On-Site Work Presence and Innovation: Empirical Evidence from Mobile Device Data

*Hanfei Li[a], Qingsong Ruan[a], Guojun Wang[b]**

Abstract

This paper investigates whether on-site work presence (OWP) promotes firm innovation. Using smartphone geolocation data matched to geofenced operating sites of Chinese A-share listed manufacturing firms, we construct nationwide workday firm-level OWP measures that capture overall, routine-hour, and overtime presence intensity. Based on 15,478 firm-year observations from 2019 to 2024, we find that workday OWP is positively associated with both innovation quantity and innovation quality. Additional analyses using non-working-day presence and different patent application modes provide consistent evidence on the innovation relevance of OWP. The results remain robust to excluding shift-work firms, removing seasonal peaks, adjusting for presence-related noise, accounting for industry-level common effects, and excluding local COVID-19 disruptions. Overall, our evidence suggests that on-site work presence remains an important organizational channel for firm innovation in an increasingly digital environment.

Keywords: On-site work presence; Mobile device data; Innovation; Patent citations

JEL Classifications: O30

Acknowledgments and Disclosure

The authors gratefully acknowledge the smartphone geolocation data provided by an annoymous securities firm.

[a] School of Economics and Management, Tongji University, Shanghai 200092, China
[b] School of Finance and Business, Shanghai Normal University, Shanghai 200234, China; email: gjwang@shnu.edu.cn

1. Introduction

Innovation is a key source of long-run competitiveness and growth, especially in manufacturing, where performance depends on problem solving, technological upgrading, and coordination across functions. Although digital communication tools have changed how employees exchange information, physical co-presence and on-site visits may remain important for innovation because they create opportunities for immediate feedback, facilitate trust, and support the transfer of tacit knowledge that is difficult to codify (Allen, 1977; Nonaka, 1994; Polanyi, 2009; Storper & Venables, 2004). This question has become more salient as firms rely more heavily on remote communication while continuing to face pressure to sustain innovative output.

A large literature shows that geographic proximity, workplace microgeography, and direct contact shape knowledge diffusion and inventive activity, and recent mobile-data studies have moved closer to measuring in-person contact. Yet most of this evidence still relies on indirect proxies, event-based settings, or geographically limited samples, leaving little direct evidence on whether routine employee presence at firm operating sites promotes firm innovation, or whether its importance differs between routine-hour and overtime presence (Atkin et al., 2022; Bai et al., 2024; Catalini, 2018; Jaffe et al., 1993; McCann, 2007; Roche, 2020; Roche et al., 2024; Testoni et al., 2022).

To address this problem, we use real-time smartphone geolocation data from a leading SDK provider to construct nationwide firm-level measures of on-site work presence for 3,004 Chinese A-share listed manufacturing firms over 2019-2024, covering 15,478 firm-year observations, and use these measures to examine whether OWP promotes firm innovation and whether its innovation relevance differs between routine-hour and overtime presence on workdays. Specifically, we collect information on the headquarters, subsidiaries, and factories of Chinese A-share listed manufacturing firms, delineate geofenced boundaries around these sites, and match device-level location signals to those geofences. Based on the resulting visit data, we construct three measures of on-site personnel presence intensity: workday overall presence intensity, workday routine-hour presence intensity, and workday overtime presence intensity. Relative to existing measures, our approach moves beyond traditional proximity-based or event-based proxies (Bai et al., 2024; Jiang

& Yuan, 2018) and measures workplace on-site presence more directly, while extending the emerging mobile-data literature to a much larger geographic scale and to routine organizational settings (Atkin et al., 2022; Barwick et al., 2023; Testoni et al., 2022; Kreindler & Miyauchi, 2023).

The main results show a robust positive association between workday OWP and both innovation quantity and innovation quality. Firms with greater workday OWP intensity produce more patent applications and invention patent applications, and they also receive more patent citations. More importantly, overtime presence has the strongest association with innovation: relative to routine-hour presence, its coefficient is about 3.4 times as large on the quantity margin and about 2.5-2.6 times as large on the quality margin. These findings are consistent with the broader literature showing that in-person contact and proximity support knowledge spillovers and inventive activity (Atkin et al., 2022; Bai et al., 2024; Roche et al., 2024), and complement the overtime literature by suggesting that the innovation relevance of overtime operates through richer on-site communication opportunities rather than longer working hours per se (Yang et al., 2025).

The further-discussion results sharpen this main message by showing that the innovation value of OWP depends strongly on the setting in which it occurs. Separate from the workday baseline, on non-working days OWP, especially at night, is more strongly associated with both patent applications and patent citations than routine workday presence, indicating that overtime-related OWP is particularly relevant for innovation. In addition, when patenting is separated into independent and joint applications, the positive association is stronger for independent patenting, especially on the quantity margin. Taken together, these results suggest that the innovation benefits of OWP are most pronounced in overtime-related settings and are realized more strongly through projects completed within the focal firm.

The heterogeneity results further show that the returns to OWP vary systematically across organizational environments. Most notably, digitalization weakens the positive association between OWP and innovation quantity, but not innovation quality. This pattern is broadly consistent with recent research suggesting that digital technologies can facilitate innovation-oriented and coordination-related actions, while rich, synchronous communication remains difficult to replace in nonroutine and collaborative work (Chauvin et al., 2024; Choi et al., 2024). The remaining heterogeneity results point in a similar direction: the COVID-19 pandemic

attenuates the innovation benefits of OWP, especially on the quality margin, while the association is stronger in firms with higher employee educational qualifications on the quantity margin and in older firms on the quality margin. Taken together, these results suggest that the innovation returns to OWP depend not only on when employees are physically present on site, but also on the organizational environment in which such presence take place.

This paper contributes to the literature in three ways. First, it provides a more direct measure of workplace on-site work presence than indirect proxies such as geographic proximity，site visits and analyst meetings, while extending the emerging mobile-data literature to a much larger geographic scale and to routine organizational settings (Atkin et al., 2022; Barwick et al., 2023; Testoni et al., 2022; Kreindler & Miyauchi, 2023). Second, we provide direct evidence that on-site work presence is associated with both the quantity and the quality of firm innovation, complementing recent work on proximity and knowledge spillovers (Bai et al., 2024; Roche et al., 2024). Third, by distinguishing between routine and overtime presence and between routine-hour, overtime, and non-working-day presence, we show that the innovation value of on-site work presence depends not only on whether on-site presence occurs, but also on when it occurs.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data, variables, and empirical design. Section 4 presents the main results. Section 5 reports robustness checks. Section 6 examines heterogeneity. Section 7 concludes.

2. Literature review and hypotheses development

2.1 On-site work presence

Prior literature has established that physical proximity and spatial distance shape the flow of knowledge within and across organizations. In R&D organizations, shorter physical distance increases the probability and frequency of direct interpersonal contact, which is indispensable for the diffusion of technical knowledge and the effective transfer of problem-solving experience (Allen, 1977). Related work on workplace microgeography similarly suggests that the spatial arrangement of organizational members affects the likelihood of informal encounters, observation, and communication across task boundaries (Hatch, 1987). In economic geography, physical

proximity is treated as a foundation of local “buzz”, because co-located actors are more likely to learn from one another, form trust, become socialized into shared practices, and sustain motivation in knowledge-intensive activities (Storper & Venables, 2004). Thus, physical proximity matters not simply because actors are geographically close, but because closeness increases the likelihood of repeated face-to-face contact and situated, context-rich interaction.

The value of such proximity-based contact is especially pronounced when knowledge is tacit rather than fully codified. Tacit knowledge is difficult to articulate, highly context dependent, and often embedded in routines, experience, and shared practice (Polanyi, 2009). Unlike codified information, tacit knowledge is not easily transferred through documents or formal information systems alone; it often requires shared experience, observation, practice, and repeated interaction through which knowledge can be interpreted and converted into shared organizational understanding (Nonaka, 1994). Media richness theory offers a complementary explanation: because equivocal and weakly codified tasks require immediate feedback and multiple cues, face-to-face communication is particularly useful for interpreting ambiguous information and aligning understanding in real time (Daft & Lengel, 1986). Although digital communication technologies have substantially expanded the possibilities for remote coordination, they do not necessarily make physical co-presence obsolete. Rather, digital communication and on-site contact may operate as complements, especially when economic interaction requires high-frequency exchange, mutual adjustment, and context-rich interpretation (Bathelt & Turi, 2011; Gaspar & Glaeser, 1998).

Despite this theoretical emphasis, prior empirical work has rarely been able to measure on-site work presence in routine organizational settings with fine temporal and spatial granularity. Existing studies often rely on indirect proxies, including geographical proximity, industrial clustering, office layout, social-network surveys, and observable meeting settings such as private meetings, site visits, or analyst interactions (Allen, 1977; Cheng et al., 2016; Hatch, 1987; Jiang & Yuan, 2018; Soltes, 2014; Sparrowe et al., 2001). These measures are useful, but they typically capture either the potential for proximity-based interaction or specific event-based contacts, rather than the intensity and timing of everyday workplace presence across firms' operating sites. Recent studies move closer to direct measurement by employing smartphone geolocation data and related mobile device data to capture face-to-face meetings, co-location, commuting flows, or broader

mobility-based interaction patterns (Atkin et al., 2022; Barwick et al., 2023; Kreindler & Miyauchi, 2023; Testoni et al., 2022). Although these approaches bring the literature closer to observing real interaction, existing mobile-data studies are still largely confined to relatively limited geographic settings. We extend that literature by constructing a nationwide, firm-level geolocation-based measure of workplace on-site work presence in China, a setting with a much larger population base and far more geographically dispersed operating sites than in prior studies.

2.2 The role of on-site work presence in innovation

Existing literature suggests that on-site work presence may affect innovation through multiple channels. From the perspective of knowledge creation and information processing, innovation depends on the recombination of heterogeneous knowledge, timely feedback, and coordinated experimentation across employees and departments. On-site presence can facilitate these processes because personnel presence at firm operating sites increases opportunities for face-to-face contact, timely feedback, informal problem solving, and mutual adjustment (Allen, 1977; McCann, 2007). The literature on localized knowledge spillovers and microgeography also suggests that direct contact and close interaction can enhance inventive activity by increasing opportunities for knowledge exchange and exploratory learning (Atkin et al., 2022; Catalini, 2018; Jaffe et al., 1993). Therefore, greater workplace on-site presence shouldincrease the likelihood that employees encounter relevant knowledge, identify problems, and coordinate solutions, thereby helping firms generate more innovation outputs. For these reasons, we propose the first hypothesis of this study:

Hypothesis 1: On-site work presence can significantly increase the quantity of firm innovation.

On-site work presence may also improve innovation quality rather than merely increasing the number of outputs. High-quality innovation often depends on the transfer of tacit knowledge, repeated critical evaluation, and the integration of complex and ambiguous information, all of which are processes for which on-site communication and face-to-face contact are especially useful (Nonaka, 1994; Polanyi, 2009; Storper & Venables, 2004). Because OWP increases opportunities for such context-rich communication, it may support deeper knowledge integration,

more effective collaborative problem solving, and more rigorous evaluation of technological alternatives.If so, OWP should contribute not only to more innovation, but also to more valuable and more influential innovation. Therefore, we propose the second hypothesis as follows:

Hypothesis 2: On-site work presence can significantly increase the quality of firm innovation.

3. Data description

3.1 Measuring on-site work presence (OWP)

We construct our measure of on-site work presence using mobile device data sourced from a leading Chinese securities firm. The provider employs geofencing technology to collect and aggregate anonymized location signals, generating daily device presence counts for listed firms' headquarters, subsidiaries and factories in real-time.

Mobile phone geolocation data have been widely adopted as an innovative data source in recent studies (Barwick et al., 2023; Kreindler & Miyauchi, 2023; Testoni et al., 2022). We construct a novel measure of on-site work presence based on smartphone geolocation data. We collaborate with a Chinese securities firm and a leading Software Development Kit (SDK) service provider to obtain anonymized device-level real-time geolocation data.[1] With user consent, this SDK continuously collects information from smartphones, including geolocation data, application usage, and behavioral records related to consumption, entertainment, and economic activities. These data are primarily used to support personalized push notification services and have been available since January 2019.[2]

Before using geolocation data to measure OWP, we need to link mobile devices to firms. We collect addresses for the headquarters, subsidiaries and factories of 4,691 A-share listed firms from the Wind database. Subsequently, we use Baidu Maps to identify the geographical locations of their headquarters, subsidiaries and factories. Each site is verified and its boundaries are

---

[1] The SDK service provider is one of the earliest entrants in China's third-party push notification technology market and has consistently maintained a leading position in the industry. As of the end of 2024, its developer service SDK had been installed over 115 billion times, covering more than 1 billion devices, with over 400 million daily active unique devices.

[2] The collection and processing of SDK data strictly comply with relevant Chinese data protection regulations. All data are anonymized to safeguard user privacy, and the SDK provider adheres to standardized processes for user consent, data minimization, and data security management. Individual users cannot be identified at any stage of the analysis.

delineated using satellite imagery and street view maps. Based on this process, we construct 14,419 geofences to represent the physical boundaries of corporate operational sites. Each geofence is drawn as a custom polygon composed of coordinate points to maximally conform to actual site boundaries. **Appendix A** summarizes the distribution of firms and their corresponding geofences across different industry categories. Manufacturing accounts for 65.12% of firms and 72.02% of geofences, with an average of 3.40 geofences per firm. Industries such as Agriculture (6.89), Health and Social Work (10.63), and Public Utilities (4.38) also exhibit relatively high geofence density per firm. Conversely, industries like Financial Services, Real Estate, and Information Technology typically have fewer geofences due to their lower reliance on physical infrastructure and logistics.

Next, we match the real-time location signals of smartphones with listed firms geofences, and calculate the device counts entering each geofence during two specific time periods of a day: regular working hours and overtime hours.[3] Based on statutory eight-hour workday and the general working hours of firms in China, we define regular working hours as 9:00-17:00 and define 19:00-23:00 as overtime hours on weekdays, to specifically capture face-to-face interaction intensity during different hours. For each day, if a device enters firm *i* geofenced area and stays for more than 15 minutes during working hours or overtime hours, the device is recorded as a valid visitor counts to firm *i*. The 15-minute threshold is set to exclude passers-by or brief stops, capturing only substantive presence that is more likely to create opportunities for meaningful on-site presence.

To distinguish device-holder identities, we use the SDK provider's app-installation data together with persistent behavioral profiles to identify and exclude three categories of external professional visitors: truck drivers, institutional researchers, and lawyers. Specifically, a device is classified as a truck-driver device if it has freight-dispatch applications operated by Full Truck Alliance, namely Huochebang or Yunmanman, installed; as an institutional-research device if it

[3] To enable efficient large-scale computation, we employed Geohash technology, a grid-based spatial indexing system that encodes space by recursively subdividing the Earth's surface into rectangular cells. Each geofence is represented by a set of 8-character Geohash strings that collectively cover its polygonal boundary, achieving a spatial precision within 19 meters. When a GPS signal is received from a mobile device, we convert its location into an 8-character Geohash string and check if this string appears in the hash string set of any firm's geofence. This matching process significantly enhances computational efficiency while maintaining high spatial accuracy.

has institution-only paid financial analysis applications such as Wind installed and its usage profile is consistent with securities-research activity; and as a lawyer device if it has professional legal-service or legal-database applications installed and its behavioral profile is consistent with legal-practice activity.[4] Then, we aggregate the valid visits during regular working hours and overtime hours across firms headquarters, subsidiaries, and factories on a given day, to obtain a timely operational indicator reflecting the daily intensity of work-related on-site presence.

Specifically, we define daily workday OWP in working hours ($OWP_Routine_{i,d}$) and overtime hours ($OWP_Overtime_{i,d}$) as follows:

$$OWP_Routine_{i,d}=\sum_{j,p=Routine} visit_{i,j,p} \quad (1)$$

$$OWP_Overtime_{i,d}=\sum_{j,p=Overtime} visit_{i,j,p} \quad (2)$$

where i is firm, j is different visitor's device, p is different specific time periods, d is a specific day of the year t. And by adding up $OWP_Routine_{i,d}$ and $OWP_Overtime_{i,d}$, we can get the overall level of employee face-to-face interactions ($OWP_All_{i,d}$) on each day.

$$OWP_ALL_{i,d}=OWP_Routine_{i,d}+OWP_Overtime_{i,d} \quad (3)$$

Finally, the annual on-site work presence index in year t is calculated as the annual average of the daily indexes, divided by the number of employees in that year to control for firm size. .

$$OWP_Routine_{i,t}=\frac{\sum_d OWP_Routine_{i,d,t}}{Employees_{i,t}\cdot N_d} \quad (4)$$

$$OWP_Overtime_{i,t}=\frac{\sum_d OWP_Overtime_{i,d,t}}{Employees_{i,t}\cdot N_d} \quad (5)$$

$$OWP_ALL_{i,t}=\frac{\sum_d OWP_All_{i,d,t}}{Employees_{i,t}\cdot N_d} \quad (6)$$

3.2 Independent Variables and Control Variables

3.2.1 Innovation quantity and quality

We measure firm innovation along two dimensions: innovation quantity and innovation quality. Following prior studies, patent applications are used to capture innovation quantity, while citation-based patent measures are used to capture innovation quality and influence

[4] Although this procedure excludes three clearly identifiable categories of external professional visitors, some other non-employee visitors may still remain in the data, such as service contractors, delivery personnel, or business visitors. Their presence is more likely to affect daytime measures than overtime measures, implying that the daytime OWP indices may partly reflect a broader mix of internal and external visits, whereas overtime OWP should more closely capture within-firm communication.

(Odziemkowska & Zhu, 2025; Shi et al., 2025; Xia et al., 2025; Yang et al., 2025). According to China National Intellectual Property Administration (CNIPA), patents are classified into three categories: invention patents, utility model patents, and design patents. Invention patents, granted for novel technical solutions related to a product, a process, or an improvement, constitute the most innovative patent type. Utility model patents are awarded for new practical technical solutions pertaining to product shape or structure, which is fit for practical use. Design patents protect novel designs involving product shape, pattern, or color, which creates an aesthetic feeling and is fit for industrial application.

To measure innovation output quantity, we first employ the total number of patent applications in all three categories (*Pat_App*) to gauge the quantity of innovation output, measured by the natural logarithm of one plus the number of annual patent applications. Among these, invention patents typically demonstrate the highest technical sophistication and are considered the most novel in China's patent system. Consequently, we also use the number of invention patent applications (*Inv_App*) as alternative measures of the quantity of innovation output.

For innovation quality, we use the annual average citations of invention patents, measured as the natural logarithm of one plus the average citations per patent (*Con_Cit*). This measure is widely used to capture the value and influence of patents, reflecting the quality of firm innovation (Yang et al., 2025). Specifically, it is defined as:.

$$Con_Cit_{i,t}=\frac{\sum_p Cit_{i,t,p}}{|P_{i,t}|} \quad (7)$$

where $P_{i,t}$ represents the set of patents held by firm i in year t, and $|P_{i,t}|$ is the number of patents in this set. $Cit_{i,t,p}$ is the citation count of patent p from firm i in year t.

Furthermore, citations are categorized into self-citations and external citations. A high level of self-citations indicates that a firm frequently cites its own patents, demonstrating a strong path-dependency and cumulative nature of its R&D, with new innovations building on past technological achievements. Excluding self-citations, citations by other firms can more objectively and truthfully reveal the industry influence, quality, and core position of a firm. Therefore, we also use the external citations of invention patents (*Ext_Cit*) to further measure the innovation quality, as shown below:

$$Ext_Cit_{i,t}=\frac{\sum_p Ext_Cit_{i,t,p}}{|P_{i,t}|} \quad (8)$$

where $Ext_Cit_{i,t,p}$ is the external citation count of patent p from firm i in year t.

3.2.2 Control variables

The control variables include firm size (*Size*), return on total assets (*Roa*), asset-liability ratio (*Lev*), proportion of fixed assets to total assets (*PPE*), cash flow (*Cashflow*), proportion of shares held by the largest shareholder (*Top1*), proportion of shares held by management (*Mshare*), board size (*Board*), the chairman concurrently serves as the general manager or not (*Dual*), percentage of independent directors (*Indep*), firm age (*Age*), R&D input (*R&D*), average employee salary (*Salary*) and firm digitization level (*Dig*). Detailed definitions of variables are provided in **Appendix B**.

3.2 Sample Selection

Our sample includes all manufacturing firms listed on China's A-share stock market that are classified under the "C" category in the 2012 China Securities Regulatory Commission (CSRC) Industry Classification. Due to data availability, our sample period spans from January 2019 to December 2024. Following prior studies, we exclude special treatment (ST) and particular treatment (PT) firms and observations with missing data.

Data for OWP are derived from mobile device visit data. Data on R&D expenditures, patent applications, and patent citations are obtained from the China Research Data Service Platform (CNRDS). Other data are collected from the China Economic and Financial Research Database (CSMAR). All continuous variables are winsorized at the top and bottom one percentile. Our final sample consists of 15,478 firm-year observations from 3,004 listed firms.

3.4 Empirical specification

To test the impact of employee face-to-face interaction on firm innovation, we construct the following regression model:

$$Innovation_{i.t}=\beta_0+\beta_1 OWP_{i,t}+Controls_{i,t}+\varepsilon_{i,t} \quad (9)$$

where $Innovation_{i,t}$ represents the innovation quantity or quality of the listed firm i in year t.In addition, we control for year and year fixed effects to account for macroeconomic shocks and industry-specific heterogeneity.

3.5 Descriptive Statistics

Table 1 reports the descriptive statistics. The mean value of total patent applications (*Pat_App*) is 3.518, and that of invention patent applications (*Inv_App*) is 2.615, The mean value of invention patent citations (*Con_Cit*) is 2.781, and that of external citations (*Ext_Cit*) is 2.655, suggesting that self-citations constitute a limited share of total invention patent citations.

The OWP is measured by the on-site work presence during regular working hours (*OWP_Routine*), during overtime hours (*OWP_Overtime*), and the sum of both (*OWP_All*), with mean values of 0.814, 0.239, and 1.056 respectively. Noted that in our calculation, the regular working time is 8 hours and the overtime time only includes 4 hours. It can be seen that dividing *OWP_Routine* by 2 is still greater than *OWP_Overtime*. This indicates that most on-site work presence occurs during regular working hours, while overtime presence remains relatively limited. The standard deviations of the three OWP measures are large relative to their means, suggesting significant cross-firm differences in work arrangements and on-site work habits.

Table 1 Descriptive statistics

This table reports the summary statistics for the main variables used in this study. The sample consists of 15,478 annual observations spanning from 2019 to 2024. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Detailed definitions of variables are provided in **Appendix B**.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	Mean	S.D.	Min	Max
Pat_App	15,478	3.518	1.446	0.000	7.248
Inv_App	15,478	2.615	1.461	0.000	6.652
Con_Cit	15,478	2.781	1.711	0.000	7.363
Ext_Cit	15,478	2.655	1.682	0.000	7.223
OWP_All	15,478	1.056	1.482	0.018	10.492
OWP_Routine	15,478	0.814	1.147	0.014	8.126
OWP_Overtime	15,478	0.239	0.347	0.003	2.323
Size	15,478	22.171	1.147	20.113	25.746
ROA	15,478	0.039	0.074	-0.253	0.236
Lev	15,478	0.391	0.192	0.058	0.903
PPE	15,478	0.215	0.126	0.014	0.587
Cashflow	15,478	0.054	0.066	-0.149	0.250
Top1	15,478	0.316	0.138	0.084	0.701
Mshare	15,478	17.432	20.256	0.000	70.046
Board	15,478	2.075	0.190	1.609	2.485
Dual	15,478	0.378	0.485	0.000	1.000
Indep	15,478	38.104	5.395	33.330	57.140

Age	15,478	3.050	0.280	2.197	3.611
R&D	15,478	0.286	1.390	0.002	12.216
Salary	15,478	1.418	1.443	0.044	8.201
Dig	15,478	0.013	0.024	0.000	0.158

4. OWP and innovation performance

4.1 Validity test of the OWP measure

To test whether the OWP can effectively capture substantive work-related on-site presence, we use two complementary validity tests. First, we exploit the exogenous shock of the COVID-19 pandemic. Theoretically, lockdown and quarantine policies during the pandemic should significantly reduce physical aggregation in the workplace, but should not directly affect non-work-related social activities(Cecchi et al., 2022). Therefore, if the *OWP_Routine* significantly decreases due to the pandemic, it provides evidence for the validity of the *OWP_Routine* measure. Second, following Xuan & Wu (2023) method for calculating satellite nighttime light intensity, we examine the relationship between face-to-face interaction during overtime presence (*OWP_Overtime*) and the satellite nighttime light brightness of the grid (500m × 500m) where the company's office is located. High-intensity overtime presence is usually accompanied by stronger economic activity and energy consumption, which should be reflected in higher nighttime light brightness. If *OWP_Overtime* is significantly positively correlated with nighttime light brightness, it further validates that OWP can effectively captures the observable physical signals generated by firms' business activities.

Specifically, we use the number of newly reported COVID-19 infections in the city where the firm is located (taking the natural logarithm after adding 1) as the core explanatory variable *COVID19* in regressions of *OWP_Routine*; and use the annual average nighttime light intensity of the grid where the firm office is located as the core explanatory variable *Brightness* in regressions of *OWP_Overtime*. **Table 2** reports the validity test results. Columns (1) and column (2) report the validity test results between *OWP_Routine* and *COVID19*, shows that the number of COVID-19 infections in the prefecture-level city where the firm is located is significantly negatively correlated with *OWP_Routine*. This finding indicates that as the local pandemic worsens, on-site work presence during working hours decreases significantly, thereby validating the validity and sensitivity of the *OWP_Routine* in measuring workplace presence intensity. Columns (3) and (4)

report the validity test results between *OWP_Overtime* and *Brightness*, shows that *Brightness* is significantly positively correlated with *OWP_Overtime*. This positive correlation indicates that higher overtime presence is reliably associated with higher levels of firm production activity as measured by satellite nighttime light intensity, and provides strong evidence for the validity of the OWP measure.

Table 2 Validity test of the OWP measure

This table reports the results of testing the validity of OWP measurements using the COVID-19 pandemic and satellite nighttime lights. Variable *COVID19* is measured by newly reported COVID-19 infections in a city, and *Brightness* is measured by the annual average satellite nighttime light brightness of the 500m×500m grid where the firm office is located. Column (1) and column (3) present the results controlling only for firm- and year-fixed effects, while column (2) and column (4) additionally include firm-level control variables. Standard errors are reported in parentheses. For brevity, coefficients on constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	*OWP_Routine*	*OWP_Routine*	*OWP_Overtime*	*OWP_Overtime*
COVID19	-0.011***	-0.010**		
	(0.004)	(0.004)		
Brightness			0.122**	0.137**
			(0.060)	(0.063)
Size		-0.178***		0.191***
		(0.019)		(0.044)
ROA		-0.174**		-0.068
		(0.083)		(0.195)
Lev		0.047		0.107
		(0.054)		(0.127)
PPE		-0.246***		-0.039
		(0.073)		(0.171)
Cashflow		-0.050		0.046
		(0.076)		(0.179)
Top1		-0.170		-0.131
		(0.110)		(0.257)
Mshare		0.000		-0.000
		(0.001)		(0.002)
Board		-0.003		0.349***
		(0.057)		(0.133)
Dual		-0.027*		-0.111***
		(0.015)		(0.034)
Indep		0.001		0.009**
		(0.002)		(0.004)
Age		0.088		0.010

		(0.162)		(0.380)
R&D		0.003		-0.007
		(0.003)		(0.008)
Salary		0.297***		0.052**
		(0.010)		(0.023)
Dig		2.321***		-0.990
		(0.508)		(1.191)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478
R-squared	0.880	0.895	0.823	0.823

4.2 Firm innovation quantity and on-site work presence

Table 3 reports the estimation results of the baseline model in Eq. (9), in which firm innovation output is measured by patent applications. Columns (1)-(3) use *Pat_App* as the dependent variable, while columns (4)-(6) use *Inv_App*. The three OWP measures are entered separately to examine whether the estimated association varies across overall, routine-hour, and overtime presence intensity. The estimated coefficients on *OWP_All* are 0.033 in column (1) and 0.032 in column (4), and both are statistically significant at the 1 percent level, indicating that higher OWP is associated with more total patent applications and more invention patent applications. Because OWP raises the likelihood of physical co-presence and face-to-face communication within firms, these results extend prior empirical evidence showing that direct contact and proximity promote knowledge spillovers and innovation (Atkin et al., 2022; Testoni et al., 2022).

Further segmentation of presence time periods reveals that, relative to *OWP_Routine*, the *OWP_Overtime* coefficient is 3.44 times as large in the *Pat_App* regression and 2.81 times as large in the *Inv_App* regression. This evidence complements the overtime literature by suggesting that the innovation consequences of overtime may partly operate through the richer opportunities for on-site communication embedded in overtime work rather than overtime hours per se (Yang et al., 2025). Regarding the control variables, the results are generally consistent with prior studies. We find that patent applications are positively related to *Size*, *Mshare* and *Board* (Messeni Petruzzelli et al., 2018; O'Connor & Rafferty, 2012; Yang et al., 2025), and negatively related to *Age*, *Salary* and *Dig* (Kong et al., 2020; Messeni Petruzzelli et al., 2018; Yang et al., 2025).

Above findings suggest that stronger OWP, especially during overtime hours, increases the

quantity of firm innovation, supporting **Hypothesis 1**.

Table 3 Baseline results: innovation quantity

This table reports the baseline results of Eq. (9) for the impact of the OWP on firm innovation quantity. Columns (1)-(3) show the regression results where the dependent variable is calculated by all patent applications (*Pat_App*) in the firm, while columns (4)-(6) show the results where the dependent variable is calculated by invention patent applications (*Inv_App*) in the firm. The core independent variables are the overall workday OWP index (*OWP_All*), the working hours index (*OWP_Routine*), and the overtime hours index (*OWP_Overtime*). The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_All	0.033***			0.032***		
	(0.010)			(0.010)		
OWP_Routine		0.041***			0.043***	
		(0.013)			(0.014)	
OWP_Overtime			0.141***			0.121***
			(0.039)			(0.041)
Size	0.416***	0.416***	0.415***	0.443***	0.443***	0.442***
	(0.027)	(0.027)	(0.027)	(0.029)	(0.029)	(0.029)
ROA	-0.179	-0.178	-0.183	-0.241*	-0.240*	-0.246*
	(0.120)	(0.120)	(0.120)	(0.127)	(0.127)	(0.127)
Lev	-0.063	-0.063	-0.063	-0.021	-0.021	-0.021
	(0.079)	(0.079)	(0.079)	(0.083)	(0.083)	(0.083)
PPE	-0.005	-0.004	-0.010	-0.047	-0.045	-0.052
	(0.106)	(0.106)	(0.106)	(0.111)	(0.111)	(0.111)
Cashflow	-0.383***	-0.383***	-0.385***	-0.180	-0.180	-0.182
	(0.110)	(0.110)	(0.110)	(0.116)	(0.116)	(0.116)
Top1	0.102	0.102	0.101	-0.143	-0.143	-0.145
	(0.159)	(0.159)	(0.159)	(0.167)	(0.167)	(0.167)
Mshare	0.002***	0.003***	0.002***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Board	0.188**	0.188**	0.190**	0.072	0.072	0.073
	(0.082)	(0.082)	(0.082)	(0.086)	(0.086)	(0.086)
Dual	0.003	0.003	0.003	-0.010	-0.010	-0.010
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Indep	0.004	0.004	0.004	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Age	-0.430*	-0.433*	-0.420*	-0.278	-0.281	-0.270
	(0.234)	(0.234)	(0.234)	(0.246)	(0.246)	(0.246)
R&D	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Salary	-0.193***	-0.192***	-0.192***	-0.123***	-0.123***	-0.121***

	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Dig	1.229*	1.234*	1.237*	1.573**	1.572**	1.592**
	(0.735)	(0.735)	(0.735)	(0.773)	(0.773)	(0.772)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.850	0.850	0.850

4.3 Firm innovation quality and on-site work presence

Table 4 reports the estimation results of the baseline model in Eq. (9), in which firm innovation quality is measured by patent citations. Columns (1)-(3) use *Con_Cit* as the dependent variable, while columns (4)-(6) use *Ext_Cit*. The three OWP measures are entered separately across columns. The estimated coefficients on *OWP_All* are 0.034 in column (1) and 0.035 in column (4), and both are statistically significant at the 1 percent level, indicating that higher OWP is associated with more total patent citations and more external patent citations. Since patent citations are widely used to capture the value and influence of innovation outputs (Brav et al., 2018), these results suggest that OWP is positively associated with firm innovation quality.

Further segmentation of presence time periods reveals that, relative to *OWP_Routine*, the *OWP_Overtime* coefficient is 2.47 times as large in the *Con_Cit* regression and 2.64 times as large in the *Ext_Cit* regression. This evidence is consistent with recent research showing that higher-value innovation relies on tacit knowledge sharing, iterative coordination, and the integration and evaluation of complex information, all of which are facilitated by on-site contact, face-to-face communication, and other rich, synchronous communication channels (Bai et al., 2024; Ghosh & Wu, 2023; Kang & Eklund, 2025; Roche et al., 2024).

Above findings suggest that stronger OWP, especially during overtime hours, improves the quality of firm innovation, supporting **Hypothesis 2**.

Table 4 Baseline results: innovation quality

This table reports the baseline results of Eq. (9) for the impact of the OWP on firm innovation quality. Columns (1)-(3) show the regression results where the dependent variable is calculated based on all citations of firm invention patents, while columns (4)-(6) show the results of the dependent variable based on the number of excluding self-citations. The core independent variables are the overall workday OWP index (*OWP_All*), the working hours index (*OWP_Routine*), and the overtime hours index (*OWP_Overtime*). The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)

VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_All	0.034***			0.035***		
	(0.010)			(0.010)		
OWP_Routine		0.045***			0.045***	
		(0.014)			(0.014)	
OWP_Overtime			0.111***			0.119***
			(0.041)			(0.041)
Size	0.567***	0.568***	0.565***	0.562***	0.562***	0.560***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
ROA	-1.046***	-1.045***	-1.051***	-1.047***	-1.045***	-1.052***
	(0.126)	(0.126)	(0.126)	(0.127)	(0.127)	(0.127)
Lev	0.318***	0.318***	0.319***	0.323***	0.323***	0.323***
	(0.082)	(0.082)	(0.082)	(0.083)	(0.083)	(0.083)
PPE	1.252***	1.254***	1.246***	1.326***	1.328***	1.320***
	(0.110)	(0.111)	(0.110)	(0.111)	(0.111)	(0.111)
Cashflow	0.418***	0.419***	0.417***	0.432***	0.433***	0.431***
	(0.115)	(0.115)	(0.115)	(0.116)	(0.116)	(0.116)
Top1	0.199	0.200	0.197	0.263	0.263	0.260
	(0.166)	(0.166)	(0.166)	(0.167)	(0.167)	(0.167)
Mshare	0.002**	0.002**	0.002**	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Board	-0.089	-0.089	-0.088	-0.126	-0.126	-0.125
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Dual	0.009	0.009	0.009	0.004	0.004	0.003
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Indep	0.006**	0.006**	0.006**	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	3.329***	3.326***	3.336***	3.515***	3.512***	3.523***
	(0.245)	(0.245)	(0.245)	(0.246)	(0.246)	(0.246)
R&D	0.013***	0.013***	0.013**	0.013**	0.013**	0.013**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Salary	-0.183***	-0.184***	-0.180***	-0.186***	-0.186***	-0.182***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Dig	3.026***	3.025***	3.056***	3.062***	3.062***	3.089***
	(0.769)	(0.769)	(0.769)	(0.773)	(0.773)	(0.772)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

4.4 Further discussion

4.4.1 Temporal context: non-working day

The temporal context of OWP may shape its innovation consequences. Prior research suggests that unstructured communication is especially important for tacit knowledge exchange, creative recombination, and problem solving (Ceci et al., 2021; Polanyi, 2009; Storper & Venables, 2004). At the same time, evidence on employee overtime suggests that additional working time does not necessarily improve all dimensions of innovation. In particular, employee overtime has been shown to increase innovation output without improving innovation quality, suggesting that the innovation consequences of extra work time depend on the nature of the underlying interaction rather than on time extension alone (Yang et al., 2025). In this setting, non-working day on-site work presence may differ from routine working-day presence in an economically meaningful way. Compared with workday presence, non-working day presence is more likely to be self-selected, less fragmented by routine tasks, and more conducive to in-depth discussion and knowledge integration. If so, its effect should be stronger not only for the quantity of innovation but also for its quality.

To further examine whether overtime-related OWP is more strongly associated with innovation, we additionally construct two non-working-day measures: non-working-day daytime presence (*OWP_NWDay*) and non-working-day nighttime presence (*OWP_NWNight*). This yields four conceptually distinct measures of OWP: workday routine interaction, workday overtime presence, non-working-day daytime interaction, and non-working-day nighttime presence. Importantly, the latter three all reflect overtime-related on-site presence.

Table 5 reports the results. We find that the estimated association between OWP and innovation is systematically stronger for the three overtime-related measures than for workday routine presence. In addition, on-site work presence on non-working days, both during the day and at night, is also positively associated with innovation and generally exhibits larger estimated effects than workday routine presence. These findings suggest that the stronger innovation effect of OWP is concentrated in overtime-related settings rather than in routine daytime presence on workdays. This pattern is consistent with the view that deeper, less fragmented, and more self-selected on-site communication opportunities are especially important for tacit knowledge transfer, creative recombination, and the production of high-quality innovation (Ceci et al., 2021; Polanyi, 2009; Storper & Venables, 2004).

Table 5 Temporal context: non-working day

This table reports additional results using OWP measures constructed from non-working days. *OWP_NWAll* denotes overall OWP intensity on non-working days, *OWP_NWDay* denotes daytime OWP intensity on non-working days, and *OWP_NWNight* denotes nighttime OWP intensity on non-working days. **Panel A** reports the results for innovation quantity, where columns (1)-(3) use *Pat_App* and columns (4)-(6) use *Inv_App* as the dependent variables. **Panel B** reports the results for innovation quality, where columns (1)-(3) use *Con_Cit* and columns (4)-(6) use *Ext_Cit* as the dependent variables. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_NWAll	0.054***			0.056***		
	(0.016)			(0.017)		
OWP_NWDay		0.074***			0.082***	
		(0.023)			(0.024)	
OWP_NWNight			0.175***			0.154***
			(0.049)			(0.052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.850	0.850	0.850

Panel B: Innovation quality

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_NWAll	0.058***			0.060***		
	(0.017)			(0.017)		
OWP_NWDay		0.083***			0.084***	
		(0.024)			(0.024)	
OWP_NWNight			0.163***			0.169***
			(0.052)			(0.052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

4.4.2 Collaboration methods: independent application vs. joint application

Patent application methods are categorized as independent and joint. Independent applications are filed by a single individual or firm. The patent rights belong entirely to the applicant, including use, transfer, and license. Joint applications involve inventions jointly

completed by multiple entities, with all parties sharing patent rights and requiring negotiation to determine patent use and management.

This distinction matters because OWP measured around the focal firm may affect independent and joint innovation outcomes differently. For innovation quantity, it may be more strongly associated with independent applications, since firm-centered OWP more directly supports internally completed projects. For innovation quality, the comparison is less straightforward: if daytime OWP captures not only internal communication but also some contact with external visitors, it may still be related to the quality of joint innovation, whereas nighttime OWP, which more closely reflects internal work presence, should remain more strongly associated with the quality of independent innovation.

To examine these possibilities, we separate the analysis of innovation quantity and innovation quality. **Table 6** reports the quantity results. **Panel A** uses all patent applications (*Pat_App*), while **Panel B** uses invention patent applications (*Inv_App*), which capture a more technologically substantive quantity margin. **Table 7** reports the quality results. **Panel A** uses all citations (*Con_Cit*), while **Panel B** uses external citations (*Ext_Cit*), which exclude self-citations and therefore provide a cleaner measure of external technological influence.

Table 6 shows that OWP is more strongly associated with independent innovation on the quantity margin. In *Panel A*, the coefficients on three OWP measures are positive and significant for both independent and joint all-patent applications, and the magnitudes are broadly similar across the two groups. In **Panel B**, the difference becomes much sharper. All three OWP measures are positive and significant for independent invention patent applications, whereas none of them is significant for joint invention patent applications. These results are consistent with the view that OWP measured around the focal firm is more closely related to internally completed projects, and that this distinction becomes more visible when the outcome is restricted to invention patents rather than total patent counts.

Table 6 Collaboration methods: innovation quantity

This table reports the results for the impact of OWP on firm innovation quantity under different patent application methods. Panel A uses all patent applications (*Pat_App*) as the dependent variable, and Panel B uses invention patent applications (*Inv_App*). In each panel, columns (1)–(3) report the results for independent applications, and columns (4)–(6) report the results for joint applications. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For

brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity (all patent)

	Independent application			Joint application		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Pat_App*	*Pat_App*	*Pat_App*
OWP_All	0.025**			0.027**		
	(0.011)			(0.012)		
OWP_Routine		0.031**			0.035**	
		(0.014)			(0.016)	
OWP_Overtime			0.114***			0.094*
			(0.042)			(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.847	0.847	0.847	0.802	0.802	0.802

Panel B: Innovation quantity (invention patent)

	Independent application			Joint application		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Inv_App*	*Inv_App*	*Inv_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_All	0.027**			0.011		
	(0.011)			(0.011)		
OWP_Routine		0.034**			0.016	
		(0.014)			(0.014)	
OWP_Overtime			0.114***			0.022
			(0.042)			(0.043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.837	0.837	0.837	0.790	0.790	0.790

Table 7 shows that the comparison is less sharp on the quality margin, but the overall pattern still points to a stronger association for independent innovation. For independent patents, all three OWP measures are positive and significant in both citation panels. For joint patents, by contrast, the coefficients are smaller and less stable. This pattern is consistent with the distinction above.

Taken together, the results suggest that OWP is more strongly associated with independent innovation than with joint innovation, especially when innovation is measured by invention patent applications or patent citations. The quantity results show that joint applications still respond on

the broader all-patent margin, but this association disappears once the analysis is restricted to invention patents. The quality results are even more one-sided, with stronger and more robust coefficients for independent patents throughout. Overall, these patterns indicate that the innovation benefits of OWP in our setting are realized primarily through independent rather than joint innovation outcomes, and our OWP measures primarily capture firm-centered on-site presence and are therefore are more closely related to independent innovation outcomes.

Table 7 Collaboration methods: innovation quality

This table reports the results for the impact of OWP on firm innovation quality under different patent application methods. Panel A uses all citations (*Con_Cit*) as the dependent variable, and Panel B uses external citations (*Ext_Cit*). In each panel, columns (1)–(3) report the results for independent applications, and columns (4)–(6) report the results for joint applications. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quality (all-citations)

	Independent application			Joint application		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Con_Cit*
OWP_All	0.032***			0.017*		
	(0.010)			(0.010)		
OWP_Routine		0.042***			0.021	
		(0.014)			(0.013)	
OWP_Overtime			0.105**			0.061
			(0.041)			(0.038)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.884	0.884	0.884	0.869	0.869	0.869

Panel B: Innovation quality (external-citations)

	Independent application			Joint application		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_All	0.033***			0.017*		
	(0.010)			(0.009)		
OWP_Routine		0.044***			0.020	
		(0.014)			(0.012)	
OWP_Overtime			0.114***			0.064*
			(0.041)			(0.037)

Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.879	0.879	0.879	0.867	0.867	0.867

5. Robustness test

5.1 Addressing measurement error from shift work

Because shift work changes the mapping between clock time and regular working hours, our classification of OWP into routine-hour and overtime presence may be subject to measurement error in firms operating rotating or night-shift systems. In such firms, presence observed during evening or nighttime hours may reflect regular scheduled work rather than overtime, while presence during standard daytime hours may not correspond to routine work for all employees. As a result, shift work can blur the distinction between *OWP_Routine* and *OWP_Overtime* and bias our estimates of their differential effects. To address this, we follow Xuan & Wu (2023) method, and crawl recruitment data from major Chinese recruitment websites. By identifying job postings containing keywords such as “shift work”, “rotating shifts”, and “night shifts” in the job descriptions, we filter out firms that explicitly implement shift work systems and remove them from the regression sample.

The regression results are shown in **Table 8**. In the regressions of innovation quantity (**Panel A**) and quality (**Panel B**), the coefficients of the core explanatory variables remain largely statistically significant. This confirms that the core conclusion that OWP promotes innovation remains robust in the sample of non-shift work companies where employees' working hours are highly synchronized.

Table 8 Robustness test: shift work

This table presents the robustness test results of OWP on firm innovation after excluding samples with shift work. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_All	0.077***			0.061***		

	(0.020)			(0.020)		
OWP_Routine		0.104***			0.085***	
		(0.026)			(0.026)	
OWP_Overtime			0.279***			0.227***
			(0.079)			(0.080)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,030	4,030	4,030	4,030	4,030	4,030
R-squared	0.819	0.819	0.819	0.809	0.809	0.809

Panel B: Innovation quality

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_All	0.043**			0.038*		
	(0.020)			(0.020)		
OWP_Routine		0.060**			0.053**	
		(0.026)			(0.026)	
OWP_Overtime			0.111			0.094
			(0.079)			(0.079)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,030	4,030	4,030	4,030	4,030	4,030
R-squared	0.856	0.856	0.856	0.851	0.851	0.851

5.2 Removing seasonal factors on business operations

Considering that certain seasons may lead to increased employee gatherings due to inherent seasonal business peaks, potentially causing a cyclical overestimation of our OWP measures, we conduct a robustness test by adjusting the measurement method of the core explanatory variables. We identify the season with the highest mean *OWP_All* within each year and exclude data from this season when calculating the firm's annual mean, thus more purely capturing the level of OWP related to firm innovation activities.

Table 9 reports the regression results based on these adjusted variables. As shown in **Panel A** and **Panel B**, in all regressions with innovation quantity and innovation quality as the dependent variables, the estimated coefficients of the three OWP variables remain highly significant at the 1% level. Furthermore, the coefficient estimates of the core explanatory variables are generally larger than the baseline regressions. This finding indicates that, after removing presence noise that may be caused by seasonal business peaks, the positive promoting effect of employee OWP on

firm innovation not only persists but also has a more pronounced effect, showing the core conclusion remains robust after excluding the interference of seasonal business factors.

Table 9 Robustness test: seasonal factors on business operations

This table presents the robustness test results of the impact of OWP on firm innovation after removing seasonal factors from the three OWP measures. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_All	0.036***			0.034***		
	(0.011)			(0.011)		
OWP_Routine		0.045***			0.043***	
		(0.014)			(0.014)	
OWP_Overtime			0.159***			0.139***
			(0.042)			(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.850	0.850	0.850

Panel B: Innovation quality						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_All	0.039***			0.040***		
	(0.011)			(0.011)		
OWP_Routine		0.050***			0.050***	
		(0.014)			(0.014)	
OWP_Overtime			0.137***			0.146***
			(0.044)			(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

5.3 Removing observable presence noise: holiday-based adjustment

To ensure that the measurement of OWP intensity accurately reflects work-related presence rather than general foot traffic interference from individuals with non-work purposes, we conduct

a robustness test using a targeted proxy for noise. Importantly, non-working-day presence may itself contain economically meaningful overtime-related communication and therefore should not be treated mechanically as noise. Instead, for each year, we identify the Spring Festival period and calculate the average daily number of observed persons during that holiday as a proxy for baseline noise. During the Spring Festival, firms are typically staffed only by on-duty employees or the minimum personnel required to maintain basic operations. As a result, the observed OWP during this period is less likely to reflect productive collaboration or innovation-related communication. We therefore subtract this Spring Festival baseline from the daily OWP and reconstruct the three adjusted measures.

Table 10 presents these regression results. In **Panel A**, the coefficients on all three OWP measures remain positive and statistically significant for both *Pat_App* and *Inv_App*. In **Panel B**, the coefficients on *OWP_All*, *OWP_Routine*, and *OWP_Overtime* also remain positive and statistically significant when innovation quality is measured by *Con_Cit* and *Ext_Cit*, although the coefficient on overtime presence is somewhat smaller than in the baseline results. Overall, these findings indicate that the positive association between OWP and firm innovation remains robust after removing baseline operational noise captured by Spring Festival staffing.

Table 10 Robustness test: holiday-based adjustment for abnormal presence

This table presents the robustness test results of the impact of OWP on firm innovation after removing presence noise from the three OWP measures. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_All	0.031***			0.033***		
	(0.011)			(0.012)		
OWP_Routine		0.037**			0.042***	
		(0.015)			(0.015)	
OWP_Overtime			0.142***			0.134***
			(0.046)			(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478

R-squared	0.862	0.862	0.862	0.850	0.850	0.850

Panel B: Innovation quality						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_All	0.030**			0.033***		
	(0.012)			(0.012)		
OWP_Routine		0.041***			0.044***	
		(0.015)			(0.015)	
OWP_Overtime			0.091*			0.105**
			(0.048)			(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

5.4 Removing unobservable visit noise: Residual-based adjustment

As a further robustness check, we adopt a residual-based approach to purge the OWP measures from potential contamination by abnormal presence that is not captured by the Spring Festival baseline. The logic is that some intra-day fluctuations in OWP may be driven by transient, non-work-related device presence that is orthogonal to the firm's regular innovation activities. To isolate the component of OWP that is systematically associated with observable firm characteristics and persistent fixed effects, we proceed as follows.

For each original OWP measure, we estimate a regression that includes the full set of firm- level control variables $Control_{i,t}$ as well as firm and year fixed effects:

$$OWP_{i,t}=\beta_0+Controls_{i,t}+\varepsilon_{i,t} \quad (10)$$

where the residual $\hat{\varepsilon}_{i,t}$ captures the variation in OWP that cannot be explained by firm fundamentals, governance characteristics, or persistent firm-year heterogeneity. We then construct a “cleaned” measure as the original value minus the residual, which is equivalent to the fitted value:

$$OWP_{i,t}^{clean}=OWP_{i,t}-\hat{\varepsilon}_{i,t} \quad (11)$$

where $F2FI_{i,t}^{clean}$ is the component of OWP that is predicted by the control variables and fixed effects. And this transformation changes the scale of the variables. Therefore, the coefficient magnitudes reported in this section are not directly comparable to those in the baseline results or other robustness tables; only the sign and statistical significance should be interpreted.

Table 11 presents the regression results using the cleaned measures. **Panel A** shows the results for innovation quantity, and **Panel B** for innovation quality. Across all specifications, the coefficients on the three cleaned OWP measures remain positive and statistically significant (mostly at the 1% level, with a few at the 10% level). These results confirm that after removing the residual variation that is orthogonal to observable firm characteristics and fixed effects, the positive association between OWP and firm innovation remains robust.

Table 11 Robustness test: residual-based adjustment for abnormal presence

This table reports the results after cleaning the three OWP measures using the residual-based adjustment described in Section 5.4. Because this transformation alters the scale of the variables, the coefficient magnitudes are not directly comparable to baseline. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_All	0.440*			0.553**		
	(0.243)			(0.255)		
OWP_Routine		0.574*			0.721**	
		(0.317)			(0.333)	
OWP_Overtime			2.031*			2.553**
			(1.122)			(1.180)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.850	0.850	0.850

Panel B: Innovation quality

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_All	1.035***			1.048***		
	(0.254)			(0.255)		
OWP_Routine		1.350***			1.367***	
		(0.332)			(0.333)	
OWP_Overtime			4.780***			4.838***
			(1.175)			(1.180)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

5.5 Removing industry specificity

To eliminate the influence of overall industry trends on workplace presence patterns or innovation cycles, we subtract the annual industry average from each OWP measure, allowing us to observe the impact of firms' own interaction intensity on innovation more purely.

Table 12 shows that, after removing the common influence at the industry level, the three OWP measures still have a significantly positive effect on the quantity and quality of firm innovation at the 1% level. This indicates that the association between OWP and firm innovation is not driven by the commonality of certain industries simultaneously exhibit high workplace presence and high innovation; therefore, the baseline conclusions are robust.

Table 12 Robustness test: industry specificity

This table presents the robustness test results of the impact of OWP on firm innovation after removing industry specificity from the three OWP measures. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_All	0.033***			0.031***		
	(0.010)			(0.010)		
OWP_Routine		0.042***			0.041***	
		(0.013)			(0.014)	
OWP_Overtime			0.135***			0.113***
			(0.039)			(0.041)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.850	0.850	0.850

Panel B: Innovation quality						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_All	0.034***			0.036***		
	(0.010)			(0.010)		

OWP_Routine		0.045***			0.046***	
		(0.014)			(0.014)	
OWP_Overtime			0.112***			0.122***
			(0.041)			(0.041)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

5.6 Excluding the influence of COVID-19 disruptions

To test the robustness of the core findings under the impact of the COVID-19 pandemic, we further restricted the sample to observations where the number of COVID-19 infections in the firm's location was zero in a year, thus excluding the interference of abnormal observations from areas affected by the pandemic.

Table 13 reports the results of this robustness test. The results show that in both **Panel A** (innovation quantity) and **Panel B** (innovation quality), the coefficients of the three OWP measures are all significantly positive at the 1% level, indicating that the positive effect of OWP on the quantity and quality of firm innovation remains robust in areas completely unaffected by the local COVID-19 infections.

Table 13 Robustness test: COVID-19-related local disruptions

This table presents the robustness test results of the impact of OWP on firm innovation after restricting the sample to firm-year observations in which the reported number of COVID-19 infections in the firm's local area is zero. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
OWP_All	0.038***			0.046***		
	(0.014)			(0.015)		
OWP_Routine		0.050***			0.059***	
		(0.019)			(0.020)	
OWP_Overtime			0.162***			0.188***
			(0.057)			(0.059)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Observations	8,373	8,373	8,373	8,373	8,373	8,373
R-squared	0.868	0.868	0.868	0.854	0.854	0.855

Panel B: Innovation quality						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
OWP_All	0.040***			0.044***		
	(0.015)			(0.015)		
OWP_Routine		0.050**			0.055***	
		(0.020)			(0.020)	
OWP_Overtime			0.158***			0.183***
			(0.060)			(0.060)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,373	8,373	8,373	8,373	8,373	8,373
R-squared	0.884	0.884	0.884	0.881	0.881	0.881

6. Heterogeneity analysis

6.1 Digitalization

Digitalization may shape the innovation returns to OWP through a substitution effect. Digital technologies expand firms' access to codified knowledge, improve communication efficiency, and facilitate coordination across departments and locations (Lenka et al., 2017; Nambisan et al., 2017; Yoo et al., 2012). As a result, digitalization can substitute for part of the role of OWP in routine communication, information transmission, and coordination. However, digital tools may not fully replace the role of on-site presence in creating opportunities for rich, synchronous, face-to-face communication in nonroutine and collaborative work (Chauvin et al., 2024). To test this possibility, we divide firms into a high digitalization group (*DigD*=1) and a low digitalization group (*DigD*=0) based on the industry-year median, and introduce dummy variable *DigD* and its interaction term with OWP for heterogeneity analysis.

The results in **Table 14** show that, for innovation quantity (**Panel A**), the coefficients on the interaction terms are all negative and statistically significant, indicating that digitalization weakens the positive association between OWP and patent applications. This pattern is consistent with a substitution effect of digitalization, whereby digital tools partially replace OWP in supporting routine innovation-related communication and coordination. For innovation quality (**Panel B**), by

contrast, the interaction terms are generally insignificant. These results indicate that digitalization attenuates the quantity effect of OWP but does not materially alter its quality effect. These results indicate that the substitution effect of digitalization is concentrated in innovation quantity rather than innovation quality, suggesting that digital tools can substitute for part of the quantity-enhancing role of OWP, but not for its role in supporting high-quality innovation.

Table 14 Heterogeneity: digitalization

This table shows the heterogeneous effect of the OWP on firm innovation activities after including firm digitalization level (*DigD*) and the interaction term of *DigD* with OWP. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
*OWP_All*DigD*	-0.024**			-0.024**		
	(0.010)			(0.010)		
OWP_All	0.046***			0.045***		
	(0.011)			(0.012)		
*OWP_Routine*DigD*		-0.031**			-0.031**	
		(0.013)			(0.013)	
OWP_Routine		0.058***			0.059***	
		(0.015)			(0.015)	
*OWP_Overtime*DigD*			-0.087**			-0.083*
			(0.042)			(0.045)
OWP_Overtime			0.184***			0.163***
			(0.044)			(0.047)
DigD	0.032	0.031	0.027	0.019	0.019	0.014
	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.850	0.850	0.850

Panel B: Innovation quality

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
*OWP_All*DigD*	-0.012			-0.016		
	(0.010)			(0.010)		
OWP_All	0.040***			0.043***		

	(0.012)			(0.012)		
*OWP_Routine*DigD*		-0.017			-0.023*	
		(0.013)			(0.013)	
OWP_Routine		0.054***			0.058***	
		(0.015)			(0.015)	
*OWP_Overtime*DigD*			-0.021			-0.032
			(0.044)			(0.045)
OWP_Overtime			0.122***			0.135***
			(0.046)			(0.047)
DigD	-0.005	-0.003	-0.012	0.001	0.003	-0.007
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

6.2 The COVID-19 pandemic

The COVID-19 pandemic may weaken the innovation effect of OWP for two reasons. First, OWP is especially important for tacit knowledge exchange, iterative feedback, and collaborative problem solving, all of which are central to innovation (Nonaka, 1994; Polanyi, 2009; Storper & Venables, 2004). Second, pandemic-related restrictions reduced mobility, disrupted workplace co-presence, and weakened many of the informal and unstructured communication channels through which such knowledge is normally shared (Cecchi et al., 2022). To examine this issue, we introduce an interaction variable between OWP and *COVID19*, and the results are reported in **Table 15**.

The results in Panel A and Panel B show that the interaction variable coefficients are both negative, indicating that the COVID-19 pandemic has, to some extent, weakened the facilitating effect of OWP among employees on firm innovation (especially innovation quality). This finding is consistent with intuition and reality: the external shock of the pandemic, through channels such as physical isolation and psychological concerns, reduced effective employees OWP, eroding the innovation benefits that OWP could originally bring. It is worth noting that this weakening effect is more widespread and significant for innovation quality (**Panel B**) than for innovation quantity (**Panel A**). This aligns with theoretical expectations, as high-quality innovation often relies more on the in-depth exchange and creative integration of tacit knowledge, and these processes are particularly sensitive to disruptions in rich, unstructured communication.

Table 15 Heterogeneity: the COVID-19 pandemic

This table shows the heterogeneous effect of the OWP on firm innovation activities after including the regional COVID-19 infections (*COVID19*) and the interaction term of *COVID19* with OWP. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
*OWP_All*COVID19*	-0.005*			-0.001		
	(0.003)			(0.003)		
OWP_All	0.035***			0.033***		
	(0.010)			(0.010)		
*OWP_Routine*COVID19*		-0.007*			-0.002	
		(0.004)			(0.004)	
OWP_Routine		0.043***			0.044***	
		(0.013)			(0.014)	
*OWP_Overtime*COVID19*			-0.012			0.001
			(0.012)			(0.013)
OWP_Overtime			0.147***			0.121***
			(0.039)			(0.041)
COVID19	0.004	0.005	0.001	0.006	0.006	0.004
	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.850	0.850	0.850

Panel B: Innovation quality

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
*OWP_All*COVID19*	-0.006**			-0.006**		
	(0.003)			(0.003)		
OWP_All	0.036***			0.037***		
	(0.010)			(0.010)		
*OWP_Routine*COVID19*		-0.008**			-0.007*	
		(0.004)			(0.004)	
OWP_Routine		0.048***			0.048***	
		(0.014)			(0.014)	
*OWP_Overtime*COVID19*			-0.029**			-0.029**
			(0.013)			(0.013)

OWP_Overtime			0.126***			0.134***
			(0.041)			(0.041)
COVID19	0.011	0.011	0.011	0.011	0.011	0.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

6.3 Employee educational qualifications

Employee educational qualifications may shape the innovation returns to OWP because a more educated workforce is generally better able to recognize, assimilate, and recombine knowledge, thereby strengthening firms' absorptive capacity and the productivity of interpersonal communication opportunities. Prior studies likewise show that highly educated human capital plays an important role in firm patenting and innovation, especially in the Chinese context (Sun et al., 2020). We measure employee educational qualifications (*Edu*) as an indicator equal to one if the share of employees with a college degree or above in total employment is above the industry-year median, and zero otherwise.

Table 16 reports the results. Regarding innovation quantity (**Panel A**), the interaction terms are all positive and significant in the *Pat_App* regressions, with coefficients of 0.028, 0.036, and 0.113, respectively. The moderating effect is strongest for overtime presence, suggesting that OWP in high-Edu firms is particularly productive in overtime settings. By contrast, the interaction terms are insignificant in the *Inv_App* regressions. Regarding innovation quality (**Panel B**), the evidence is limited. Most interaction terms are statistically insignificant, except *OWP_Routine*Edu* in the *Con_Cit* regression, which is positive and significant at the 10 percent level. Overall, the results suggest that employee educational qualifications mainly strengthen the quantity effect, rather than the quality effect, of OWP on firm innovation.

Table 16 Heterogeneity: employee educational qualifications

This table shows the heterogeneous effect of the OWP on firm innovation activities after including the interaction term of employee educational qualifications (*Edu*) and the interaction term of *Edu* with OWP. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
*OWP_All*Edu*	0.028**			0.008		
	(0.012)			(0.013)		
OWP_All	0.017			0.028**		
	(0.012)			(0.013)		
*OWP_Routine*Edu*		0.036**			0.009	
		(0.016)			(0.016)	
OWP_Routine		0.020			0.037**	
		(0.016)			(0.016)	
*OWP_Overtime*Edu*			0.113**			0.045
			(0.049)			(0.052)
OWP_Overtime			0.079*			0.097*
			(0.047)			(0.050)
Edu	0.065**	0.065**	0.068***	0.081***	0.082***	0.079***
	(0.026)	(0.026)	(0.025)	(0.027)	(0.027)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.851	0.851	0.851

Panel B: Innovation quality

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
*OWP_All*Edu*	0.020			0.011		
	(0.012)			(0.013)		
OWP_All	0.023*			0.029**		
	(0.013)			(0.013)		
*OWP_Routine*Edu*		0.028*			0.017	
		(0.016)			(0.016)	
OWP_Routine		0.029*			0.036**	
		(0.016)			(0.017)	
*OWP_Overtime*Edu*			0.056			0.016
			(0.052)			(0.052)
OWP_Overtime			0.081			0.110**
			(0.050)			(0.050)
Edu	0.044*	0.042	0.052**	0.037	0.035	0.045*
	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

6.4 Firm age

Firm age may also moderate the innovation returns to OWP. Younger firms are often viewed as more flexible and more willing to experiment, which may help them benefit from new knowledge combinations (Coad et al., 2016). Older firms, however, possess richer accumulated knowledge, more established routines, and stronger organizational capability to recognize, absorb, and recombine knowledge, all of which may help them transform on-site communication opportunities into more valuable innovation outcomes (Messeni Petruzzelli et al., 2018; Nonaka, 1994). Therefore, we introduce firm age (Age) and its interaction terms with three OWP measures into the model, and the results are reported in **Table 17**.

Regarding the quantity of innovation (**Panel A**), only the interaction term between *OWP_Overtime* and *Age* is significant in terms of total patent applications (coefficient 0.217, $p < 0.1$), while other interaction terms are not significant. This indicates that the positive effect of OWP on innovation quantity is not significantly different among firms of different age groups, with only overtime presence during overtime slightly contributing to increase patent application output in mature firms. Regarding the quality of innovation (**Panel B**), firm age exhibits a significant heterogeneous effect, with the coefficients of the interaction terms between all OWP measures and *Age* being significantly positive at the 1% level. This suggests that the positive effect of OWP on innovation quality is mainly present in mature firms. Mature firms, with their long-accumulated R&D experience, stable collaboration networks, and mature innovation management systems, are able to more effectively transform daily on-site presence into high-quality innovative results with lasting impact.

Table 17 Heterogeneity: firm age

This table shows the heterogeneous effect of the OWP on firm innovation activities after including the interaction term of firm age (*Age*) and the interaction term of *Age* with OWP. **Panel A** shows the results for innovation quantity, and **Panel B** shows the results for innovation quality. The regressions control for year and firm fixed effects. Standard errors are reported in parentheses. For brevity, coefficients on control variables, constants and fixed effects are omitted. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation quantity						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Pat_App*	*Pat_App*	*Pat_App*	*Inv_App*	*Inv_App*	*Inv_App*
*OWP_All*Age*	0.002			-0.007		
	(0.015)			(0.016)		

OWP_All	0.032***			0.035***		
	(0.012)			(0.012)		
*OWP_Routine*Age*		-0.002			-0.012	
		(0.020)			(0.021)	
OWP_Routine		0.042***			0.047***	
		(0.016)			(0.016)	
*OWP_Overtime*Age*			0.039			-0.016
			(0.063)			(0.066)
OWP_Overtime			0.125***			0.128***
			(0.047)			(0.050)
AgeD	0.096**	0.099**	0.090**	0.051	0.053	0.048
	(0.041)	(0.042)	(0.041)	(0.044)	(0.044)	(0.043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.862	0.862	0.862	0.850	0.850	0.850

Panel B: Innovation quality

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Con_Cit*	*Con_Cit*	*Con_Cit*	*Ext_Cit*	*Ext_Cit*	*Ext_Cit*
*OWP_All*Age*	0.038**			0.035**		
	(0.016)			(0.016)		
OWP_All	0.018			0.020		
	(0.012)			(0.012)		
*OWP_Routine*Age*		0.049**			0.045**	
		(0.021)			(0.021)	
OWP_Routine		0.023			0.026	
		(0.016)			(0.016)	
*OWP_Overtime*Age*			0.134**			0.128*
			(0.066)			(0.066)
OWP_Overtime			0.055			0.065
			(0.049)			(0.050)
AgeD	-0.019	-0.020	-0.011	-0.032	-0.033	-0.025
	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)	(0.043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,478	15,478	15,478	15,478	15,478	15,478
R-squared	0.892	0.892	0.892	0.887	0.887	0.887

7. Conclusions

This paper studies whether employee OWP promotes firm innovation. Using anonymized

smartphone geolocation data, we construct nationwide firm-level measures of OWP for Chinese A-share listed manufacturing firms by matching device-level location signals to geofenced firm operating sites. These measures allow us to distinguish between overall presence intensity, routine-hour presence intensity, and overtime presence intensity. The resulting data provide a direct measure of on-site presence that increases opportunities for face-to-face communication in routine organizational settings at a scale that has not been achieved in most existing studies.

Our results show a robust positive association between OWP and both the quantity and the quality of firm innovation. Firms with greater QWP intensity produce more patent applications and invention patent applications, and they also receive more patent citations and external citations. Among the three measures, overtime presence has the strongest association with innovation outcomes. This pattern is consistent across the baseline specifications and remains visible when innovation is examined from both quantity and quality perspectives. Taken together, the evidence suggests that OWP remains an important input into firm innovation, even in an increasingly digital workplace.

The further-discussion results show that the innovation relevance of OWP also depends on the setting in which it occurs.Non-working-day presence, especially at night, are more strongly associated with both patent applications and patent citations than routine workday presence, indicating that more concentrated and less fragmented on-site communication environments are particularly relevant for innovation. In addition, when patenting is separated into independent and joint applications, the positive association is stronger for independent patenting, especially on the invention-patent and citation margins. Taken together, these results suggest that the innovation benefits of OWP are most pronounced in overtime-related settings and are realized more strongly through projects completed within the focal firm.

Finally, the heterogeneity results show that the returns to OWP vary systematically across organizational environments. Digitalization weakens the association between OWP and innovation quantity, but not innovation quality, suggesting that digital tools may substitute for routine coordination but not for deeper knowledge integration. The COVID-19 pandemic attenuates the innovation benefits of OWP, especially for innovation quality, consistent with the idea that high-value innovation is particularly sensitive to disruptions in tacit knowledge exchange. The positive association is also stronger in firms with higher employee educational qualifications on

the quantity margin and in older firms on the quality margin, suggesting that the innovation returns to OWP vary with organizational environment characteristics.

More broadly, this paper contributes to the literature by moving the measurement of OWP from indirect proxies and geographically limited mobile-data settings to a nationwide firm-level setting. It also contributes by showing that OWP is linked not only to how much firms innovate, but also to how valuable those innovations are. Even in a workplace increasingly shaped by digital tools, on-site work presence remains an important and difficult-to-replace component of the innovation process.

Reference

Allen, T. J. (1977). *Managing the Flow of Technology*. MIT Press.

Atkin, D., Chen, M. K., & Popov, A. (2022). *The Returns to Face-to-Face Interactions: Knowledge Spillovers in Silicon Valley* (Working Paper No. 30147). National Bureau of Economic Research.

Bai, J. (Jianqiu), Jin, W., & Zhou, S. (2024). Proximity and Knowledge Spillovers: Evidence from the Introduction of New Airline Routes. *Management Science*, *70*(11), 7464–7485.

Barwick P. J., Liu Y., Patacchini E., & Wu Q. (2023). Information, Mobile Communication, and Referral Effects. *American Economic Review*, *113*(5), 1170–1207.

Bathelt, H., & Turi, P. (2011). Local, global and virtual buzz: The importance of face-to-face contact in economic interaction and possibilities to go beyond. *Geoforum*, *42*(5), 520–529.

Brav, A., Jiang, W., Ma, S., & Tian, X. (2018). How does hedge fund activism reshape corporate innovation? *Journal of Financial Economics*, *130*(2), 237–264.

Catalini, C. (2018). Microgeography and the Direction of Inventive Activity. *Management Science*, *64*(9), 4348–4364.

Cecchi, M. A., Grant, S., Seiler, M., Turner, N., Adams, R., & Goffin, K. (2022). How COVID-19 Impacted The Tacit Knowledge and Social Interaction of Global NPD Project Teams. *Research-Technology Management*, *65*(2), 41–52.

Ceci, F., Lazoi, M., Lezzi, M., & Mohammad, H. (2021). Fostering knowledge sharing in the innovation process: Information and communication technology-based versus face-to-face relationships. *Knowledge and Process Management*, *28*(3), 302–316.

Chauvin, J., Choudhury, P., & Fang, T. P. (2024). Working Around the Clock: Temporal Distance, Intrafirm Communication, and Time Shifting of the Employee Workday. *Organization Science*, *35*(5), 1660–1681.

Cheng, Q., Du, F., Wang, X., & Wang, Y. (2016). Seeing is believing: Analysts' corporate site visits. *Review of Accounting Studies*, *21*(4), 1245–1286.

Choi, I., Cantor, D., Han, K., & George, J. (2024). Dual Pathways of Value Creation from Digital Strategic Posture: Contingent Effects of Competitive Actions and Environmental Uncertainty. *Management Information Systems Quarterly*, *48*(1), 409–426.

Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: Does firm age play a role? *Research Policy*, *45*(2), 387–400.

Daft, R. L., & Lengel, R. H. (1986). Organizational Information Requirements, Media Richness and Structural Design. *Management Science*.

Gaspar, J., & Glaeser, E. L. (1998). Information Technology and the Future of Cities. *Journal of Urban Economics*, *43*(1), 136–156.

Ghosh, S., & Wu, A. (2023). Iterative Coordination and Innovation: Prioritizing Value over Novelty. *Organization Science*, *34*(6), 2182–2206.

Hatch, M. J. (1987). Physical Barriers, Task Characteristics, and Interaction Activity in Research and Development Firms. *Administrative Science Quarterly*, *32*(3), 387–399.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations*. *The Quarterly Journal of Economics*, *108*(3), 577–598.

Jiang, X., & Yuan, Q. (2018). Institutional investors' corporate site visits and corporate innovation. *Journal of Corporate Finance*, *48*, 148–168.

Kang, H., & Eklund, J. C. (2025). Fast Friends: The Impact of Short-Term Visits on Firms' Invention Outcomes. *Organization Science*, *36*(3), 1154–1176.

Kong, D., Wang, Y., & Zhang, J. (2020). Efficiency wages as gift exchange: Evidence from corporate innovation in China. *Journal of Corporate Finance*, *65*, 101725.

Kreindler, G. E., & Miyauchi, Y. (2023). Measuring Commuting and Economic Activity inside Cities with Cell Phone Records. *The Review of Economics and Statistics*, *105*(4), 899–909.

Lenka, S., Parida, V., & Wincent, J. (2017). Digitalization Capabilities as Enablers of Value

Co-Creation in Servitizing Firms. *Psychology & Marketing*, *34*(1), 92–100.

McCann, P. (2007). Sketching Out a Model of Innovation, Face-to-face Interaction and Economic Geography. *Spatial Economic Analysis*.

Messeni Petruzzelli, A., Ardito, L., & Savino, T. (2018). Maturity of knowledge inputs and innovation value: The moderating effect of firm age and size. *Journal of Business Research*, *86*, 190–201.

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital Innovation Management: Reinventing Innovation Management Research in a Digital World. *Management Information Systems Quarterly*, *41*(1), 223–238.

Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science*, *5*(1), 14–37.

O'Connor M., & Rafferty M. (2012). Corporate Governance and Innovation. *Journal of Financial and Quantitative Analysis*, *47*(2), 397–413.

Odziemkowska, K., & Zhu, Y. (2025). How Social Movements Catalyze Firm Innovation. *Organization Science*, *36*(4), 1221–1241.

Polanyi M. (2009). *The Tacit Dimension*. University of Chicago Press.

Roche, M. P. (2020). Taking Innovation to the Streets: Microgeography, Physical Structure, and Innovation. *The Review of Economics and Statistics*, *102*(5), 912–928.

Roche, M. P., Oettl, A., & Catalini, C. (2024). Proximate (Co-)Working: Knowledge Spillovers and Social Interactions. *Management Science*, *70*(12), 8245–8264.

Shi, Y., Sampson, R. C., Goldfarb, B., & Corredoira, R. A. (2025). The Changing Nature of Firm Innovation: Short-Termism and Influential Innovation in U.S. Public Firms. *Management Science*.

Soltes, E. (2014). Private Interaction Between Firm Management and Sell-Side Analysts. *Journal of Accounting Research*, *52*(1), 245–272.

Sparrowe, R. T., Liden, R. C., Wayne, S. J., & Kraimer, M. L. (2001). Social networks and the performance of individuals and groups. *Academy of Management Journal*, *44*(2), 316–325.

Storper, M., & Venables, A. J. (2004). Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography*, *4*(4), 351–370.

Sun, X., Li, H., & Ghosal, V. (2020). Firm-level human capital and innovation: Evidence from

China. *China Economic Review*, *59*, 101388.

Testoni, M., Sakakibara, M., & Chen, M. K. (2022). Face-to-face interactions and the returns to acquisitions: Evidence from smartphone geolocational data. *Strategic Management Journal*, *43*(13), 2669–2702.

Xia, D., Cassiman, B., & Wehrheim, D. (2025). Escaping Product Market Rivalry Through Innovation. *Management Science*.

Yang, J., Fan, D., & Li, C. (2025). Employee Overtime and Innovation Dilemma. *Journal of Business Ethics*.

Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for Innovation in the Digitized World. *Organization Science*, *23*(5), 1398–1408.

Xuan, Y., & Wu, K. (2023). Overtime Work and Labor Income Share: Empirical Evidence Based on Satellite Night Light. *The Journal of World Economy*, *46*(10), 217–240.

Appendix A Distribution of firms and geofences across industries

This table summarizes the industry distribution of firms and associated geofences in the dataset we construct for 4,691 A-share listed firms in China. The geofences correspond to firm-specific operational sites, including headquarters, subsidiaries, and manufacturing factories. Columns (1) and (2) report the number and proportion of firms in each industry. Columns (3) and (4) show the total number of geofences and the average number of geofences per firm, respectively.

		Firms		Geofences	
		(1)	(2)	(3)	(4)
Industry category		#	%	#	Avg.
A	Agriculture, forestry, animal husbandry, and fishery	46	0.98	317	6.89
B	Mining	77	1.64	283	3.68
C	Manufacturing	3,055	65.12	10,385	3.40
D	Production and supply of electricity, heat, gas, and water	130	2.77	569	4.38
E	Construction	105	2.24	270	2.57
F	Wholesale and retail trade	181	3.86	533	2.94
G	Transportation, storage, and postal services	102	2.17	286	2.80
H	Accommodation and catering services	9	0.19	25	2.78
I	Information transmission, software, and IT services	393	8.38	542	1.38
J	Financial services	128	2.73	158	1.23
K	Real estate	111	2.37	131	1.18
L	Leasing and business services	62	1.32	101	1.63
M	Scientific research and technical services	97	2.07	180	1.86
N	Water conservancy, environment, and public facilities	91	1.94	334	3.67
O	Resident services, repairs, and other services	1	0.02	1	1.00
P	Education	12	0.26	16	1.33
Q	Health and social work	16	0.34	170	10.63
R	Culture, sports, and entertainment	62	1.32	75	1.21
S	Comprehensive	13	0.28	43	3.31
	Total	4,691	100.00	14,419	

Appendix B Variable description

Variable			Definition
Dependent Variable	Innovation quantity	*Pat_App*	Ln (1 + all patent applications)
		Inv_App	Ln (1 + invention patent applications)
	Innovation quality	*Con_Cit*	Ln (1 + averaged invention patent citations including self-citations)
		Ext_Cit	Ln (1+averaged invention patent citations excluding self-citations)
Independent Variable	*OWP*	*OWP_All*	The total intensity of on-site work presence between regular working hours (9:00-17:00) and overtime working hours (19:00-23:00) on workdays
		OWP_Routine	The intensity of on-site work presence during regular working hours (9:00-17:00) on workdays
		OWP_Overtime	The intensity of on-site work presence during overtime hours (19:00-23:00) on workdays
Control Variable		*Size*	Ln (book value of total assets)
		ROA	Net profits / total assets
		Lev	Total liabilities / total assets
		PPE	Net fixed assets / total assets
		Cashflow	Net cash flow from operating activities / total assets
		Top1	The percentage of shares owned by the largest shareholder
		Mshare	The percentage of shares owned by the firm management
		Board	Ln (the number of board directors)
		Dual	If the chairman also serves as CEO, the value is 1, otherwise is 0
		Indep	The percentage of independent board directors
		Age	Ln (1+current year-establishing year)
		R&D	R&D expense / operating income
		Salary	Ln (total employee compensation) / total number of employees
		Dig	The percentage of digitization-related words in annual reports×100