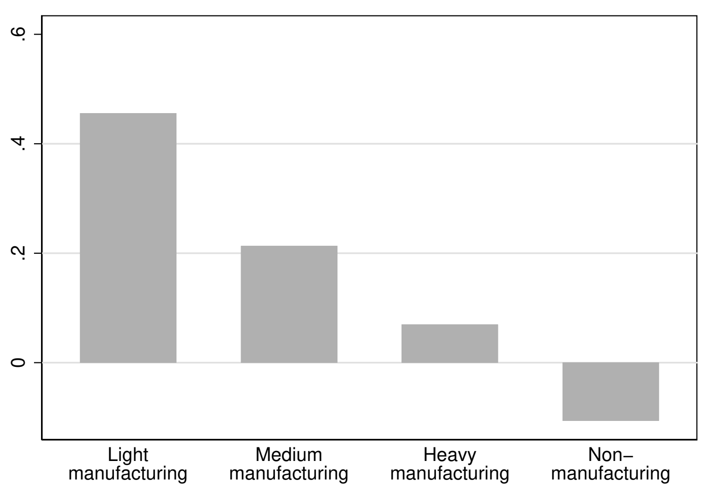


Figure 5: Relationships between wage or R&D expenditure and innovation output across sectors
This figure shows scatter plots, with fitted lines, for light manufacturing, medium manufacturing, heavy manufacturing, and non-manufacturing sectors. In each panel, the horizontal axis represents either wages or R&D expenditure, while the vertical axis shows innovation output. The data is described in Figure 3.

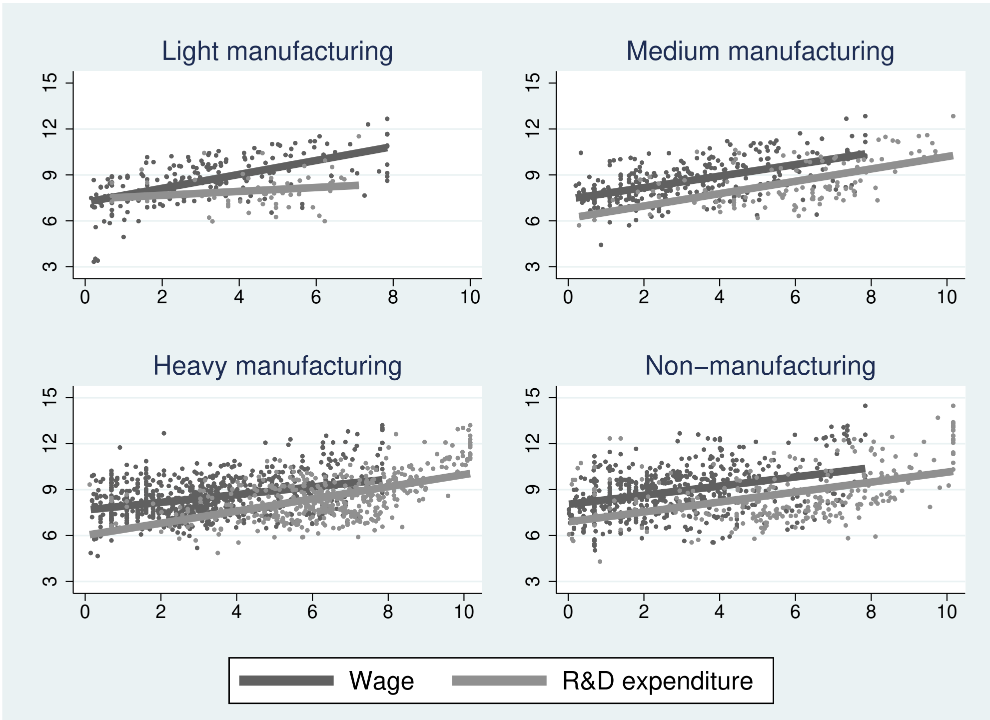


Figure 6: Timeline for legislation and data collection

This figure illustrates key milestones and data collection periods related to Korea's 52-hour workweek law. A dotted line marks the effective date, highlighting its significance across multiple timelines. The first timeline indicates employment measurement, the second depicts the period for time data collection, and the final indicates the point for innovation data collection. The data is collected by the Korea Labor Institute through its biennial Workplace Panel Survey.

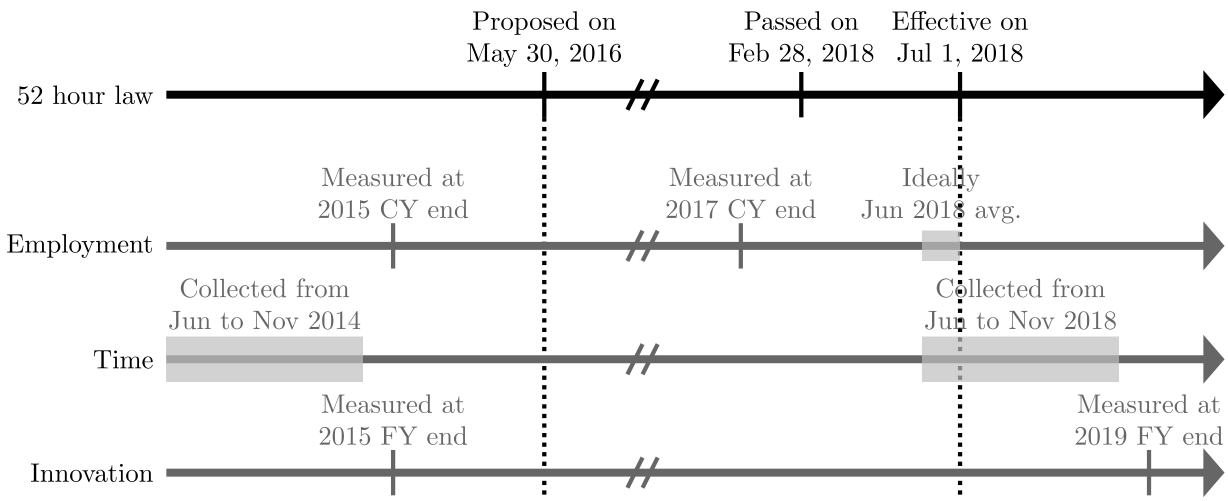
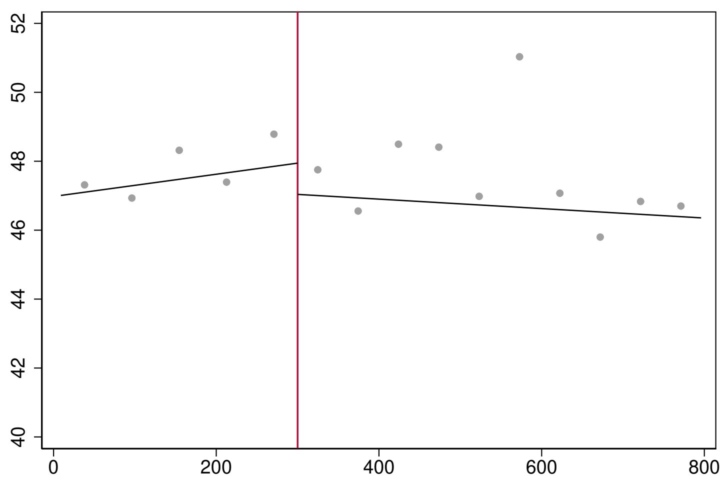


Figure 7: Pre-law continuity in outcomes

This figure illustrates the impact of the law on weekly work hours (y-axis) in Panel A and innovation output (y-axis) in Panel B. It presents binned scatter plots with fitted lines, separately estimated for establishments above and below the 300-employee threshold, indicated by a red vertical line. Weekly work hours data come from surveys conducted between June and November 2014. Innovation output is measured by capitalized intellectual properties as of the end of the 2015 fiscal year, and employment size (x-axis) is measured at the end of the 2015 calendar year. The data is described in Figure 3.

Panel A. Weekly work hours



Panel B. Innovation output across sectors

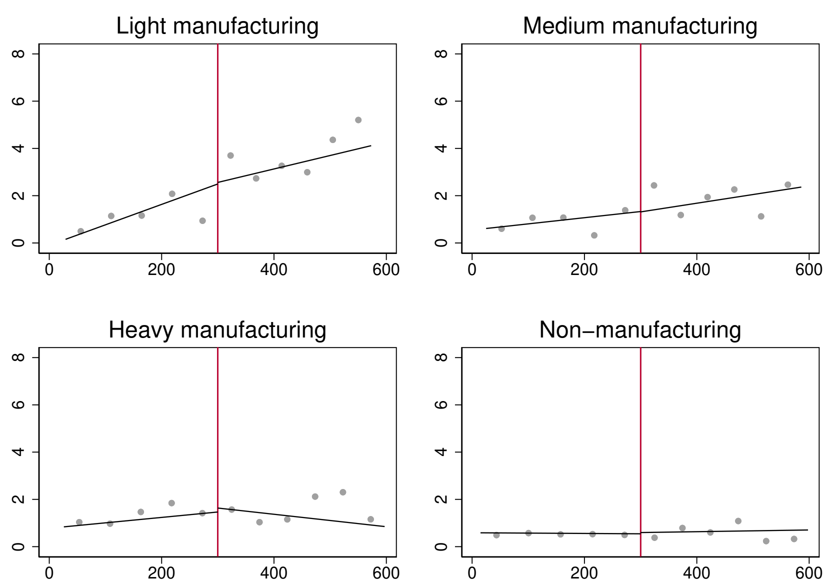


Figure 8: Law's effects on weekly work hours

This figure illustrates the impact of the law on weekly work hours (y-axis). It utilizes binned scatter plots with fitted lines, separately estimated for establishments above and below the 300-employee threshold, indicated by a red vertical line. Data on weekly work hours are collected from surveys conducted between June and November 2018, and employment size (x-axis) is measured at the end of the 2017 calendar year. The data is described in Figure 3.

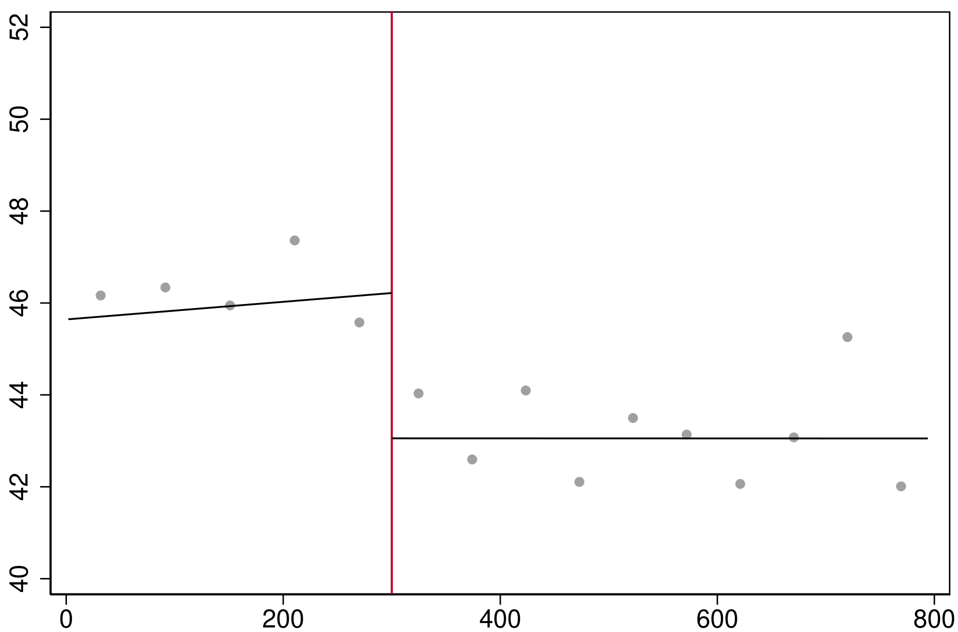


Figure 9: Law's impact on the distribution of weekly work hours
This figure displays the distribution of weekly work hours surveyed in 2016 (light gray) and 2018 (gray) at the top and 2016 (light gray) and 2020 (dark gray) at the bottom, using overlapping histograms and normal density curves. It highlights the impact of the 52-hour cap, marked by a vertical red line, on weekly work hours (x-axis). The data is described in Figure 3.

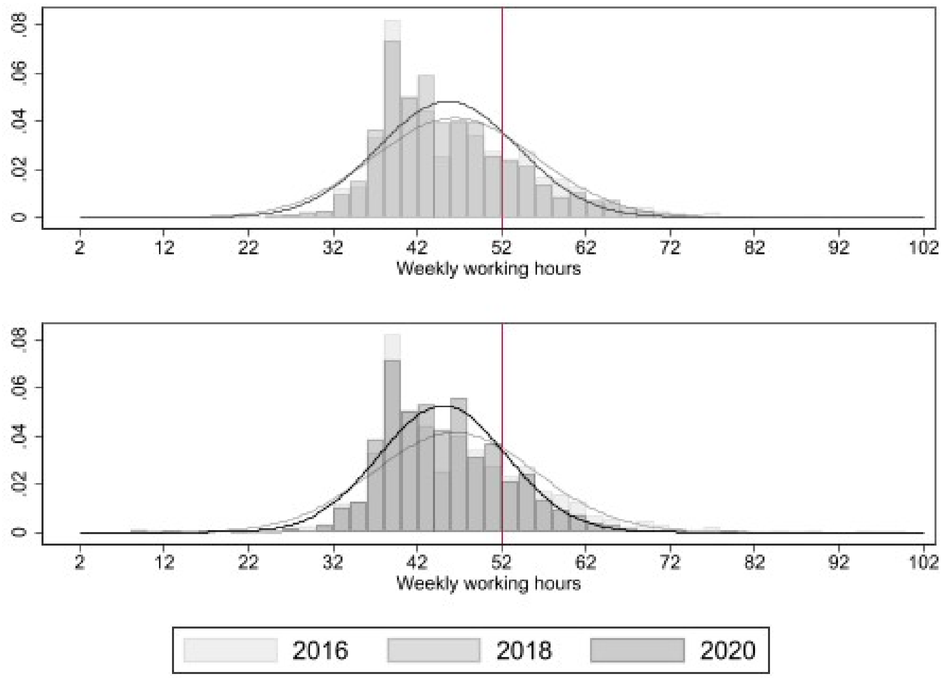


Figure 10: Law's effects on innovation output across sectors
This figure illustrates the impact of the law on innovation output (y-axis) across four sectors, as defined in Figure 3. It utilizes binned scatter plots with fitted lines, separately estimated for establishments above and below the 300-employee threshold, indicated by a red vertical line. Innovation output is measured by log-transformed capitalized intellectual properties at the end of the 2019 fiscal year. The data is described in Figure 3.

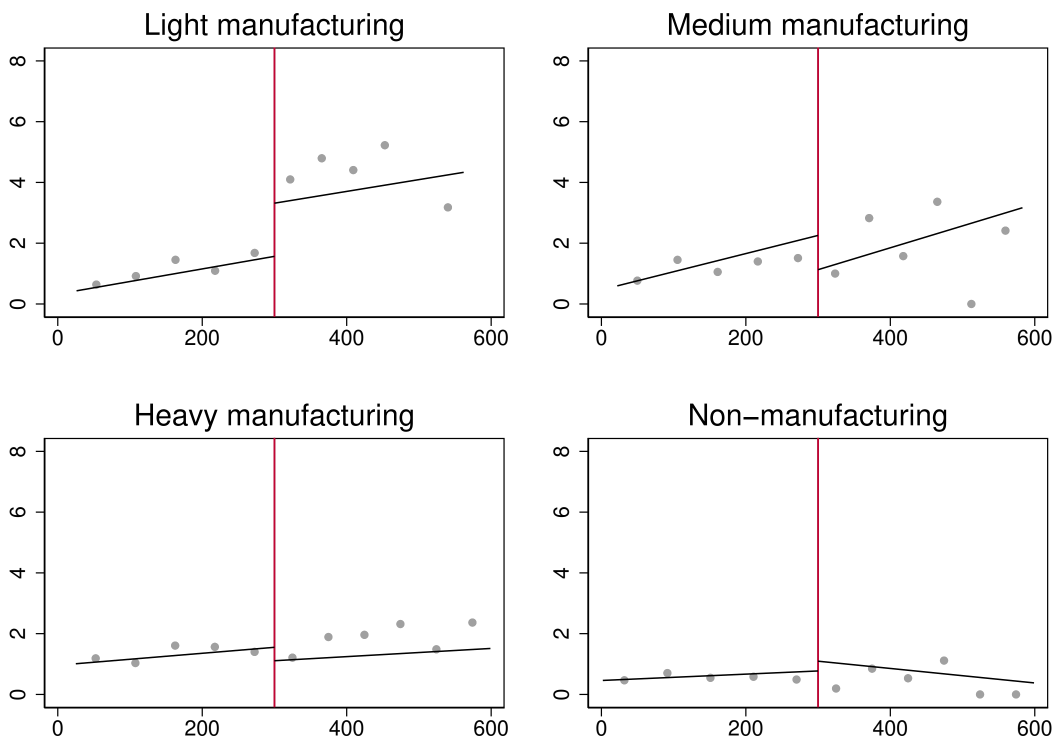


Figure 11: Law's effects on innovation: patent applications
This figure illustrates the impact of the law on innovation output across four sectors, as defined in Figure 3. Innovation output is measured by average patent applications for each year. The data is sourced from Korea Intellectual Property Rights Information Service.

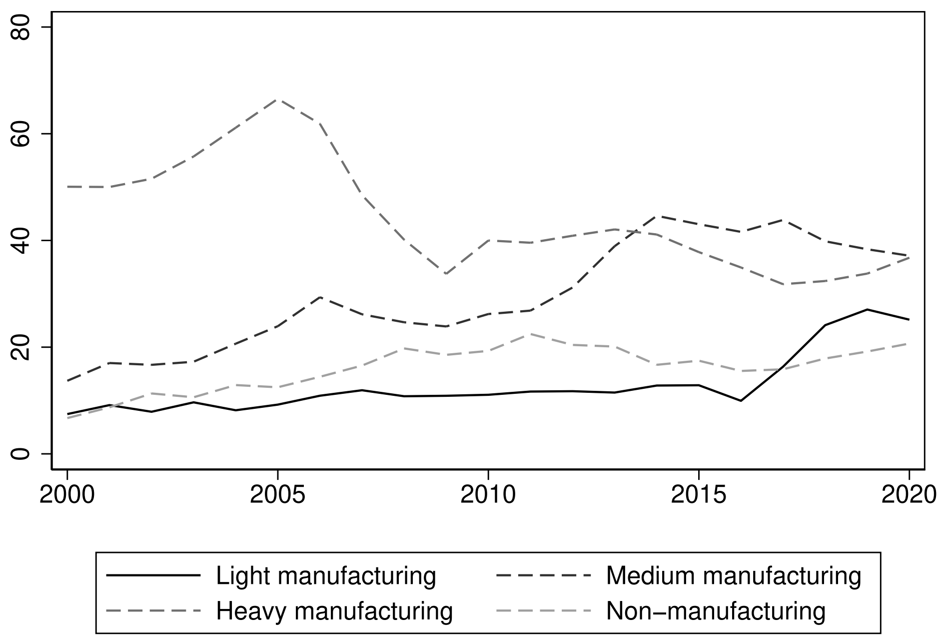


Table 1: Chronology of legislation and enforcement

This table presents a detailed chronology of key milestones related to the legislation and enactment of the 52-hour workweek law. The information is from a May 2018 publication by the Ministry of Employment and Labor (`https://www.moel.go.kr/policy/policydata/view.do?bbs_seq=20180500487`), which explains the revised Labor Standard Act, and the National Assembly's legislative tracking system (`https://likms.assembly.go.kr`).

Dates	Information
Early developments from the administration	
March 5, 2012	The Economic, Social, and Labor Council (ESLC; previously the Tripartite Commission) launches the Public Interest Committee for Shortened Work Hours.
July 17, 2013	The ESLC's Public Interest Committee announces its recommendation regarding shorter work hours.
September 19, 2014	ESLC installs the Special Committee for Labor Market Structural Reform.
December 23, 2014	The ESLC's Special Committee reaches a consensus on principles and direction for the labor market structural reform.
April 9, 2015	... temporarily suspends discussions due to disagreements.
August 29, 2015	... resumes discussions.
September 15, 2015	... decides upon a tripartite agreement for labor market structure reform, including a 52-hour work week and phased application by business size.
Follow-up legislative developments	
September 16, 2015	159 members of the 19^{th} National Assembly propose partial amendments to the Labor Standards Act to reduce work hours (bill no. 1916864).
May 29, 2016	The bill is discarded with the closure of the 19^{th} National Assembly.
May 30, 2016	122 members of the 20^{th} National Assembly reintroduce the amendments to the Labor Standards Act for work hour reduction (bill no. 2000028).
February 27, 2018	The bill is resolved as a proposal by the 20^{th} National Assembly's Environment and Labor Committee after ten rounds of discussion.
February 28, 2018	... approved by the Legislation and Judiciary Committee.
February 28, 2018	... passes in the National Assembly Plenary Session.
Enforcement by the administration	
March 3, 2018	The resolution is confirmed by the State Council.
March 20, 2018	... announced by the Ministry of Government Legislation.
July 1, 2018	... enforced for establishments with 300 or more employees.
July 1, 2019	... enforced for exempt sectors among establishments with 300 or more employees.
January 1, 2020	... enforced for establishments with 50 to less than 300 employees.
July 1, 2021	... enforced for establishments with 5 to less than 50 employees.

Table 2: Sectoral classification and employment size distribution of establishments
Panel A provides a comparison across three different industry classification systems: the North American Industrial Classification System (NAICS), the two-digit Standard Industrial Classification (SIC), and the proprietary classification used by the Workplace Panel Survey (WPS) for stratification purposes. The non-manufacturing sector does not include agriculture, mining, and public administration. Panel B reports the distribution of establishments across employment-size ranges for each sector defined in Panel A. The figures indicate the number of sample establishments, with the percentage relative to the total number of population establishments - drawn from the Census on Establishments provided through MDIS (Micro Data Integrated Service) - shown in parentheses, by sector and employment range. Since the WPS sample is designed based on this census, the population counts are aligned accordingly. For example, 18 sampled establishments with 300–399 employees in the light manufacturing sector represent 78.3% of all population establishments in that sector and employment range. The data is described in Figure 3.

Panel A. Comparison with other industry classification systems

	NAICS	Two-digit SIC	WPS
Light manufacturing	31	10-15	Light
Medium manufacturing	32	16-18	Light
		19-23	Chemical
Heavy manufacturing	33	24, 25, 29-31	Metal, automobiles, and transportation
		26-28	Electrical, electronics, and precision
		32, 33	Light
Non-manufacturing	42-81	35, 36	Electricity, gas, and water supply
		37-39, 45-47, 55, 56, 59, 60, 90, 91, 94-98	Personal services
		41, 42	Construction
		49-52, 61	Distribution services
		58, 62-66, 68-75	Business services
		84-87, 99	Social services

Panel B. Distribution of establishments by employment range

	[30, 99]	[100, 199]	[200, 299]	[300, 399]	[400, 499]	[500, 599]
Light manufacturing	64	44	16	18	6	3
	(2.9%)	(11.0%)	(17.2%)	(78.3%)	(31.6%)	(27.3%)
Medium manufacturing	109	53	23	15	12	6
	(3.1%)	(8.6%)	(16.7%)	(25.9%)	(54.5%)	(30.0%)
Heavy manufacturing	296	98	46	42	38	15
	(3.1%)	(5.7%)	(10.5%)	(24.1%)	(40.9%)	(27.3%)
Non-manufacturing	395	160	83	54	41	14
	(1.2%)	(2.9%)	(5.4%)	(8.6%)	(11.2%)	(6.0%)

Table 3: Covariate balances

This table compares characteristics of establishments with 300 to 499 employees in columns 1 and 2 and those with 100 to 299 employees in columns 3 and 4. Columns 1 and 3 report the number of observations (N), and columns 2 and 4 the mean values for each variable. Columns 5 and 6 present the differences in means between the two groups and their respective standard errors (S.E.). The data is described in Figure 3. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
# Employees	[300,500)		[100,300)			
Variable	N	Mean	N	Mean	(2)-(4)	S.E.
ln(#Employees)	189	5.96	342	5.06	0.88***	0.03
ln(#Indirect employees)	189	1.26	342	0.83	0.48	0.33
ln(#Incoming skilled employees)	189	1.55	342	1.11	0.42*	0.25
ln(#Outgoing employees)	189	3.29	342	2.22	1.04***	0.21
ln(Capitalized IPs)	189	1.26	342	0.94	0.24	0.22
ln(Capitalized R&D)	189	1.17	342	1.26	-0.07	0.38
ln(Expensed R&D)	189	1.76	342	2.08	-0.25	0.35
ln(PPE)	189	8.80	342	8.63	0.06	0.35
ln(Software)	189	2.20	342	1.44	0.90**	0.41
ln(Assets)	189	10.82	342	10.20	0.47**	0.23
Capitalized R&D/Assets	189	0.01	342	0.01	0.00	0.01
Intangible assets/Assets	189	0.02	342	0.02	0.00	0.01
PPE/Assets	189	0.28	342	0.34	-0.06	0.04
EBIT/Assets	168	0.05	286	0.06	-0.01	0.01
EBIT/Sales	170	0.04	289	0.06	-0.01	0.01
Wage/Sales	189	0.34	342	0.31	0.05	0.04
Wage per employee	189	33.06	342	33.82	-2.47	3.28
Sales/Total work hours	155	0.20	280	0.20	-0.02	0.04
Union	189	0.37	342	0.34	0.01	0.06
Penalize low performers	189	0.08	342	0.16	-0.03	0.04
Reward skill improvements	188	0.25	335	0.30	-0.04	0.06
Flexible hours or days	189	0.04	342	0.06	-0.03	0.03
% Employees over 55	189	0.19	342	0.18	0.03	0.04
% Employees below 35	189	0.27	342	0.26	-0.00	0.03
Owner manager	189	0.61	342	0.73	-0.09	0.07
CEO being the largest shareholder	189	0.38	342	0.66	-0.23***	0.07
Business group affiliation	189	0.16	342	0.05	0.08	0.06
Foreign ownership	189	0.07	342	0.03	0.02	0.02
Largest shareholder ownership	153	57.78	284	61.57	-7.44*	4.32

Table 4: Law's effects on labor time

This table presents coefficient estimates from the regressions of weekly work hours in Panel A and of indicators for overtime and weekend work in Panel B. In Panel B, the indicators are defined as follows: they equal one if employees engage in overtime work during weekdays in columns 1 to 3, occasionally work on weekends in columns 4 to 6, or regularly work on weekends with more than 23 regular workdays per month in columns 7 to 9. The regressor is $\mathbb{1}[E \geq 300]$, an indicator set to one for establishments with 300 or more employees at the end of the 2017 fiscal year. The sample includes establishments with 600 or fewer employees in columns 1, 4, and 7, those with 100 to 500 employees in columns 2, 5, and 8, and those with 200 to 400 employees in columns 3, 6, and 9. Control variables include total assets, capitalized R&D spending, intangible assets, capital intensity, wage expenditure, and union presence, all measured as of the end of the 2017 fiscal year, as defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A. Intensive margin

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Weekly work hours					
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	-3.2926***	-3.9297***	-3.6570***	-2.0239**	-2.9633***	-2.6679**
	(0.789)	(0.832)	(1.377)	(0.819)	(0.890)	(1.322)
ln(Assets)				-0.0428	0.0861	0.2467
				(0.240)	(0.523)	(0.743)
Capitalized R&D/Assets				0.7124	13.8973	-7.8212
				(10.128)	(16.953)	(31.534)
Intangible assets/Assets				5.5149	-8.9043	8.9131
				(10.268)	(13.271)	(24.657)
PPE/Assets				2.2359*	0.8878	5.0647
				(1.186)	(1.723)	(4.484)
Wage/Sales				-2.5232*	-1.4942	1.6154
				(1.497)	(2.734)	(4.189)
Union				-0.5519	-1.0426	1.0752
				(0.727)	(0.966)	(2.119)
2-digit SIC FE				✓	✓	✓
# Observations	1494	703	284	1494	703	284
Adjusted R^2	0.00486	0.0263	0.0325	0.143	0.169	0.206

Panel B. Extensive margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	Overtime on weekdays			Occasional weekend work			Regular weekend work		
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	-0.0035	-0.1182*	-0.0615	0.0364	-0.0144	0.0782	-0.0445*	-0.1179***	-0.1281***
	(0.065)	(0.071)	(0.089)	(0.070)	(0.073)	(0.087)	(0.026)	(0.042)	(0.046)
ln(Assets)	0.0011	0.0383	0.0614	0.0112	0.0099	0.0367	-0.0160	0.0270	-0.0241
	(0.017)	(0.028)	(0.041)	(0.016)	(0.028)	(0.033)	(0.013)	(0.019)	(0.020)
Capitalized R&D/Assets	0.8754	0.6077	2.2306	-1.1609***	0.3086	3.7716	0.2369	-0.6671*	-0.0742
	(0.700)	(0.983)	(1.833)	(0.429)	(1.226)	(2.357)	(0.437)	(0.348)	(0.736)
Intangible assets/Assets	1.0846	-1.5477	0.6456	0.9363	-0.5564	0.4224	-0.5040**	0.0971	-0.5023
	(0.729)	(1.082)	(1.215)	(0.727)	(1.044)	(1.225)	(0.247)	(0.590)	(0.839)
PPE/Assets	0.0009	0.0509	0.0037	0.0276	0.1756	0.0739	0.1267**	0.0172	-0.1850
	(0.084)	(0.129)	(0.269)	(0.078)	(0.134)	(0.276)	(0.056)	(0.069)	(0.190)
Wage/Sales	-0.1633	-0.1154	0.0143	0.1233	-0.0146	0.0429	-0.0560	0.1139	-0.0399
	(0.109)	(0.170)	(0.251)	(0.106)	(0.215)	(0.288)	(0.072)	(0.120)	(0.191)
Union	-0.0584	-0.0012	-0.0442	-0.0545	-0.0104	-0.0867	0.0269	0.0064	0.0272
	(0.044)	(0.061)	(0.100)	(0.047)	(0.064)	(0.096)	(0.033)	(0.049)	(0.040)
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	1494	703	284	1494	703	284	1494	703	284
Adjusted R^2	0.160	0.190	0.217	0.125	0.127	0.125	0.0642	0.0821	0.0627

Table 5: Law's effects on innovation output

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) as of the end of the 2019 fiscal year. In Panel A, the regressor is $\mathbb{1}[E \geq 300]$, an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. Panel B includes this regressor and its interaction with $\mathbb{1}[s = L]$, an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. The sample includes establishments with 600 or fewer employees in columns 1 and 4, those with 100 to 500 employees in columns 2 and 5, and those with 200 to 400 employees in columns 3 and 6. Control variables used in Panel A are listed in Table 4. In Panel B, control variables also include interactions between employment and sector indicators, each set to one for the four sectors. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A. Full sample

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	ln(Capitalized IPs)					
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	0.3221	0.2246	0.0691	-0.0220	0.0262	0.1077
	(0.246)	(0.287)	(0.382)	(0.241)	(0.237)	(0.380)
ln(Assets)				0.2410***	0.2559**	0.4034**
				(0.062)	(0.101)	(0.190)
Capitalized R&D/Assets				8.7668***	10.6591***	16.9817*
				(2.829)	(3.567)	(9.197)
Intangible assets/Assets				0.5839	7.4860**	0.7997
				(1.345)	(2.936)	(3.774)
PPE/Assets				-0.2058	-0.1037	0.1324
				(0.257)	(0.455)	(1.204)
Wage/Sales				-0.5626	-1.0632*	-0.9566
				(0.373)	(0.624)	(0.901)
Union				-0.1987	0.1875	0.1664
				(0.179)	(0.320)	(0.466)
ln(#Employees)$\times\eta_{s(i)}$				✓	✓	✓
2-digit SIC FE				✓	✓	✓
# Observations	1306	618	242	1306	618	242
Adjusted R^2	0.000491	0.000121	-0.00387	0.122	0.177	0.201

Panel B. By sector

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	ln(Capitalized IPs)					
Sample	Light manufacturing			All sectors		
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	2.2187***	2.8308***	3.1643**	-0.0358	-0.2070	0.5172
	(0.545)	(0.726)	(1.483)	(0.280)	(0.339)	(0.649)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$				2.3942***	3.0203***	2.6053*
				(0.708)	(0.888)	(1.378)
ln(#Employees)$\times\eta_{s(i)}$				✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓
# Observations	129	72	28	1306	618	242
Adjusted R^2	0.511	0.377	0.420	0.123	0.181	0.260

Table 6: Law's effects on innovation output: robustness to alternative methods

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs). Panel A applies fuzzy regression discontinuity design (RDD), while Panel B employs the difference-in-differences (DiD) method. The sample includes establishments in the light manufacturing sector in Panel A and in Panel B, columns 1 and 2, and all sectors in Panel B, columns 3 and 4. Sectors are defined in Table 3. The sample is restricted to establishments with 600 or fewer employees in Panel A, columns 1 to 3 and Panel B, columns 1 and 2, and those with 100 to 500 employees in Panel A, columns 4 to 6 and Panel B, columns 3 and 4. The variables T_{i0} and T_{i1} are indicators set to one for establishments with 300 or more employees at the end of the 2015 calendar year (the latest pre-proposal data point) and 2017 calendar year (the latest pre-enforcement data point), respectively. The centered forcing variable $\widetilde{E}_{i0}$ is the log-transformed employee count at the end of the 2015 calendar year E_{i0} minus the log of 300. Post is an indicator equal to one for 2019 (the earliest post-enforcement year) and zero for 2015 (the latest pre-proposal year). All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A. Fuzzy RDD

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Light manufacturing					
Bandwidth	± 300			± 200		
	First-stage		Second-stage	First-stage		Second-stage
Dep. Var.	T_1	$T_1 \times \widetilde{E_0}$	ln(Capitalized IPs)	T_1	$T_1 \times \widetilde{E_0}$	ln(Capitalized IPs)
T_1			4.8883***			5.7505**
			(1.138)			(2.459)
$T_1 \times \widetilde{E_0}$			-2.6637*			-3.1134
			(1.567)			(2.360)
T_0	0.6629***	0.0155		0.5467**	0.0528	
	(0.201)	(0.022)		(0.262)	(0.058)	
$T_0 \times \widetilde{E_0}$	0.5340	1.0250***		0.4327	1.0767***	
	(0.418)	(0.017)		(0.529)	(0.065)	
$\widetilde{E_0}$	0.0347	-0.0122	-0.0002	0.1848	-0.0638	-0.7378
	(0.034)	(0.012)	(0.374)	(0.179)	(0.064)	(1.694)
2-digit SIC FE	✓	✓	✓	✓	✓	✓
F-statistics	44.76	3007.04		4.16	1712.85	
# Observations	124	124	124	56	56	56

Panel B. DiD

	(1)	(2)	(3)	(4)
Dep. Var.	*ln*(Capitalized IPs)			
Sample	Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200
T_0 × Post	2.4224*	3.5458***	-0.1233	-0.3228
	(1.275)	(1.113)	(0.133)	(0.233)
$T_0 \times$ Post $\times \mathbb{1}[s = L]$			2.5457**	3.8686***
			(1.273)	(1.125)
Establishment FE	✓	✓	✓	✓
2-digit SIC × Year FE	✓	✓	✓	✓
# Observations	172	76	1,970	796
Adjusted R^2	0.327	0.364	0.604	0.653

Table 7: Innovation incentives as a complement of leisure time

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) as of the end of the 2019 fiscal year. The regressors are interactions between $\mathbb{1}[E \geq 300]$, $\mathbb{1}[s = L]$, and a mediator. $\mathbb{1}[E \geq 300]$ is an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. $\mathbb{1}[s = L]$ is an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. The mediator varies by column: Do not penalize low-performers (columns 1 to 4) is the inverse of Penalize low-performers, defined as an indicator set to one for establishments that penalize low-performers through wage cuts, promotion restrictions, or warnings rather than tolerate them via mentor-mentee programs, training, or role adjustments to improve fit. Reward skill improvements (columns 5 to 8) is an indicator set to one for establishments that raise base salaries based on the skill improvements. Both mediators are measured as of the end of the 2017 calendar year. The sample includes establishments with 600 or fewer employees in columns 1 and 3 and those with 100 to 500 employees in columns 2 and 4. Control variables are listed in Table 5, Panel B. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	ln(Capitalized IPs)							
Mediator =	Do not penalize low-performers				Reward skill improvements			
Sample	Light manufacturing		All sectors		Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	1.4677***	2.0603***	0.2870	0.0850	1.9429***	2.5072***	-0.0429	-0.2538
	(0.439)	(0.545)	(0.705)	(0.834)	(0.505)	(0.678)	(0.340)	(0.391)
Mediator			0.0051	0.0531			0.1703	0.2268
			(0.185)	(0.402)			(0.150)	(0.285)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			1.7691*	2.5583*			1.9689***	2.5981***
			(0.940)	(1.326)			(0.685)	(0.872)
$\mathbb{1}[E \geq 300] \times$ Mediator	1.3878**	1.4019*	-0.3670	-0.3354	2.5532***	2.5924**	0.2983	0.0890
	(0.636)	(0.719)	(0.721)	(0.857)	(0.969)	(1.097)	(0.538)	(0.504)
$\mathbb{1}[s = L] \times$ Mediator			0.7334**	0.6073			-0.7380**	-0.5125
			(0.366)	(0.775)			(0.356)	(0.612)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L] \times$ Mediator			1.4215	1.1342			3.0311***	2.9778***
			(0.905)	(1.276)			(1.027)	(1.143)
Constant	-1.1851	4.1115	-1.2241*	-2.0019	-1.2850	4.0468	-1.2186*	-1.9810
	(1.262)	(3.561)	(0.662)	(1.801)	(1.275)	(3.579)	(0.658)	(1.773)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	129	72	1306	618	128	72	1276	602
Adjusted R^2	0.512	0.380	0.121	0.177	0.519	0.391	0.121	0.170

Table 8: Flexible hours or days as a substitute for leisure time

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) as of the end of the 2019 fiscal year. The regressors are interactions between $\mathbb{1}[E \geq 300]$, $\mathbb{1}[s = L]$, and Flexible work hours or days. $\mathbb{1}[E \geq 300]$ is an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. $\mathbb{1}[s = L]$ is an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. Flexible work hours or days is an indicator set to one if employees have the flexibility to adjust their work hours or days as of the end of the 2017 calendar year. The sample includes establishments with 600 or fewer employees in columns 1 and 3 and those with 100 to 500 employees in columns 2 and 4. Control variables are listed in Table 5, Panel B. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.	ln(Capitalized IPs)			
Sample	Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	2.2997***	2.9501***	0.1184	-0.1882
	(0.568)	(0.751)	(0.286)	(0.344)
Flexible hours or days			0.2045	-0.0980
			(0.234)	(0.360)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			2.4012***	3.0739***
			(0.716)	(0.906)
$\mathbb{1}[E \geq 300]$ × Flexible hours or days	-1.8249***	-2.4320***	-1.8002***	-0.4924
	(0.561)	(0.649)	(0.599)	(0.529)
$\mathbb{1}[s = L]$ × Flexible hours or days			1.1503	0.8984
			(1.191)	(1.118)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$ × Flexible hours or days			-0.9559	-1.9087
			(1.409)	(1.332)
Constant	-1.2356	3.7526	-1.2221*	-1.8876
	(1.263)	(3.532)	(0.634)	(1.734)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓
Controls	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓
# Observations	129	72	1306	618
Adjusted R^2	0.508	0.374	0.126	0.177

Table 9: Law's effects on production inputs and outputs

This table presents coefficient estimates from regressions examining production inputs and outputs. In Panel A, production output is measured by the ratio of sales to total hours worked. Here, sales are from the end of the 2019 fiscal year, while total hours worked are calculated by multiplying average weekly work hours (collected from June to November 2018) by the average number of employees during 2018 and then annualizing. Panel B reports results for labor inputs, distinguishing between direct employment (columns 1-4) and indirect employment (columns 5-8), while Panel C shows changes in labor composition, measured by the number of incoming skilled employees (columns 1-4) and the number of outgoing employees (columns 5-8). Panel D examines two forms of capital input: property, plant, and equipment (PPE) (columns 1-4) and capitalized software (columns 5-8). Panel E investigates expenditures to increase capital in house, proxied by expensed R&D (columns 1-4) and capitalized R&D (columns 5-8). In Panels B through E, the dependent variables are observed at the end of 2019 and log-transformed after adding one. Panel F measures profitability using the ratio of earnings before interest and taxes (EBIT) to total assets (columns 1-4) and EBIT to sales (columns 5-8). EBIT and sales are measured at the end of fiscal year 2019, while total assets are measured at the beginning of the fiscal year. The regressor is $\mathbb{1}[E \geq 300]$ and its interaction with $\mathbb{1}[s = L]$. $\mathbb{1}[E \geq 300]$ is an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. $\mathbb{1}[s = L]$, an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. The sample includes establishments with 600 or fewer employees in odd-numbered columns and those with 100 to 500 employees in even-numbered columns. Control variables are listed in Table 5, Panel B. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A. Production output

	(1)	(2)	(3)	(4)
Dep. Var.	Sales/Total work hours			
Sample	Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	-0.0145	0.0748	-0.0323	-0.0038
	(0.073)	(0.079)	(0.057)	(0.050)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			0.0985	0.1111
			(0.111)	(0.098)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓
Controls	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓
# Observations	125	72	1244	586
Adjusted R^2	0.543	0.528	0.444	0.448

Panel B. Employee count

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(#Employees)				*ln*(#Indirect employees)			
Sample	Light mfg.		All sectors		Light mfg.		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	0.0216	0.2301	-0.0321	0.0262	-0.3159	0.1838	0.7783**	0.1858
	(0.132)	(0.185)	(0.033)	(0.042)	(0.547)	(0.805)	(0.343)	(0.369)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			0.0542	0.1733			-1.2696*	0.3463
			(0.143)	(0.189)			(0.683)	(1.015)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	131	73	1358	641	131	73	1358	641
Adjusted R^2	0.840	0.590	0.884	0.761	0.174	0.252	0.102	0.0736

Panel C. Changes in employee composition

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(#Incoming skilled employees)				*ln*(#Outgoing employees)			
Sample	Light mfg.		All sectors		Light mfg.		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	-0.6079	-0.9725	0.1466	0.0041	-0.3449	-0.2041	0.0730	0.1820
	(0.604)	(0.817)	(0.226)	(0.290)	(0.466)	(0.469)	(0.209)	(0.282)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			-0.9128	-1.0650			-0.5622	-0.2499
			(0.614)	(0.861)			(0.425)	(0.559)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	131	73	1358	641	131	73	1358	641
Adjusted R^2	0.176	0.242	0.168	0.228	0.373	0.0710	0.233	0.154

Panel D. Labor-replacing vs. augmenting capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	ln(PPE)				ln(Software)			
Sample	Light mfg.		All sectors		Light mfg.		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	-0.1657	0.1031	-0.3445**	-0.1495	0.5426	0.9699	0.3673	1.2769**
	(0.305)	(0.390)	(0.168)	(0.211)	(1.033)	(1.167)	(0.437)	(0.575)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			0.3168	0.3514			-0.2597	0.0281
			(0.366)	(0.467)			(0.992)	(1.488)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	129	72	1306	618	129	72	1306	618
Adjusted R^2	0.857	0.843	0.784	0.820	0.242	0.0347	0.167	0.201

Panel E. R&D expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	ln(Expensed R&D)				ln(Capitalized R&D)			
Sample	Light mfg.		All sectors		Light mfg.		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	-1.1369	1.2438	-0.7027*	0.2526	0.1916	0.1096	0.0649	-0.0567
	(1.333)	(1.933)	(0.402)	(0.528)	(0.443)	(0.249)	(0.452)	(0.558)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			-0.1263	1.0092			-0.0527	0.3381
			(1.394)	(1.986)			(0.617)	(0.696)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	129	72	1314	621	129	72	1306	618
Adjusted R^2	0.00504	-0.0999	0.226	0.291	0.133	-0.0931	0.117	0.167

Panel F. Profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	EBIT/Assets				EBIT/Sales			
Sample	Light mfg.		All sectors		Light mfg.		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	0.0580**	0.0459	-0.0159	-0.0051	0.0295	-0.0033	-0.0023	-0.0024
	(0.028)	(0.043)	(0.016)	(0.022)	(0.028)	(0.044)	(0.038)	(0.036)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			0.0706**	0.0449			0.0426	-0.0051
			(0.033)	(0.051)			(0.052)	(0.059)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	129	72	1302	618	129	72	1305	618
Adjusted R^2	0.179	0.342	0.100	0.135	0.199	0.343	0.187	0.219

Table 10: Cultural explanation for suboptimal pre-law time allocation

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) as of the end of the 2019 fiscal year. The regressors are interactions between $\mathbb{1}[E \geq 300]$, $\mathbb{1}[s = L]$, and a mediator. $\mathbb{1}[E \geq 300]$ is an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. $\mathbb{1}[s = L]$ is an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. The mediator is an indicator defined differently in each panel; % Employees below 35 in Panel A equals one if the percentage of employees under the age of 35 is above its sample median, while % Employees over 55 in Panel B equals one if the percentage of employees aged 55 or above is above its sample median, both as of the end of the 2017 calendar year. The sample includes establishments with 600 or fewer employees in columns 1 and 3 and those with 100 to 500 employees in columns 2 and 4. Control variables are listed in Table 5, Panel B. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	ln(Capitalized IPs)							
Mediator =	% Employees aged 55 or above				% Employees under 35			
Sample	Light manufacturing		All sectors		Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	2.0171***	2.6804***	0.2916	0.2237	3.3943***	3.9888***	-0.3577	-0.4791
	(0.574)	(0.729)	(0.401)	(0.446)	(0.788)	(1.089)	(0.244)	(0.331)
Mediator			-0.0936	0.2583			0.3346**	0.4587*
			(0.136)	(0.285)			(0.135)	(0.242)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			2.1176**	1.6514			3.4904***	4.3591***
			(0.866)	(1.059)			(0.743)	(1.057)
$\mathbb{1}[E \geq 300] \times$ Mediator	0.7162	0.5230	-0.7636*	-0.9920**	-1.4425*	-1.4202	0.7872*	0.7602
	(0.825)	(1.035)	(0.423)	(0.468)	(0.786)	(0.961)	(0.474)	(0.478)
$\mathbb{1}[s = L] \times$ Mediator			0.3780	-1.5972***			-0.5704	-0.3799
			(0.409)	(0.537)			(0.379)	(0.506)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L] \times$ Mediator			0.8239	2.5629**			-1.7141*	-2.0838**
			(0.948)	(1.094)			(0.875)	(0.986)
Constant	-1.2419	3.8536	-1.1166*	-1.8615	-1.2386	3.9947	-1.3454**	-2.0468
	(1.263)	(3.579)	(0.646)	(1.689)	(1.264)	(3.582)	(0.636)	(1.755)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	129	72	1306	618	129	72	1306	618
Adjusted R^2	0.508	0.368	0.123	0.191	0.510	0.376	0.131	0.197

Table 11: Agency explanations for suboptimal pre-law time allocation

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) as of the end of the 2019 fiscal year. The regressors are interactions between $\mathbb{1}[E \geq 300]$, $\mathbb{1}[s = L]$, and a mediator. $\mathbb{1}[E \geq 300]$ is an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. $\mathbb{1}[s = L]$ is an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. The mediator is an indicator defined differently in each panel; Owner manager in Panel A equals one if an establishment is not run by professional CEOs, CEO being the largest shareholder in Panel A equals one if the CEO is also the largest shareholder, Business group affiliation in Panel B equals one if an establishment is affiliated to conglomerates, and Foreign ownership in Panel B equals one if foreign ownership is above its sample median, all as of the end of the 2017 calendar year. The sample includes establishments with 600 or fewer employees in columns 1 and 3 and those with 100 to 500 employees in columns 2 and 4. Control variables are listed in Table 5, Panel B. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A. Separation of ownership and control

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	ln(Capitalized IPs)							
Mediator =	Owner manager				CEO being the largest shareholder			
Sample	Light manufacturing		All sectors		Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	2.0804***	2.2275**	-0.2397	-0.7403*	2.6236***	3.1695***	-0.0329	0.1988
	(0.695)	(1.064)	(0.379)	(0.422)	(0.707)	(1.059)	(0.384)	(0.452)
Mediator			-0.1160	-0.1630			0.1824	0.5821**
			(0.140)	(0.319)			(0.131)	(0.272)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			2.8228***	3.0079***			2.7524***	2.9651**
			(0.820)	(1.118)			(0.867)	(1.181)
$\mathbb{1}[E \geq 300] \times$ Mediator	0.2354	0.9200	0.3332	0.8412	-0.8329	-0.6221	0.0653	-0.5375
	(0.923)	(1.089)	(0.468)	(0.512)	(0.764)	(0.988)	(0.437)	(0.419)
$\mathbb{1}[s = L] \times$ Mediator			0.2065	-0.6835			-0.6218	-0.8195
			(0.478)	(0.682)			(0.417)	(0.594)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L] \times$ Mediator			-0.7448	-0.1252			-0.7480	-0.1514
			(0.952)	(1.098)			(0.823)	(1.005)
Constant	-1.2678	3.5966	-1.0519	-1.8112	-1.1822	3.8505	-1.3435**	-1.9948
	(1.266)	(3.601)	(0.650)	(1.789)	(1.266)	(3.564)	(0.669)	(1.704)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	129	72	1306	618	129	72	1306	618
Adjusted R$\hat{2}$	0.507	0.371	0.121	0.183	0.509	0.369	0.123	0.191

Panel B. Long-term shareholder orientation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	ln(Capitalized IPs)							
Mediator =	Business group affiliation				Foreign ownership			
Sample	Light manufacturing		All sectors		Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	2.2814***	2.9269***	0.0079	-0.2035	2.2267***	2.9270***	-0.2549	-0.4228
	(0.596)	(0.757)	(0.296)	(0.349)	(0.596)	(0.755)	(0.311)	(0.360)
Mediator			0.8756***	1.0883**			-0.1239	-0.2982
			(0.309)	(0.483)			(0.188)	(0.400)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			2.3709***	3.0931***			2.3876***	3.1275***
			(0.779)	(0.938)			(0.754)	(0.890)
$\mathbb{1}[E \geq 300] \times$ Mediator	-0.5267	-0.9562	-0.5606	-0.4698	-0.0363	-0.4736	1.0096*	1.1551*
	(0.579)	(0.760)	(0.720)	(0.723)	(1.051)	(1.296)	(0.549)	(0.675)
$\mathbb{1}[s = L] \times$ Mediator			-1.3469**	-1.0490			-0.1713	0.1502
			(0.671)	(0.959)			(0.632)	(0.855)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L] \times$ Mediator			0.0427	-0.4945			0.0153	-0.6618
			(1.082)	(1.250)			(1.082)	(1.402)
Constant	-1.2596	3.7038	-1.0141	-1.6816	-1.2534	3.7343	-1.1999*	-1.8713
	(1.263)	(3.569)	(0.625)	(1.651)	(1.265)	(3.564)	(0.642)	(1.712)
ln(#Employees)$\times \eta_{s(i)}$			✓	✓			✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	129	72	1306	618	129	72	1306	618
Adjusted R^2	0.507	0.369	0.131	0.190	0.507	0.367	0.122	0.182

Table A1: Variable definitions

This table provides the definitions of the variables used in this study. The data is described in Figure 3. The financial statement information collected at the firm level is transformed into establishment-level data using the conversion variable KLI provided, considering factors such as each establishment's contribution to the firm's sales. Internet Appendix Section A provides further details on the conversion procedure.

Variable	Definition
ln(#Employees)	Log of one plus number of employees (epq1011)
ln(#Indirect employees)	Log of one plus number of indirect employees (epq9008)
ln(#Incoming skilled employees)	Log of one plus number of incoming regular skilled employees (epq8021)
ln(#Outgoing employees)	Log of one plus number of outgoing employees (epq8045)
Weekly work hours	Average weekly work hours (per_week)
Overtime	Average daily overtime hours on regular workdays
Work hours on weekends	Average daily work hours on weekend workdays
Monthly regular workdays	Number of regular workdays per month
Monthly weekend workdays	Number of weekend workdays per month
Overtime on weekdays	One if employees work overtime on weekdays and zero otherwise
Occasional weekend work	One if employees work on weekends occasionally and zero otherwise
Regular weekend work	One if employees work more than 23 days per month and zero otherwise
ln(Capitalized IPs)	Log of one plus capitalized intellectual properties (IPs) (fpq4020)
ln(Capitalized R&D)	Log of one plus capitalized R&D spending (fpq4026)
ln(Expensed R&D)	Log of one plus expensed R&D spending (aq3019)
ln(PPE)	Log of one plus property, plant, and equipment (fpq4004)
ln(Software)	Log of one plus capitalized software (fpq4024)
ln(Assets)	Log of one plus total assets (fpq4002)
Capitalized R&D/Assets	Capitalized R&D spending (fpq4026) divided by total assets (fpq4002)
Intangible Assets/Assets	Intangible assets (fpq4018) less capitalized intellectual properties (fpq4020) and capitalized R&D (fpq4026), divided by total assets (fpq4002)
PPE/Assets	Property, plant, and equipment (fpq4004) divided by total assets (fpq4002)
EBIT/Assets	Earnings before interest and taxes (fpq2020 + fpq2021) divided by total assets (fpq4002)
EBIT/Sales	Earnings before interest and taxes (fpq2020 + fpq2021) divided by sales revenue (fpq2001)
Wage/Sales	Wage expenditure (fpq5001) divided by sales revenue (fpq2001)
Wage per employee	Wage expenditure divided by the average number of employees over the fiscal year (fpq5002)
Sales/Total work hours	Sales revenue (fpq2001) divided by the total work hours of all employees; the denominator is calculated as the product of yearly work hours per employee (per_week$\times$52) and the average number of employees (epq1001/2 + epq1011/2)

Variable	Definition
Union	One if an establishment is unionized (epq7014) and zero otherwise
Penalize low performers	One if an establishment punishes low performers (cq1030r1, cq1030r4, cq1030r5, cq1030r7, cq1030r9) and zero otherwise
Reward skill improvements	One if an establishment raises base salary based on employees' skill improvements (cq2124r4, cq2224r4, cq2324r4) and zero otherwise
Flexible hours or days	One if employees have flexibility to set their working hours (dq3025) or days (dq3027)
% Employees over 55	One if the share of employees over 55 years old (epq6001) is above the sample median and zero otherwise
% Employees below 35	One if the share of employees below 35 years old (epq6002) is above the sample median and zero otherwise
Owner manager	One if a firm has a owner-manager and zero otherwise (aq2004)
CEO being the largest shareholder	One if a CEO is the largest shareholder of the firm (aq2007r1) and zero otherwise
Business group affiliation	One if a firm is a business group or its affiliate (aq2006) and zero otherwise
Foreign ownership	One if the share of foreign ownership (aq2005) is above the sample median and zero otherwise
Largest shareholder ownership	One if the share of largest shareholder (aq2009) is above the sample median and zero otherwise

INTERNET APPENDIX

Time to Innovate

Sunwoo Hwang and Sooji Kim

A Workplace Panel Survey (WPS)

The WPS provides a broad range of variables that quantifies the characteristics of establishments that employ 30 or more regular employees from 2005 to 2021. At the time of this writing, the dataset is available up to the latest survey year of 2021. These establishments are selected through stratified sampling and, once sampled, remain in the panel unless it ceases operations.

Korean Labor Institute (KLI), a government-funded research body, conducts surveys, codes variables using survey responses, and releases updated versions of the WPS every two years. The KLI defines strata based on ten industries and four size groups[12]. Establishments are randomly selected to represent each stratum and be contacted for participation in surveys. Table 2 provides a list of the ten industries. The four size groups are determined based on the number of regular employees: 30-99, 100-299, 300-499, and 500 or more. The KLI excludes agricultural, forestry, fishery, and mining industries. Version 1.81 of the WPS User's Guide (available in Korean) provides further details about the survey and data construction. We further exclude public-sector establishments and sole proprietors to focus specifically on corporations.

Financial statement figures are collected at the firm level and converted into establishment-level figures for multi-unit establishments, establishments belonging to a firm with multiple establishments. To facilitate this conversion, the WPS offers a variable called "transr." This variable represents the ratio of sales for a specific multi-unit establishment to the total sales of the firm to which the establishment belongs. In cases where this ratio is unavailable, the variable "transr" takes on the inverse of the total number of multi-unit establishments that comprise the parent firm. By utilizing this variable, financial statement figures are adjusted and attributed to the respective establishment-level units within multi-unit firms.

In every analysis, observations are weighted by the inverse of their probability of being sampled for inclusion in the panel. This weighting procedure accounts for the fact that observations represent varying numbers of establishments. For instance, a small establishment employing 50 individuals may represent 200 establishments within the same industry, region, and size group, while a large establishment employing 500 individuals may only represent two establishments.

Within a regression framework, the probability weight serves to correct each establishment's contribution to point estimates and standard errors. Consider a linear regression model in matrix form, $y = X\beta + u$, which yields an ordinary least squares estimator for β, $\hat{\beta} = (X'X)^{-1}X'y$. To implement the weighting-based correction, we multiply each row of X and y by the square root of the corresponding weight, denoted as $\sqrt{w_i}$, where w_i is the number of establishments that establishment i represents. The weight assigned to an establishment determines its impact on the mean and residual sum of squares within the variance-covariance matrix. An illustration of how STATA implements this correction and derives coefficients and standard errors using survey data and weights can be found in Dupraz (2013). Lastly, the KLI accounts for the likelihood of establishment survival and non-responses in subsequent surveys in computing the probability

[12] The stratification is based on 12 industries, five regions, and four size groups for establishments sampled before 2015.

weights. This adjustment ensures the weights accurately reflect the representation of establishments in the overall population.

Figure B1: Public interest in the 52-hour workweek law
This figure displays the Google Trends search volume indices created based on two search queries of "52 hours" and "52 hours per week" (both in Korean) over the period from January 1, 2016 (the year the bill was proposed) to December 2021 (the end of our sample period).

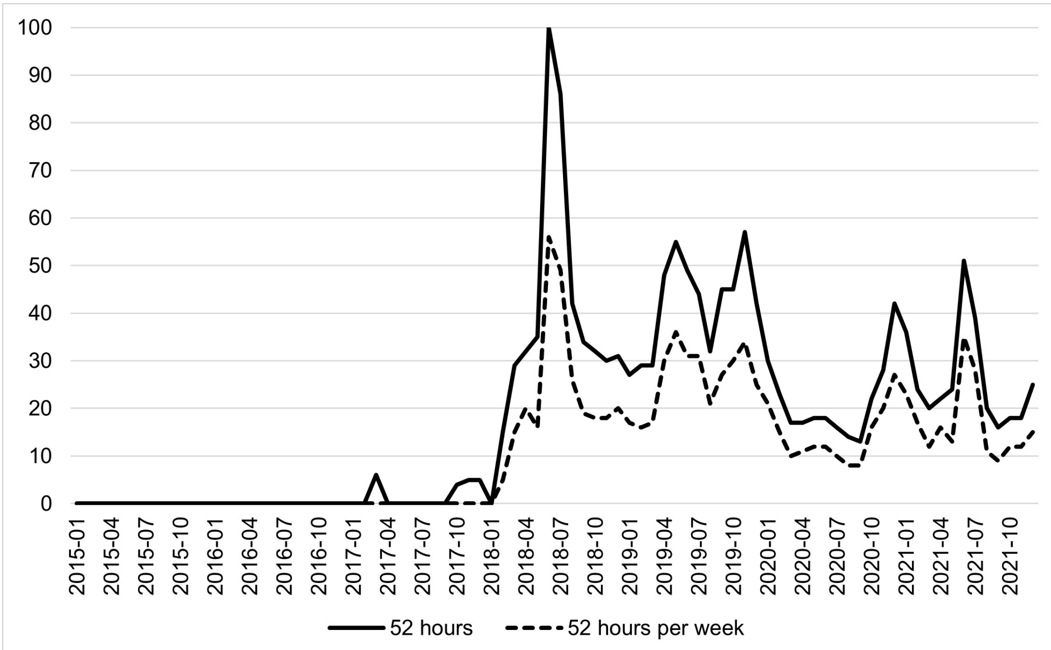
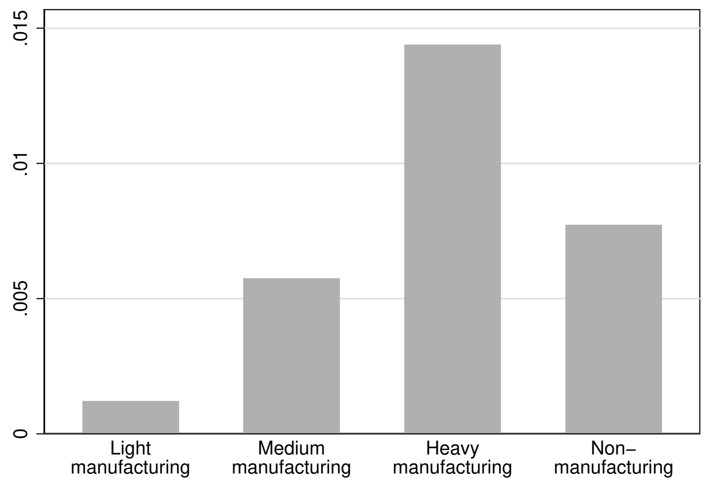


Figure B2: Innovation capital
This figure presents bar charts displaying innovation input in Panel A and innovation output in Panel B across four sectors, as defined in Figure 3. Innovation input is measured by capitalized R&D, and innovation output by capitalized intellectual properties (IPs), both normalized by total assets. The data is described in Figure 3.

Panel A. Capitalized R&D / Total assets



Panel B. Capitalized IPs / Total assets

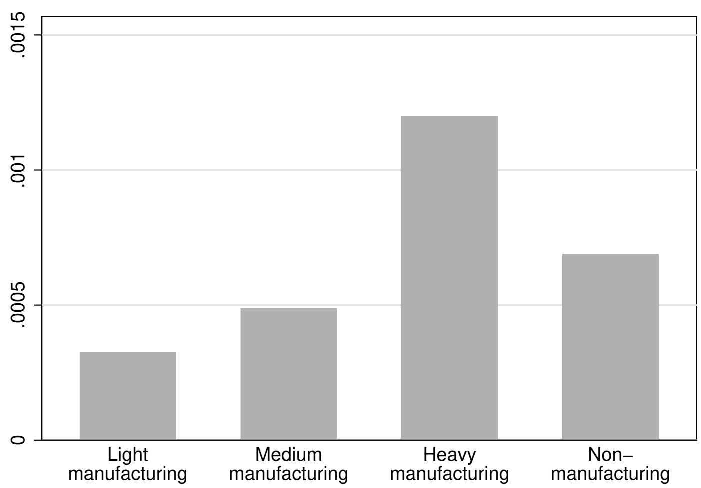
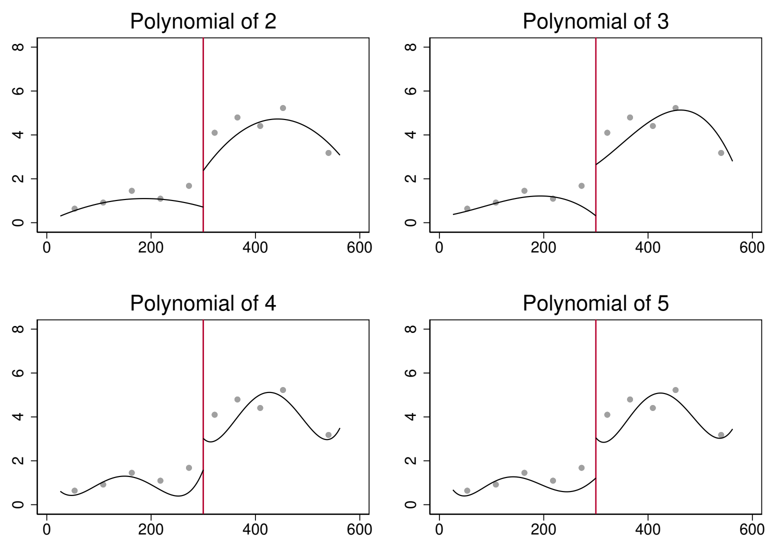


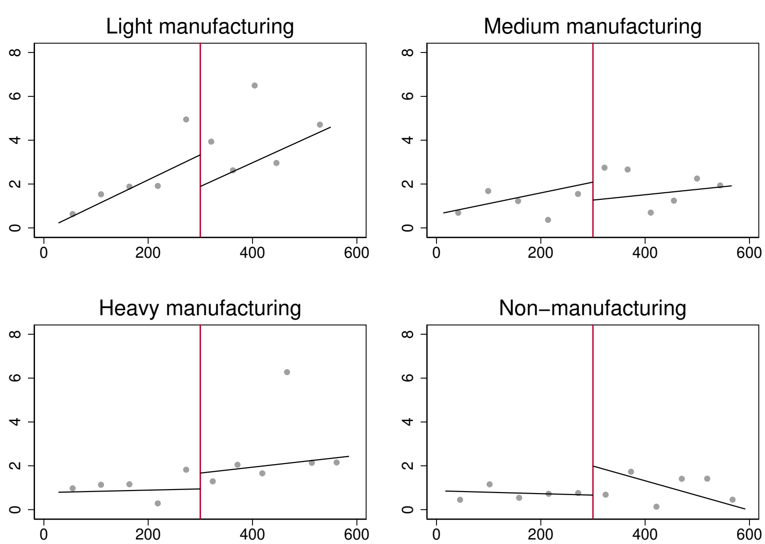
Figure B3: Law's effects on innovation output: robustness checks

This figure examines the robustness of the law's impact on innovation output, measured as log-transformed capitalized intellectual properties (IPs). Panels A to D plot innovation output (vertical axis) against employment size (horizontal axis), around a threshold at 300 employees (red vertical line). Each plot displays binned scatter points with separately fitted curves. Panel A assesses robustness using polynomial fits of orders 2 to 5 for the light manufacturing sector, defined in Figure 3. Panel B checks pre-law continuity by comparing innovation output from the 2015 fiscal-year end to employment size in the 2013 calendar-year end. Panels A, C, and D measure employment size as of the end of calendar year 2017. Panel C depicts the economy-wide innovation effect. Panel D presents annual regression discontinuity (RD) plots for the light manufacturing sector (2014-2021). Panel E summarizes annual differences in mean innovation outputs for the same sector, with 95% confidence intervals. For Panels D and E, innovation output reflects end-of-period capitalized IP values in odd fiscal years and beginning-of-period values in even fiscal years. The data is described in Figure 3.

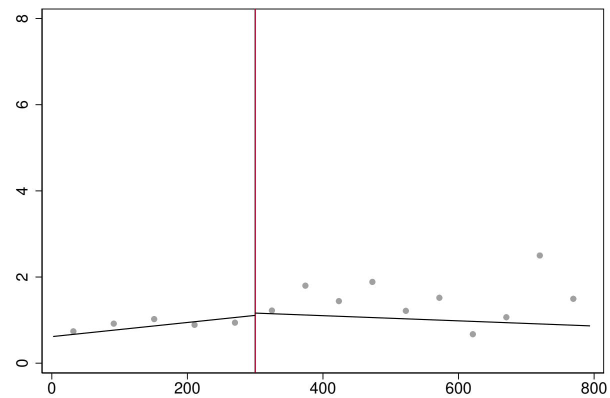
Panel A. Higher-order polynomial specifications in light manufacturing



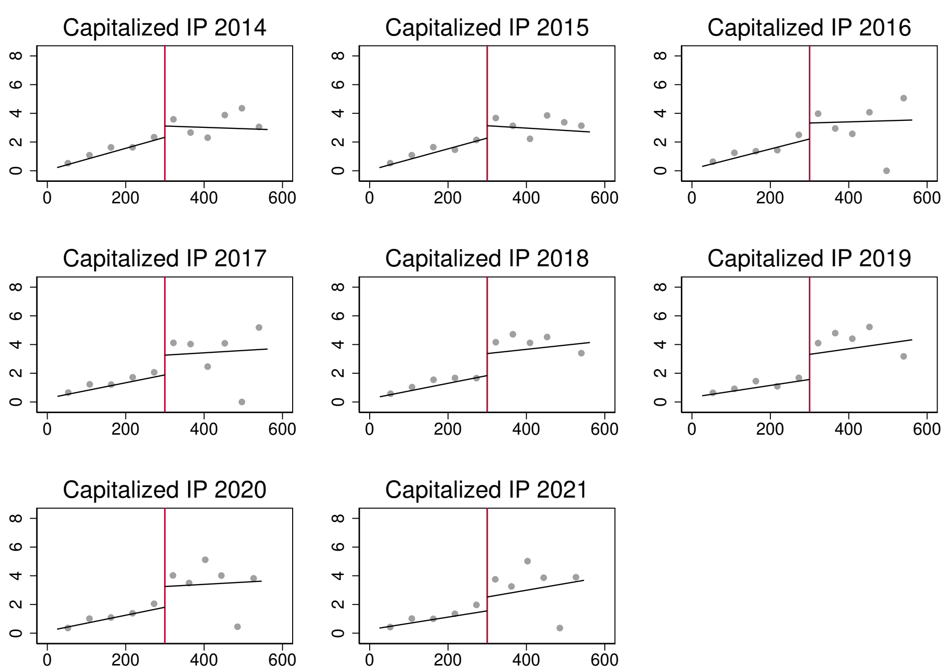
Panel B. Pre-law continuity using 2013 employment



Panel C. Economy-wide impact



Panel D. Impacts in light manufacturing across years (RD plots)



Panel E. Impacts in light manufacturing across years (difference in means)

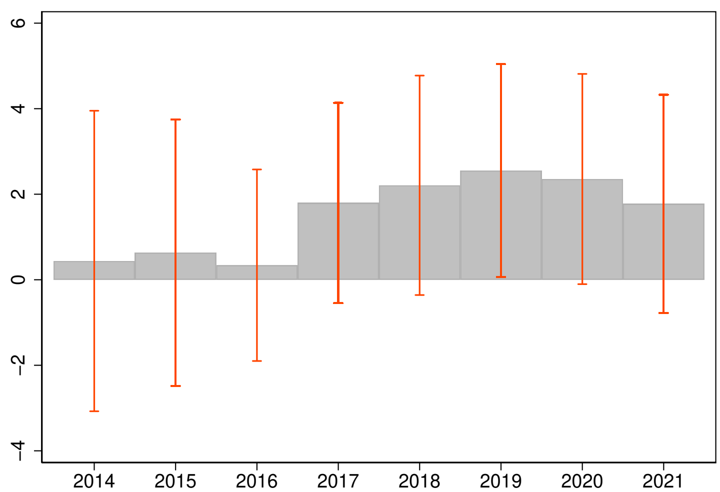


Figure B4: Law's impact on the distribution of weekly work hours excluding June 2018 observations
This figure displays the distribution of weekly work hours surveyed in 2016 (light gray) and 2018 (gray) at the top and 2016 (light gray) and 2020 (dark gray) at the bottom, using overlapping histograms and normal density curves. The sample excludes establishments surveyed in June 2018, a month before the law's enforcement from July through November. It highlights the impact of the 52-hour cap, marked by a vertical red line, on weekly work hours (x-axis). The data is described in Figure 3.

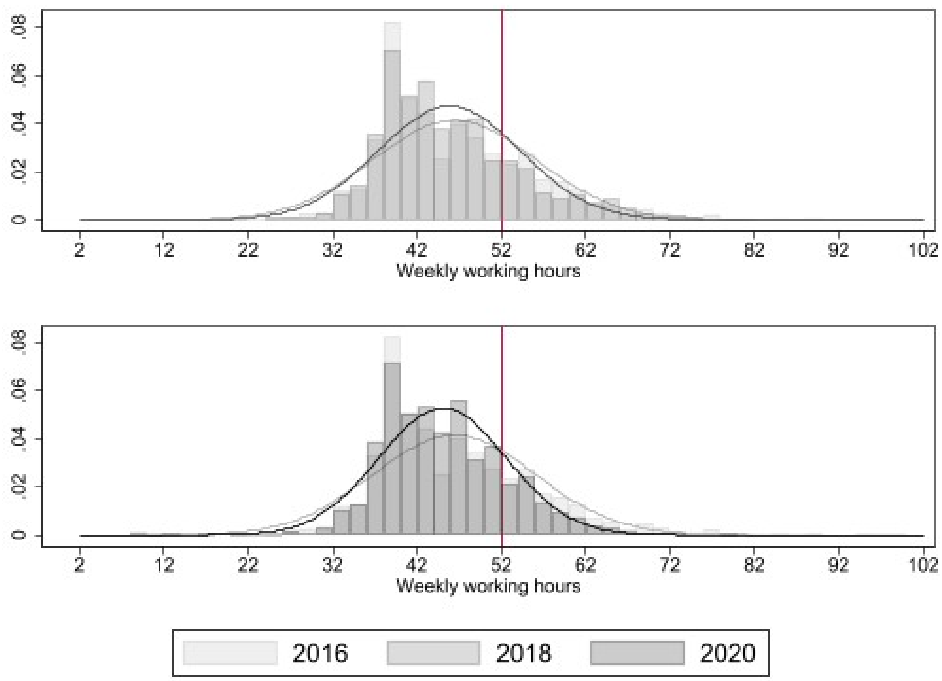


Table B1: Summary statistics

This table presents summary statistics for each variable used in this study. The data, covering the survey years from 2015 to 2021, is described in Figure 3. All variables are defined in Table A1 and are winsorized at the 1% level.

Variables	N	Mean	S.D.	25^{th} pct.	50^{th} pct.	75^{th} pct.
ln(#Employees)	6609	4.15	0.68	3.64	3.97	4.51
ln(#Indirect employees)	6609	0.77	1.50	0.00	0.00	0.69
ln(#Incoming skilled employees)	6609	0.87	1.11	0.00	0.00	1.61
ln(#Outgoing employees)	6609	1.94	1.26	1.10	1.95	2.83
Weekly work hours	6372	45.36	7.79	38.66	43.96	50.01
Overtime	6372	0.68	0.90	0.00	0.00	1.25
Work hours on weekends	6372	3.28	3.65	0.00	0.00	8.00
Monthly regular workdays	6372	21.26	4.00	21.00	21.00	22.00
Monthly weekend workdays	6372	1.52	2.04	0.00	0.00	3.04
Overtime on weekdays	5565	0.47	0.50	0.00	0.00	1.00
Occasional weekend work	5565	0.44	0.50	0.00	0.00	1.00
Regular weekend work	5565	0.12	0.33	0.00	0.00	0.00
ln(Capitalized IPs)	6609	0.79	1.62	0.00	0.00	0.69
ln(Capitalized R&D)	6609	0.80	2.10	0.00	0.00	0.00
ln(Expensed R&D)	6609	1.70	2.68	0.00	0.00	4.26
ln(PPE)	6609	7.79	2.30	6.44	8.15	9.26
ln(Software)	6609	1.07	1.91	0.00	0.00	1.70
ln(Assets)	6609	9.55	5.55	8.59	9.41	10.42
Capitalized R&D/Assets	6609	0.01	0.03	0.00	0.00	0.00
Intangible assets/Assets	6609	0.02	0.06	0.00	0.00	0.01
PPE/Assets	6609	0.33	0.26	0.08	0.29	0.52
EBIT/Assets	6134	0.06	0.10	0.02	0.05	0.10
EBIT/Sales	6197	0.05	0.15	0.02	0.04	0.08
Wage/Sales	6609	0.29	0.23	0.12	0.21	0.39
Wage per employee	6609	41.00	25.33	21.38	39.94	57.22
Sales/Total work hours	1244	0.22	0.41	0.05	0.09	0.20
Union	6609	0.17	0.38	0.00	0.00	0.00
Penalize low performers	6271	0.14	0.35	0.00	0.00	0.00
Reward skill improvements	6437	0.24	0.43	0.00	0.00	0.00
Flexible hours or days	6609	0.11	0.32	0.00	0.00	0.00
% Employees over 55	6609	0.18	0.20	0.04	0.11	0.24
% Employees below 35	6609	0.28	0.22	0.11	0.24	0.40
Owner manager	6609	0.78	0.42	1.00	1.00	1.00
CEO being the largest shareholder	6609	0.68	0.47	0.00	1.00	1.00
Business group affiliation	6609	0.06	0.24	0.00	0.00	0.00
Foreign ownership	6609	0.04	0.17	0.00	0.00	0.00
Largest shareholder ownership	5814	69.43	27.43	47.06	70.00	100.00
Population size = 87,923.904, # Strata = 37						

Table B2: Law's effects on time

This table presents coefficient estimates from the regressions of weekly work hours in Panel A, indicators for overtime and weekend work in Panel B, and overtime and weekend work hours in Panel C. The indicators used in Panel B are defined in Table 4. In Panel C, the dependent variables are weekday overtime hours in columns 1 to 3 and weekend work hours per day in columns 4 to 9. The regressor in Panels A and B is $\mathbb{1}[E \geq 300]$, an indicator set to one for establishments with 300 or more employees at the end of the 2017 fiscal year. Panel C includes this regressor and its interaction with the three indicators used as dependent variables in Panel B. The sample includes establishments with 600 or fewer employees in columns 1, 4, and 7, those with 100 to 500 employees in columns 2, 5, and 8, and those with 200 to 400 employees in columns 3, 6, and 9. Control variables are listed in Table 4. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A. Intensive margin effects from the sample excluding observations surveyed in June 2018

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Weekly work hours					
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	-3.2468***	-3.9859***	-4.2371***	-2.5844***	-3.2520***	-3.0046*
	(0.964)	(0.990)	(1.628)	(0.955)	(1.070)	(1.554)
Controls				✓	✓	✓
2-digit SIC FE				✓	✓	✓
# Observations	1138	546	225	1138	546	225
Adjusted R^2	0.00446	0.0255	0.0402	0.150	0.185	0.236

Panel B. Placebo tests on extensive margin effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	Overtime on weekdays			Occasional weekend work			Regular weekend work		
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	0.0193	0.0120	0.0648	0.0309	0.0088	-0.0750	-0.0252	-0.0202	0.0017
	(0.052)	(0.053)	(0.075)	(0.050)	(0.054)	(0.079)	(0.016)	(0.014)	(0.020)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	1799	808	324	1799	808	324	1799	808	324
Adjusted R^2	0.141	0.195	0.302	0.0890	0.206	0.208	0.0744	0.0867	0.0270

Panel C. Intensive margin effects conditional on extensive margin effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	Overtime hours on weekdays			Weekend work hours			Weekend work hours		
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	-0.0022	0.0949*	-0.0107	0.0056	0.2033	0.0304	-0.1962	-0.2954	0.3322
	(0.028)	(0.056)	(0.042)	(0.099)	(0.177)	(0.160)	(0.368)	(0.437)	(0.569)
Overtime on weekdays	1.3672***	1.3790***	1.5422***						
	(0.035)	(0.063)	(0.088)						
$\mathbb{1}[E \geq 300] \times$ Overtime on weekdays	-0.1174	-0.2037	-0.2394						
	(0.130)	(0.139)	(0.152)						
Occasional weekend work				6.1656***	5.9421***	6.2848***			
				(0.136)	(0.264)	(0.306)			
$\mathbb{1}[E \geq 300] \times$ Occasional weekend work				-1.1267***	-1.0332**	-0.6693			
				(0.422)	(0.448)	(0.480)			
Regular weekend work							0.1159	-0.0824	0.3653
							(0.350)	(0.484)	(0.942)
$\mathbb{1}[E \geq 300] \times$ Regular weekend work							-1.7101**	-1.5809	-2.4436**
							(0.801)	(1.041)	(1.140)
Constant	-0.0266	0.3772	0.0547	-0.3062	-0.4688	-1.2441	1.5429	1.6088	-1.3357
	(0.132)	(0.319)	(0.384)	(0.486)	(1.331)	(1.315)	(1.175)	(2.200)	(2.778)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	1494	703	284	1494	703	284	1494	703	284
Adjusted R^2	0.720	0.677	0.770	0.800	0.756	0.874	0.125	0.153	0.198

Table B3: Law's effects on innovation output in sectors other than manufacturing using other methodologies

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs), using fuzzy regression discontinuity (fuzzy RDD). Light manufacturing and three other sectors are defined in Table 3. The sample includes establishments with 100 to 500 employees. T_{i0} and T_{i1} are indicators set to one for establishments with 300 or more employees at the end of 2015 calendar year (pre-proposal) and 2017 calendar year (pre-enforcement), respectively. E_{i0} is centered forcing variable, calculated by log-transformed employment at the end of calendar year 2015 subtracted by log of 300. Post is an indicator equals one for year 2019 and zero for year 2015. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	Medium manufacturing			Heavy manufacturing			Non-manufacturing		
Bandwidth	± 200			± 200			± 200		
	First-stage		Second-stage	First-stage		Second-stage	First-stage		Second-stage
Dep. Var.	T_1	$E_0 \times T_1$	ln(IPs)	T_1	$E_0 \times T_1$	ln(IPs)	T_1	$E_0 \times T_1$	ln(IPs)
T_0	0.9334***	0.0058		0.8181***	0.0244		0.5589***	-0.0663	
	(0.056)	(0.007)		(0.106)	(0.026)		(0.134)	(0.055)	
$E_0 \times T_0$	-0.1768	0.9559***		-0.3704	0.7351***		0.3753	0.9411***	
	(0.144)	(0.057)		(0.516)	(0.225)		(0.255)	(0.085)	
E_0	0.0675	-0.0060	0.0921	0.0829*	-0.0031	-0.9610*	0.0433	0.0562	0.0097
	(0.057)	(0.006)	(1.090)	(0.047)	(0.007)	(0.547)	(0.043)	(0.062)	(0.299)
T_1			-0.0231			1.5091			0.4687
			(1.421)			(0.936)			(0.672)
$E_0 \times T_1$			-0.5139			-2.7996			-0.9501
			(3.008)			(2.486)			(0.777)
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
F-statistics	157.22	155.9		39.16	22.11		30.4	63.17	
# Observations	84	84	84	176	176	176	298	298	298

Table B4: Placebo tests

This table presents coefficient estimates from the regressions of two outcomes: weekly work hours in columns 1 to 3 and innovation output in columns 4 to 6. Weekly work hours are collected from July 2016 through March 2017, while innovation output is measured by capitalized intellectual properties (IPs) as of the end of the 2017 fiscal year. In columns 1 to 3, the regressor is $\mathbb{1}[E \geq 300]$, an indicator set to one for establishments with 300 or more employees at the end of the 2015 calendar year. Columns 4 to 6 include this regressor and its interaction with $\mathbb{1}[s = L]$, an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. The sample includes establishments with 600 or fewer employees in columns 1 and 4, those with 100 to 500 employees in columns 2 and 5, and those with 200 to 400 employees in columns 3 and 6. Control variables used in columns 1 to 3 are listed in Table 4, while additional control variables in columns 4 to 6 include interactions between employment and sector indicators, each set to one for the four sectors. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Weekly work hours			ln(Capitalized IPs)		
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	-1.3478	-1.0623	-1.1526	-0.1613	-0.4794	-0.1210
	(0.844)	(0.828)	(0.982)	(0.218)	(0.327)	(0.491)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$				1.4406*	1.6392	1.6672
				(0.797)	(1.117)	(1.321)
ln(#Employees)$\times\eta_{s(i)}$				✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓
# Observations	1799	808	324	1335	606	241
Adjusted R^2	0.111	0.200	0.225	0.114	0.196	0.237

Table B5: Law's effects on wage

This table presents coefficient estimates from the regressions of wage per employee as of the end of the 2019 fiscal year. In columns 1 to 3, the regressor is $\mathbb{1}[E \geq 300]$, an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. Columns 4 to 6 include this regressor and its interaction with $\mathbb{1}[s = L]$, an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. The sample includes establishments with 600 or fewer employees in columns 1 and 3 and those with 100 to 500 employees in columns 2 and 4. Control variables are listed in Table 5, Panel B. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.	Wage per employee			
Sample	Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	4.7179	4.5769	0.1347	-7.7307
	(9.727)	(12.144)	(4.956)	(5.104)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			6.6448	10.1036
			(9.711)	(11.919)
$ln(\#\text{Employees}) \times \eta_{s(i)}$			✓	✓
Controls	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓
# Observations	129	72	1294	610
Adjusted R^2	0.196	0.385	0.272	0.336

Table B6: Law's effects on innovation outputs in light manufacturing sectors across fiscal years
This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) of end-of-period values for odd fiscal years and beginning-of-period values for even fiscal years. The regressor is $\mathbb{1}[E \geq 300]$, an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. The sample includes establishments with 200 to 400 employees. Control variables are listed in Table 4. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	ln(Capitalized IPs)							
Sample year	2014	2015	2016	2017	2018	2019	2020	2021
Bandwidth	± 100							
$\mathbb{1}[E \geq 300]$	1.2174	1.4337	0.5912	2.3454*	2.7612*	3.1643**	3.2351**	2.6253*
	(1.810)	(1.563)	(1.165)	(1.279)	(1.512)	(1.483)	(1.401)	(1.425)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	28	28	31	34	28	28	28	28
Adjusted R^2	0.387	0.422	0.494	0.472	0.341	0.420	0.454	0.382

Table B7: Law's effects on innovation outputs in compliers

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) as of the end of the 2019 fiscal year. The regressor is $\mathbb{1}[E \geq 300]$, an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. For the establishments with 300 or more employees, the sample is limited to establishments surveyed from July through November 2018, after the law's enforcement, and the compliers whose weekly work hours do not exceed 52 hours. The sample includes establishments with 600 or fewer employees in columns 1 and 4, those with 100 to 500 employees in columns 2 and 5, and those with 200 to 400 employees in columns 3 and 6. Control variables are listed in Table 5, Panel B. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	ln(Capitalized IPs)					
Sample	Light manufacturing			All sectors		
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	2.2467***	2.8472***	3.5644**	0.0325	-0.3465	-0.3117
	(0.641)	(0.759)	(1.500)	(0.345)	(0.381)	(0.604)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$				2.3866***	3.1539***	3.5910**
				(0.790)	(0.934)	(1.402)
ln(#Employees)$\times\eta_{s(i)}$				✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓
# Observations	120	65	23	1232	557	206
Adjusted R^2	0.498	0.346	0.484	0.123	0.175	0.305

Table B8: Law's effects on innovation outputs in sectors other than light manufacturing

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) as of the end of the 2019 fiscal year. The regressor is $\mathbb{1}[E \geq 300]$, an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. The analysis is segmented by sector, with medium manufacturing in columns 1 to 3, heavy manufacturing in columns 4 to 6, and non-manufacturing in columns 7 to 9, as defined in Table 3. The sample includes establishments with 600 or fewer employees in columns 1, 4, and 7, those with 100 to 500 employees in columns 2, 5, and 8, and those with 200 to 400 employees in columns 3, 6, and 9. Control variables are listed in Table 4. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	ln(Capitalized IPs)								
Sample	Medium manufacturing			Heavy manufacturing			Non-manufacturing		
Bandwidth	± 300	± 200	± 100	± 300	± 200	± 100	± 300	± 200	± 100
$\mathbb{1}[E \geq 300]$	-0.2744	-1.9632	-4.8766	-0.2033	-0.6997	2.4068**	0.1106	0.2798	0.1844
	(0.807)	(1.384)	(3.095)	(0.461)	(0.645)	(1.138)	(0.364)	(0.414)	(0.704)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Observations	168	83	31	442	192	74	567	271	109
Adjusted R^2	0.0709	0.138	0.0466	0.0492	0.0757	0.158	0.201	0.267	0.397

Table B9: Agency explanations for suboptimal pre-law time allocation: Largest shareholder ownership

This table presents coefficient estimates from the regressions of innovation output, measured by capitalized intellectual properties (IPs) as of the end of the 2019 fiscal year. The regressors are interactions between $\mathbb{1}[E \geq 300]$, $\mathbb{1}[s = L]$, and a mediator. $\mathbb{1}[E \geq 300]$ is an indicator set to one for establishments with 300 or more employees at the end of the 2017 calendar year. $\mathbb{1}[s = L]$ is an indicator set to one for establishments in the light manufacturing sector. Sectors are defined in Table 3. The mediator, Largest shareholder ownership, equals one if the ownership of the largest shareholders is above its sample median as of the end of the 2017 calendar year. The sample includes establishments with 600 or fewer employees in columns 1 and 3 and those with 100 to 500 employees in columns 2 and 4. Control variables are listed in Table 5, Panel B. All variables are defined in Table A1. The data is described in Figure 3. Robust (White) standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.	ln(Capitalized IPs)			
Sample	Light manufacturing		All sectors	
Bandwidth	± 300	± 200	± 300	± 200
$\mathbb{1}[E \geq 300]$	3.3347***	4.0848***	0.1383	-0.3700
	(0.795)	(1.030)	(0.359)	(0.406)
Largest shareholder ownership			-0.1426	0.0060
			(0.130)	(0.229)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L]$			3.1457***	4.4878***
			(0.896)	(1.154)
$\mathbb{1}[E \geq 300] \times$ Largest shareholder ownership	-1.4435	-1.4497	-0.2441	0.0133
	(0.979)	(1.128)	(0.400)	(0.436)
$\mathbb{1}[s = L] \times$ Largest shareholder ownership			-0.0592	-0.0644
			(0.413)	(0.613)
$\mathbb{1}[E \geq 300] \times \mathbb{1}[s = L] \times$ Largest shareholder ownership			-0.7618	-1.3024
			(0.993)	(1.130)
Constant	-0.3925	2.8997	-0.9393	-3.6054**
	(1.460)	(3.622)	(0.678)	(1.764)
ln(#Employees)$\times\eta_{s(i)}$			✓	✓
Controls	✓	✓	✓	✓
2-digit SIC FE	✓	✓	✓	✓
# Observations	101	57	1124	511
Adjusted R^2	0.380	0.399	0.122	0.248

Table B10: Patent characteristics by sector and industry

This table presents the most frequent Cooperative Patent Classification (CPC) codes observed in patent data across sectors and industries. Panel A shows the top CPC codes at the one-digit level by sector. Panel B displays the top CPC codes at the three-digit level by sector, while Panel C focuses on the top three-digit CPC codes by industry within the light manufacturing sector. The data is sourced from the Korea Intellectual Property Rights Information Service (KIPRIS).

Panel A. Most frequent one-digit CPC code by sector

Light manufacturing		Medium manufacturing		Heavy manufacturing		Non-manufacturing	
CPC	%	CPC	%	CPC	%	CPC	%
Human necessities (A)	54.8	Chemistry; metallurgy (C)	32.4	Electricity (H)	31.7	Physics (G)	40.1
Chemistry; metallurgy (C)	23.1	Human necessities (A)	18.8	Physics (G)	22.8	Electricity (H)	20.5
Textiles; paper (D)	9.4	Electricity (H)	17.2	Performing operations; transporting (B)	21.0	Performing operations; transporting (B)	9.5
Performing operations; transporting (B)	7.6	Performing operations; transporting (B)	14.5	Mechanical engineering; lighting; heating; weapons; blasting (F)	12.0	Human necessities (A)	9.1
Fixed constructions (E)	2.2	Physics (G)	9.9	Chemistry; metallurgy (C)	5.4	Fixed constructions (E)	8.2
Physics (G)	1.8	Textiles; paper (D)	3.0	Human necessities (A)	4.3	Chemistry; metallurgy (C)	6.4

Panel B. Most frequent three-digit CPC code by sector

Light manufacturing		Medium manufacturing		Heavy manufacturing		Non-manufacturing	
CPC	%	CPC	%	CPC	%	CPC	%
Foodstuffs; non-alcoholic beverages; oils, fats, waxes (A23)	32.0	Electric elements (H01)	13.8	Electric elements (H01)	10.1	Instruments for measuring or checking (G06)	27.2
Tobacco and tobacco products (C12)	12.1	Medical or veterinary science; hygiene (A61)	13.1	Electric communication technique (H04)	8.9	Electric communication technique (H04)	15.8
Medical or veterinary science; hygiene (A61)	8.9	Macromolecular compounds; plastics (C08)	12.8	Vehicles in general (B60)	7.7	Measuring instruments (G01)	5.5
Macromolecular compounds; plastics (C08)	4.5	Dyes; paints; polishes; natural resins (C09)	6.5	Instruments for measuring or checking (G06)	7.3	Medical or veterinary science; hygiene (A61)	3.6
Tobacco; cigars; cigarettes (A24)	4.1	Organic chemistry (C07)	6.4	Electric digital data processing (G06)	6.8	Building (E04)	2.5
Organic chemistry (C07)	3.4	Other personal or household articles (A45)	3.4	Measuring instruments (G01)	4.2	Animal husbandry; care of birds, fishes, insects (B01)	2.2

Panel C. Most frequent three-digit CPC code by industry within the light manufacturing sector

SIC 10		SIC 11		SIC 12		SIC 13		SIC 14		SIC 15	
CPC	%	CPC	%	CPC	%	CPC	%	CPC	%	CPC	%
Foodstuffs; non-alcoholic beverages (A23)	47.2	Foodstuffs; non-alcoholic beverages (A23)	43.4	Tobacco products (A24)	76.8	Perfumery, cosmetics, cleaning agents (D03)	14.9	Plastics & resins (A41)	33.3	Footwear (non-leather) (A43)	45.3
Tobacco & tobacco products (C12)	16.5	Tobacco & tobacco products (C12)	37.3	Furniture & furnishings (A47)	5.1	Organic chemicals; dyes (D06)	14.6	Construction materials (E04)	20.3	Food preparations (A45)	18.7
Medical & surgical instruments (A61)	11.4	Medical & surgical instruments (A61)	9.6	Medical & surgical instruments (A61)	4.0	Cleaning agents (D04)	10.7	Measuring instrument (G06)	4.1	Mining / construction machinery (B29)	12.0
Plastics; synthetic rubber in primary form (C08)	6.7	Leather & fur products (B65)	2.4	Leather & fur products (B65)	3.0	Chemical compounds (D02)	7.8	Food preparations (A45)	3.3	Toys, games, sports goods (A63)	2.7
Organic chemistry (C07)	5.4	Live animals & animal products (A01)	2.4	Jewelry & related articles (G09)	2.0	Medical & surgical instruments (A61)	5.2	Perfumery, cosmetics, cleaning agents (D03)	2.4	Electric communication equipment (H04)	2.7
Leather & fur products (B65)	3.8	Live animals & animal products (A01)	1.2	Meat & edible meat offal (B01)	2.0	Dairy products (C02)	4.5	Dairy products (C02)	2.4	Plastics in primary forms (C08)	2.7
Cereal & flour products (A21)	2.3	Sugars & sugar confectionery (C13)	1.2	Printing; recorded media (D21)	2.0	Meat & edible meat offal (B01)	3.9	Medical & surgical instruments (A61)	2.4	Engines, turbines, motors (F16)	1.3
Live animals & animal products (A01)	0.8	Instruments & appliances (B67)	1.2	Basic electric components (H01)	1.0	Leather & fur products (B65)	2.9	Ships & floating structures (B63)	2.4	Cement & concrete (B32)	1.3
Furniture; lighting; prefab buildings (A47)	0.6	Vegetable textile fibres (C14)	1.2	Footwear (B08)	1.0	Utility-related machinery (E06)	2.6	Paints and cleaning preparations (D06)	2.4	Tobacco products (A24)	1.3
Alcoholic beverages (A22)	0.5	–	–	Power generation equipment (F23)	1.0	Inorganic chemicals (D01)	2.6	Inorganic chemicals (D01)	2.4	Measuring instrument (G06)	1.3

References

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