

The Cost of Constant Availability: On-Call Work, Occupational AI Exposure, and Psychological Distress

Chunyang Su

succya@163.com

Shanghai Jiao Tong University

Research Article

Keywords: on-call work, constant availability, psychological distress, working time, AI exposure

Posted Date: September 7th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10776732/v1>

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Additional Declarations: No competing interests reported.

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Abstract

Workers are increasingly expected to remain reachable beyond their formal working hours, yet research on working time continues to focus primarily on time actually spent working. This study examines whether constant availability constitutes a distinct temporal burden and whether its consequences vary across occupational contexts. Using the 2020 and 2022 China Family Panel Studies, we find that on-call work is associated with greater psychological distress, longer working hours, and more frequent night and weekend work. Accounting for these realized working-time demands only modestly reduces the psychological-distress gap, while higher labor income does not offset it. Further analyses reveal a notable contrast: occupational AI exposure is associated with a weaker psychological penalty of constant availability, despite stronger extensions of on-call work into nights and weekends. This divergence suggests that technological context may reshape how temporal intrusion translates into psychological strain rather than simply reducing work demands. The findings identify availability time—time that must remain reserved for possible work demands—as a distinct dimension of contemporary job quality.

Keywords: on-call work; constant availability; psychological distress; working time; AI exposure

1 Introduction

Working time is a central dimension of job quality, but it is usually measured through realized labor inputs such as weekly hours, overtime, night work, and weekend work. A growing literature links long and nonstandard working hours to poorer health and well-being (Virtanen et al., 2018; Rugulies et al., 2021). Yet these measures capture only the time workers actually spend working. They say less about situations in which workers are formally off duty but must still remain reachable and ready to respond.

The spread of mobile communication and flexible work arrangements has made this form of constant availability increasingly salient. Workers may be required to answer messages, handle unexpected requests, or remain prepared for recall even during nominally nonwork time. Such requirements can interfere with psychological detachment and recovery (Sonnentag & Fritz, 2007, 2015; Sonnentag et al., 2017) and resemble the response pressure described in research on workplace telepressure (Barber & Santuzzi, 2015; Barber et al., 2019). On-call work therefore provides an institutionally grounded setting in which to distinguish actual working time from availability time—time that must remain reserved for possible work demands even when no task is currently being performed.

This distinction raises two questions. First, is the psychological cost associated with on-call work mainly explained by longer hours and more frequent night or weekend work, or does constant availability impose an additional burden beyond realized working time? Second, does higher pay compensate for this burden? On-call jobs may involve greater responsibility or scarce skills and therefore offer higher earnings, but monetary rewards need not eliminate the nonmonetary cost of constrained recovery and reduced control over nonwork time.

Using the 2020 and 2022 waves of the China Family Panel Studies, this study examines these questions by relating on-call work to psychological distress, working-time patterns, and labor income. Pooled estimates are complemented by individual fixed-effects models and a series of robustness checks. As a further extension, the analysis also considers occupational AI exposure as a technological boundary condition. Because more AI-exposed occupations may combine stronger digital connectivity with different ways of responding to work demands, AI exposure may alter both the temporal and psychological consequences of constant availability.

This study contributes to the literature in three ways. First, it extends working-time research from realized hours to availability time, highlighting the burden created when nominally nonwork time remains reserved for work. Second, it shows that conventional working-time measures explain only part of the psychological cost associated with constant availability and that higher income does not eliminate this cost. Third, the further analysis suggests that technological context matters: occupational AI exposure is associated with stronger night- and weekend-work intrusion but a weaker psychological penalty of constant availability. Technological context may therefore reshape both the temporal and psychological consequences of constant availability.

2 Theoretical Analysis and Research Hypotheses

2.1 Conceptualizing Constant Availability: From Actual Working Time to Availability Time

Traditional research on working time focuses primarily on realized labor inputs, such as weekly hours, overtime, night work, and weekend work. These indicators answer the question of “how long workers actually worked,” but they do not fully capture another form of time constraint: even when workers are not continuously performing tasks, job requirements may oblige them to remain reachable, recallable, and ready to resume work quickly during nonwork time. This study refers to this institutional requirement as “availability time.” The concept does not concern whether a task has already occurred; rather, it concerns whether workers must continuously reserve attention, mobility, and scheduling capacity for possible work demands. Availability time therefore overlaps with actual working time but is not equivalent to it. Availability constraints are consistent with established work-nonwork boundary perspectives (Nippert-Eng, 1996; Ashforth et al., 2000; Clark, 2000; Kossek et al., 2012).

This distinction has become increasingly important in recent research on working time. Recent studies more explicitly differentiate between flexibility controlled by employees and flexibility driven by organizational demands. Using a French employee panel linked to employer–employee data, Erhel et al. (2024) show that employer-oriented flexible working-time arrangements are associated with poorer worker health, whereas greater control over working time can buffer these adverse effects. Brogle et al. (2024), in their study of work–nonwork boundary crafting, likewise show that individuals actively adjust boundary permeability to reduce cross-domain interference. Golden et al. (2026) further demonstrate that working-time volatility, short-notice scheduling, and irregular shifts are significantly associated with lower subjective well-being even after weekly hours are controlled. Taken together, these findings indicate that the welfare implications of working time depend not only on “how many hours” are worked, but also on whether those hours are predictable, controllable, and genuinely at the worker’s disposal.

In parallel, recent research on digital connectivity has increasingly distinguished “constant availability” from technology use per se. Using event-based diary data, Chen, Conroy, and Crain (2024) find that multiple forms of after-hours ICT use undermine psychological detachment, with particularly strong associations for email and instant messaging. Earlier evidence similarly links after-hours communication technologies to work-life conflict (Boswell & Olson-Buchanan, 2007). He et al. (2024) conceptualize after-hours workplace telepressure as the psychological pressure to respond quickly to work-related messages and show that task interdependence and the belief that responsiveness is rewarded both intensify this pressure. Studies published in 2025 further show that after-hours connectivity may generate a sense of control and performance benefits while simultaneously being associated with resource depletion, ICT anxiety, psychological distress, and work alienation (Chen & Zhang, 2025; Li et al., 2025; Quan et al., 2025). These findings suggest that on-call work is not merely a form of digital work behavior; rather, it is better understood as a responsiveness requirement shaped by job design and organizational norms.

Accordingly, the notion of “on-call work” used here emphasizes whether workers’ control over nonwork time is constrained by work requirements. A worker may receive no call at all on a Saturday, so recorded weekend working time may be zero. Yet if the worker must keep a phone available throughout the day, avoid activities that cannot be interrupted, or remain able to return to work at short notice, that nominally nonwork time still bears a clear work-related character. For this reason, if on-call work were simply another expression of long working hours, its relationship with psychological distress should fall sharply once weekly hours, night work, and weekend work are controlled. If the relationship persists, conventional working-time measures do not fully capture the time-boundary pressure created by constant availability.

2.2 Constant Availability, Psychological Detachment, and Psychological Distress

Constant availability may increase psychological distress primarily by impeding psychological detachment. Psychological detachment refers to temporarily disengaging from work activities and work-related thoughts during nonwork time and is a core component of recovery. This role is well established in recovery research and meta-analytic evidence (Sonnetag & Fritz, 2007; Sonnetag et al., 2017; Wendsche & Lohmann-Haislah, 2017; Steed et al., 2021). Although the concept originates in earlier recovery research (Sonnetag & Bayer, 2005; Sonnetag & Fritz, 2015), more recent evidence has substantially strengthened its empirical foundation. Sonnetag, Kark, and Venz (2024) show that leader support for recovery promotes employees’ psychological detachment, while Sonnetag (2024), drawing on control theory, identifies persistent work-related cognitions and rumination after work as central processes that prevent detachment.

More direct recent evidence comes from longitudinal and diary studies. Cho, Steege, and Pavek (2024) show that psychological detachment plays an important role in the relationships linking workload to fatigue and sleep. Related evidence among hospital-based nurses also links psychological detachment to burnout (Cho et al., 2025). Nakamura and Kobayashi (2024) report that blurred work–life boundaries make psychological detachment more difficult in work-from-home settings. Blake et al. (2025), using a prospective cohort design, find that better psychological detachment predicts better mental health, lower anxiety, and greater life satisfaction one year later. Using representative longitudinal data from the German Socio-Economic Panel, Baktash and Pütz (2025) document stable associations between psychological detachment and affect, job satisfaction, domain satisfaction, and overall

life satisfaction. The meta-analysis by Grant, Buchanan, and Shockley (2025) further shows that vacations significantly improve employee well-being and that psychological detachment is among the most beneficial recovery experiences.

Constant availability may hinder psychological detachment because it keeps potential work goals activated during nonwork time. Even in the absence of an actual task, workers may repeatedly check their phones, monitor possible notifications, avoid activities that would prevent a rapid response, and reserve time within family or leisure plans for potential work demands. Diary evidence from Chen et al. (2024) shows that after-hours ICT access reduces subsequent psychological detachment, while Schlachter et al. (2025) find that even voluntary work-related ICT use during nonwork time depletes self-regulatory resources, weakens detachment, and harms affective well-being that evening and on the following day. Booker et al. (2025) further introduce the idea of “connectivity agency,” emphasizing that workers’ ability to decide when to connect to work is an important resource for work–family boundary management and recovery. Rasulova and Tanova (2025) likewise find that when technology is experienced as a demand rather than a resource, it is associated with greater burnout and turnover intentions.

The link between persistent connectivity pressure and mental health is also supported more directly. Using two-wave data from a Chinese financial institution, Li, Chen, and Yuan (2025) find significant relationships among after-hours work connectivity, psychological contract breach, and psychological distress, with particularly high distress when connectivity is high and organizational support is low. Qin et al. (2025), studying Chinese teachers, further show that telepressure can increase burnout through work-related rumination; Yuan et al. (2024) demonstrate that an organizational psychosocial safety climate is associated with psychological detachment and burnout. Recent research on telepressure likewise shows that pressure to respond quickly to work messages can increase burnout through pathways such as work-related rumination. Of particular relevance, Buechel and Solinas (2025) identify a “detachment paradox”: managers recognize that employees’ detachment after work benefits well-being and performance, yet may penalize detachment in evaluations when it is interpreted as weaker work commitment. This suggests that constant availability is not simply a matter of individual boundary-management preferences; it may also be shaped by organizational culture and career-advancement norms.

The psychological cost of on-call work may therefore arise from sustained vigilance and impaired recovery that are distinct from conventional working hours. Based on the above reasoning, the study proposes:

Hypothesis H1: Holding other factors constant, on-call work is significantly associated with higher psychological distress among workers.

2.3 Working-Time Encroachment: Total Hours, Nonstandard Timing, and Time Predictability

Constant availability is not entirely separate from actual working time. On-call jobs often require workers to handle unexpected tasks and may therefore involve longer weekly hours and more frequent night and weekend work. Recent research on working time and health further indicates that weekly hours alone are insufficient to characterize time burdens. Using a nationally representative Japanese survey and accounting for nonrandom selection, Ma, Kawakami, and Inui (2024) find that longer working hours are significantly associated with poorer mental health.

Erhel et al. (2024) likewise show that long hours, overtime, night and weekend work, insufficient uninterrupted rest, and the inability to know work schedules in advance are all associated with poorer health.

Recent studies have also placed growing emphasis on the timing and predictability of work. Kim, Hu, and Harold (2025) show that last-minute additions to or reductions in scheduled shifts can trigger perceptions of psychological contract breach and shape employee responses. Golden et al. (2026) find that short-notice scheduling, irregular shifts, and fluctuations in working hours are negatively associated with subjective well-being independently of weekly hours. Izumi's (2025) study of a Japanese working-hours exemption regime provides a related insight: increases in hours and income do not necessarily harm health by themselves, but adverse health consequences become more pronounced when workers lack discretion over when and how they work. Thus, the length of working time and workers' control over it need to be considered jointly.

For this reason, weekly hours, night work, and weekend work are not treated as mechanical mediators. Instead, they are introduced as competing explanations for the association attributed to availability time. If on-call work significantly increases these realized time inputs, then on-call status is clearly accompanied by intensified working time. If the on-call coefficient remains after all of these measures enter the model, actual hours and nonstandard work periods can explain only part of the relationship. This empirical design provides a clearer distinction between “working longer” and “being constantly available.”

Hypothesis H2a: On-call work is significantly associated with longer weekly working hours and more frequent night and weekend work.

Hypothesis H2b: After conventional working-time indicators—including weekly hours, night work, and weekend work—are controlled, the positive relationship between on-call work and psychological distress remains.

2.4 Income Compensation, Pricing of Job Attributes, and Nonmonetary Costs

Constant availability does not necessarily imply that on-call jobs are worse along every dimension. The compensating-differentials framework in labor economics holds that wages may price not only labor itself but also risk, inconvenience, time restrictions, and other nonwage job attributes (Rosen, 1986). Recent empirical work provides more refined support for this classic argument. Evidence nevertheless suggests that compensating differentials are often incomplete and that workers place substantial value on nonwork time and alternative work arrangements (Bonhomme & Jolivet, 2009; Mas & Pallais, 2017, 2019). Maestas et al. (2023) show that working conditions constitute an important component of total labor compensation, while a choice experiment by Van Landeghem et al. (2024) finds that job seekers attach substantial monetary value to working-time flexibility, remote work, and job security; many require sizable wage increases to accept less desirable nonwage job attributes.

Research since 2025 has further highlighted systematic trade-offs among working hours, flexibility, and other job amenities. Garro-Marín, Thakral, and Tô (2025) examine combinations and substitutions between work hours and job amenities within a compensating-differentials framework. Ferreira et al. (2025) show that compensation for job risks and undesirable working conditions is often incomplete in actual labor markets. Jacobi, Hamjediers, and Naujoks

(2025), studying flexible working time in Germany, further document occupational and gender inequalities in access to flexible arrangements, indicating that nonwage job attributes are not evenly distributed.

Particularly relevant is the finding by He et al. (2024) that when employees believe rapid responsiveness is rewarded, task interdependence is more likely to translate into after-hours telepressure. This suggests that responsiveness requirements and economic rewards may form a perceptible exchange relationship. The empirical analysis in this study permits a related test: if on-call work is associated with higher labor income, yet its positive association with psychological distress persists after income is controlled, economic returns and psychological costs can be viewed as coexisting rather than offsetting one another.

This study does not, however, interpret the income result as a strict causal estimate of compensating wage differentials. On-call status is not randomly assigned, and on-call jobs may also involve greater responsibility, higher skill requirements, or different organizational positions, all of which may affect wages. A more precise interpretation is therefore an “income-compensation association”: on-call workers receive some economic return, but that return is insufficient to cover all of the nonmonetary welfare costs associated with constant availability.

Hypothesis H3a: On-call work is significantly associated with higher labor income.

Hypothesis H3b: After labor income is controlled, the positive relationship between on-call work and psychological distress remains.

3 Data, Variables, and Empirical Strategy

3.1 Data Source and Sample Selection

The data come from the China Family Panel Studies (CFPS), administered by the Institute of Social Science Survey at Peking University. The CFPS uses a nationwide, multilevel, longitudinal design and continuously collects socioeconomic information at the individual, household, and community levels, providing an important micro-level data source for research on employment, family life, and health in China (Xie et al., 2014; Xie & Hu, 2014). This study uses the 2020 and 2022 waves because the core on-call measure and the working-time information required for the analysis are available with relatively consistent definitions in both waves.

Sample construction follows three steps. First, the analysis retains the main employment sample and observations from 2020 and 2022. Second, observations with missing values for on-call status or CES-D are excluded. Third, to ensure that coefficient changes across sequential specifications are not mechanically driven by changes in sample composition, the baseline, working-time, and income models use the same complete-case sample. The final sample contains 14,819 person-year observations representing 10,744 unique individuals. Of these, 4,075 individuals are observed in both waves, and 1,119 change on-call status between the two waves, providing the principal within-person identifying variation for the individual fixed-effects models.

3.2 Variable Definitions

(1) Psychological distress. Psychological distress is measured using the eight-item Center for Epidemiologic Studies Depression Scale (CES-D8) provided by the CFPS. Respondents report the frequency of several negative and positive emotional states during the previous week; positively worded items are reverse coded and the items are

summed. The scale is recoded to range from 0 to 24, with higher scores indicating more depressive symptoms and greater psychological distress. The CES-D was originally developed by Radloff (1977), and the abbreviated CES-D8 has been widely used in large-scale social surveys and CFPS-based research. Existing studies using the CFPS likewise employ the 0–24 scoring convention to measure depressive symptoms.

(2) On-call work. The core explanatory variable, `always_on_call`, is binary. It equals 1 if the respondent’s work arrangement requires them to be available for work or remain on call at any time, and 0 otherwise. This measure differs from actual overtime hours: it captures an institutional requirement that workers remain reachable, recallable, and responsive, and therefore more closely reflects constant availability than realized labor input.

(3) Working-time indicators. The study uses three measures: weekly working hours, frequency of night work, and frequency of weekend work. Weekly working hours measure actual hours worked per week. Night-work and weekend-work frequencies use the original CFPS frequency measures, with higher values indicating more frequent work during nonstandard periods. To reduce the influence of clearly implausible values, weekly working hours are restricted to a reasonable range in the main analysis. The mean weekly working time in the common analytical sample is 51.917 hours.

(4) Labor income. The natural logarithm of labor income is used. Income is both an important dimension of workers’ economic welfare and a key variable for examining whether on-call jobs are associated with compensating returns. Because income is jointly related to job level, skills, and work effort, the income regressions are not interpreted as strict causal estimates of compensating wage differentials, but as empirical evidence on the structure of income compensation.

(5) Control variables. Individual and household controls include age, age squared, gender, urban residence, rural hukou, years of education, partner status, and self-rated health. Job-level controls include whether the worker has a labor contract, whether the worker holds a managerial position, and the number of employment benefits received. The baseline models further absorb year fixed effects and province fixed effects, and standard errors are clustered at the individual level to account for possible serial correlation in the error term for repeated observations of the same person.

3.3 Descriptive Statistics

Table 1 reports descriptive statistics for the common analytical sample. The mean CES-D score is 5.379, with a standard deviation of 3.767, and 50.7% of person-year observations are in on-call work. Mean weekly working time is 51.917 hours, while night-work and weekend-work frequencies display substantial individual variation. Unadjusted comparisons by on-call status show that on-call workers have higher CES-D scores, longer weekly hours, more frequent night and weekend work, and higher labor income than workers who are not on call.

Table 1. Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Psychological distress (CES-D, 0–24)	14819	5.379	3.767	0.000	24.000
On-call work	14819	0.507	0.500	0.000	1.000
Weekly working hours	14819	51.917	16.738	0.100	112.000
Night-work frequency	14819	2.322	2.037	1.000	7.000
Weekend-work frequency	14819	3.963	1.485	1.000	5.000

Variable	N	Mean	Std. Dev.	Min	Max
Log labor income	14819	10.574	1.245	0.000	14.403
Age	14819	38.316	10.900	16.000	65.000
Female	14819	0.420	0.494	0.000	1.000
Urban residence	14819	0.651	0.477	0.000	1.000
Rural hukou	14819	0.630	0.483	0.000	1.000
Years of education	14819	11.261	4.168	0.000	22.000
Has a partner	14819	0.767	0.423	0.000	1.000
Self-rated health	14819	3.319	1.018	1.000	5.000
Labor contract	14819	0.621	0.485	0.000	1.000
Managerial position	14819	0.136	0.342	0.000	1.000
Number of employment benefits	14819	2.399	2.339	0.000	5.000

Note: The sample is the common complete-case sample used in the main analysis. Higher CES-D scores indicate greater psychological distress. Night work and weekend work use the original frequency coding.

3.4 Econometric Model Specification

First, the pooled 2020 and 2022 sample is used to estimate the baseline relationship between on-call work and psychological distress:

$$CESD_{it} = \alpha + \beta OnCall_{it} + \gamma' X_{it} + \lambda_t + \mu_p + \varepsilon_{it} \quad (1)$$

where $CESD_{it}$ denotes the CES-D psychological-distress score for individual i in year t ; $OnCall_{it}$ is the on-call-work indicator; X_{it} is a vector of individual, household, and job controls; λ_t and μ_p denote year fixed effects and province fixed effects, respectively; and ε_{it} is the error term. The coefficient of primary interest is β . Standard errors are clustered at the individual level. To prevent coefficient changes from being mechanically induced by changing sample sizes, all columns in the main analysis use the same complete-case sample.

Second, to distinguish “actual working time” from “availability time,” explanatory variables are added sequentially:

$$CESD_{it} = \alpha + \beta OnCall_{it} + \theta W_{it} + \delta Income_{it} + \gamma' X_{it} + \lambda_t + \mu_p + \varepsilon_{it} \quad (2)$$

W_{it} sequentially includes weekly working hours, night-work frequency, and weekend-work frequency, while $Income_{it}$ is the logarithm of labor income. The analysis does not focus on a conventional mediation proportion; instead, it examines the stability of the $OnCall$ coefficient as these working-time measures are introduced. If β falls sharply and loses statistical significance, the association between on-call work and psychological distress can largely be explained by actual working time. If β declines only modestly, the availability requirement contains information beyond conventional working-time measures. The percentage attenuation of the coefficient is reported descriptively and is not interpreted as a causal mediated share.

Third, repeated observations are used to estimate an individual fixed-effects model that controls for time-invariant individual heterogeneity:

$$CESD_{it} = \alpha_i + \beta OnCall_{it} + \theta W_{it} + \delta Income_{it} + \lambda_t + \varepsilon_{it} \quad (3)$$

where α_i denotes individual fixed effects, which absorb time-invariant characteristics such as personality, early family background, and relatively stable occupational preferences. Because direct within-person identification of β comes from individuals whose on-call status changes across the two waves, the effective sample and statistical power of the fixed-effects models are lower than those of the pooled models. The fixed-effects estimates are therefore used primarily as a supplementary check on selection rather than as a design that fully resolves endogeneity and identifies a causal effect.

4 Empirical Results

4.1 Baseline Results

Table 2 reports the baseline regressions of psychological distress on on-call work. Column (1) controls only for year and province fixed effects; the coefficient on on-call work is 0.274 and statistically significant at the 1% level. After individual and household characteristics—including age, gender, hukou, education, partner status, and health—are added in Column (2), the coefficient rises to 0.424. Column (3) further controls for labor contracts, managerial positions, and employment benefits, yielding a coefficient of 0.443, again significant at the 1% level. The coefficient does not weaken as controls are introduced, suggesting that simple demographic composition and job structure do not account for the higher psychological distress among on-call workers. In the fully adjusted model, on-call status is associated with a 0.443-point higher CES-D score, equivalent to approximately 11.8% of the sample standard deviation, consistent with the standardized estimates reported below. The control variables generally have the expected signs: female gender and rural hukou are associated with greater psychological distress, whereas more years of education, having a partner, better self-rated health, having a labor contract, and receiving more employment benefits are associated with lower distress.

Table 2. On-Call Work and Psychological Distress: Baseline Regressions

Variable	(1)	(2)	(3)
On-call work	0.274*** (0.066)	0.424*** (0.063)	0.443*** (0.064)
Age		0.110*** (0.025)	0.122*** (0.025)
Age squared		-0.002*** (0.000)	-0.002*** (0.000)
Female		0.332*** (0.068)	0.317*** (0.068)
Urban residence		-0.044 (0.076)	-0.019 (0.076)
Rural hukou		0.183** (0.078)	0.139* (0.079)
Years of education		-0.124***	-0.101***

Variable	(1)	(2)	(3)
		(0.010)	(0.011)
Has a partner		-1.052***	-1.050***
		(0.096)	(0.095)
Self-rated health		-0.993***	-0.994***
		(0.034)	(0.034)
Labor contract			-0.199**
			(0.077)
Managerial position			-0.111
			(0.090)
Number of employment benefits			-0.057***
			(0.018)
Constant	5.240***	8.887***	8.720***
	(0.046)	(0.535)	(0.538)
Observations	14,819	14,819	14,819
R ²	0.013	0.112	0.114
Individual/household controls	No	Yes	Yes
Job controls	No	No	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes

*Note: Robust standard errors clustered at the individual (PID) level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Column (1) controls only for year and province fixed effects; Column (2) adds individual and household controls; Column (3) further adds job controls. All columns use the same common complete-case sample.*

4.2 Working-Time Consequences, Competing Explanations, and Income Compensation

Table 3 presents the three sets of results that form the empirical core of the study. Panel A first examines whether on-call work is associated with greater realized working-time inputs. After controlling for individual and household characteristics, job characteristics, year fixed effects, and province fixed effects, on-call workers work an average of 1.922 more hours per week, score 0.654 units higher on night-work frequency, and 0.314 units higher on weekend-work frequency. All three coefficients are significant at the 1% level. Thus, on-call work is not merely a “psychological expectation”; it is associated with longer working time and a greater concentration of work in nonstandard periods, supporting Hypothesis H2a.

Panel B then examines whether these realized working-time inputs explain the relationship between on-call work and psychological distress. The on-call coefficient is 0.443 in the baseline specification, falls to 0.418 after weekly hours are added, to 0.381 after night work is included, and to 0.375 after weekend work is added. After labor income is additionally controlled, the coefficient is 0.381 and remains significant at the 1% level. Relative to the baseline coefficient of 0.443, the fully adjusted coefficient is approximately 14.0% smaller. This attenuation indicates that longer hours and nonstandard work periods explain part of the psychological-distress gap among on-call workers, but

not most of it. In other words, the time-boundary pressure embodied in the requirement to remain available cannot be fully captured by “how many hours were actually worked,” supporting Hypothesis H2b.

Notably, weekly hours and night-work frequency are themselves significantly and positively associated with CES-D, whereas weekend work is not statistically significant in the full specification. This pattern suggests that night work may intrude more directly on rest and sleep-related recovery than weekend work. Nevertheless, the central conclusion does not depend on the significance of any single working-time indicator; it rests on the relative stability of the on-call coefficient after multiple conventional working-time measures enter the model jointly.

Panel C examines income compensation. On-call work is significantly and positively associated with the logarithm of labor income, with a baseline coefficient of 0.063. After weekly hours, night work, and weekend work are added, the coefficient remains 0.054 and statistically significant at the 1% level. Given the small log-point magnitude, the result is best interpreted as a modest income premium associated with on-call jobs rather than as substantial compensation. Combined with Panel B—where income is negatively associated with psychological distress but the on-call coefficient does not fall after income is controlled—the results reveal a structure in which economic returns and psychological costs coexist: income has a protective association with psychological distress, but it is insufficient to offset the psychological cost of constant availability. The evidence therefore supports both H3a and H3b.

Table 3. On-Call Work, Intensified Working Time, and Income Compensation

Panel A. On-Call Work and Working-Time Consequences

Variable	Weekly working hours	Night work	Weekend work
On-call work	1.922*** (0.273)	0.654*** (0.036)	0.314*** (0.025)
Observations	14,819	14,819	14,819
R ²	0.148	0.057	0.161
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes

Panel B. Can Conventional Working-Time Measures Explain the Psychological-Distress Gap?

Variable	(1) Baseline	(2) + Weekly hours	(3) + Night work	(4) + Weekend work	(5) + Income
On-call work	0.443*** (0.064)	0.418*** (0.064)	0.381*** (0.064)	0.375*** (0.064)	0.381*** (0.064)
Weekly working hours		0.013*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.011*** (0.002)
Night-work frequency			0.062*** (0.016)	0.059*** (0.016)	0.059*** (0.016)
Weekend-work frequency				0.027 (0.023)	0.027 (0.024)
Log labor income					-0.104***

Variable	(1) Baseline	(2) + Weekly hours	(3) + Night work	(4) + Weekend work	(5) + Income
					(0.029)
Observations	14,819	14,819	14,819	14,819	14,819
R ²	0.114	0.117	0.118	0.118	0.119
Controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes

Panel C. On-Call Work and Income Compensation

Variable	(1) Labor income	(2) + Working-time measures
On-call work	0.063*** (0.019)	0.054*** (0.020)
Weekly working hours		0.005*** (0.001)
Night-work frequency		-0.001 (0.005)
Weekend-work frequency		-0.005 (0.008)
Observations	14,819	14,819
R ²	0.191	0.195
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Province fixed effects	Yes	Yes

Note: Panels A–C use the same common complete-case sample (N = 14,819). Controls include individual and household characteristics and job characteristics, together with year and province fixed effects. Robust standard errors clustered at the individual level are reported in parentheses.

4.3 Standardized Comparisons: Psychological Cost, Working-Time Intensification, and Income Compensation

Because CES-D, working hours, work-frequency measures, and income are expressed in different units, Table 4 standardizes each dependent variable within survey year to permit comparison of the conditional associations across outcomes. The strongest association is between on-call work and night work (0.321 standard deviations), followed by weekend work (0.211 standard deviations). The associations with CES-D and weekly hours are 0.118 and 0.115 standard deviations, respectively, whereas the association with labor income is only 0.050 standard deviations. These results further indicate that the most pronounced empirical features of on-call work are nonstandard-hours work and stronger time-boundary encroachment, while the relative magnitude of income compensation is small. Placing these outcomes on a common scale reveals how a single work-arrangement characteristic is simultaneously related to multiple outcomes in different directions and of different magnitudes, providing a common metric for the subsequent discussion of compensation and nonmonetary costs.

Table 4. Standardized Associations of On-Call Work with Psychological, Time, and Income Outcomes

Variable	CES-D	Weekly hours	Night work	Weekend work	Labor income
On-call work	0.118*** (0.017)	0.115*** (0.016)	0.321*** (0.017)	0.211*** (0.017)	0.050*** (0.016)
Observations	14,819	14,819	14,819	14,819	14,819
R ²	0.113	0.148	0.057	0.161	0.187
Controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes

Note: Dependent variables are standardized within survey year. All models control for individual and household characteristics, job characteristics, year fixed effects, and province fixed effects; standard errors are clustered at the individual level. Coefficients are expressed in standard-deviation units.

4.4 Robustness Checks

To assess whether the baseline findings depend on a particular survey year, measure of psychological distress, fixed-effects structure, sample composition, or control specification, five sets of robustness checks are conducted. All checks retain the on-call work–psychological distress relationship as the central focus and, where possible, preserve the same control framework used in the baseline model. The results are summarized in Table 5.

4.4.1 Estimates by Survey Year

First, the model is estimated separately for the 2020 and 2022 samples. The on-call coefficients are 0.350 and 0.398, respectively, and both are statistically significant at the 1% level. The direction and magnitude are similar across the two years, indicating that the baseline result is not driven by a particular survey wave or macro-level environment. Because each specification uses a single-year cross section, these two columns include province fixed effects but not year fixed effects.

4.4.2 Alternative Measures of Psychological Distress

Second, to reduce dependence on the specific CES-D8 scale, the analysis uses standardized CES-D20 and $\ln(\text{CES-D} + 1)$ as alternative dependent variables. The corresponding on-call coefficients are 0.094 and 0.055, both significant at the 1% level. Although coefficients are not directly comparable across different scales and transformations, the direction and statistical significance of the focal variable remain unchanged, indicating that the main result is not an artifact of the particular scale used to measure psychological distress.

4.4.3 More Stringent Province-by-Year Fixed Effects

Third, separate year and province fixed effects are replaced with province-by-year fixed effects, which absorb common economic, labor-market, and public-health shocks experienced by each province in each survey year. The on-call coefficient is 0.374, remains statistically significant at the 1% level, and is very close to the coefficient of 0.381 in the fully adjusted main specification. Thus, province-level time-varying common shocks are unlikely to account for the positive association between on-call work and psychological distress.

4.4.4 Balanced Panel Sample

Fourth, to reduce concerns that entry into and exit from the analytical sample change its composition, the sample is restricted to workers observed in both 2020 and 2022. In this balanced panel, the on-call coefficient is 0.281 and remains statistically significant. Although smaller than in the fully adjusted pooled model, the coefficient does not change sign and is consistent with the attenuation observed in the individual fixed-effects estimates. This suggests that some cross-sectional differences may reflect individual selection, but the main relationship does not disappear.

4.4.5 Control Specification and Sample Definition

Finally, robustness is assessed with respect to both control variables and sample selection. Because self-rated health and psychological distress may respond to common contemporaneous health shocks, the model is re-estimated without self-rated health; the on-call coefficient is 0.378 and is virtually unchanged. The analysis then uses the maximum available baseline sample rather than the strict common complete-case sample, yielding an on-call coefficient of 0.439, again significant at the 1% level. These results indicate that the baseline finding is not mechanically generated by the inclusion of self-rated health or by the common-sample restriction.

Table 5. Robustness Checks

Variable	2020	2022	CES-D20 (z-score)	ln(CES-D + 1)	Province × year FE	Balanced panel	Excluding health control	Maximum sample
On-call work	0.350*** (0.087)	0.398*** (0.088)	0.094*** (0.016)	0.055*** (0.012)	0.374*** (0.065)	0.281*** (0.088)	0.378*** (0.067)	0.439*** (0.064)
Weekly working hours	0.012*** (0.003)	0.011*** (0.003)	0.003*** (0.001)	0.002*** (0.000)	0.011*** (0.002)	0.011*** (0.003)	0.012*** (0.002)	
Night-work frequency	0.064*** (0.022)	0.056** (0.022)	0.015*** (0.004)	0.013*** (0.003)	0.060*** (0.016)	0.065*** (0.023)	0.076*** (0.017)	
Weekend-work frequency	-0.000 (0.031)	0.056* (0.032)	0.006 (0.006)	0.007 (0.005)	0.028 (0.024)	0.016 (0.032)	0.043* (0.024)	
Log labor income	-0.089** (0.040)	-0.115*** (0.042)	-0.026*** (0.007)	-0.013** (0.005)	-0.103*** (0.030)	-0.039 (0.043)	-0.121*** (0.032)	
Observations	7,292	7,527	14,819	14,819	14,819	8,150	14,819	14,994
R ²	0.123	0.118	0.118	0.104	0.122	0.109	0.052	0.115
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	—	—	Yes	Yes	—	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	—	Yes	Yes	Yes
Province × year fixed effects	No	No	No	No	Yes	No	No	No

Note: Columns (1) and (2) use single-year samples and therefore do not include year fixed effects. Column (5) absorbs province-by-year fixed effects. Columns (1)–(7) are estimated using the fully adjusted control framework, whereas Column (8) uses the maximum available baseline sample. Except in Column (8), working-time and income measures are the same as in the main specification. Standard errors are clustered at the individual level.

4.5 Heterogeneity Analysis

To identify whether the psychological cost of on-call work differs across groups of workers, the analysis conducts subgroup regressions along four dimensions—partner status, education, age, and social ties—and formally tests differences in coefficients across groups. For a more concise and intuitive presentation of these differences, Figure 1 reports the on-call coefficients and their 95% confidence intervals for each subgroup.

4.5.1 Differences by Partner Status

By partner status, the estimated on-call coefficient is 0.367 for workers with a partner and 0.548 for workers without a partner; both are significant at the 1% level. The association is therefore stronger among workers without a partner. One possible explanation is that a stable partnership can provide emotional support, help with daily responsibilities, and a buffer against stress. Without this source of support, impaired recovery and work–life boundary intrusion associated with constant availability may translate more directly into psychological strain.

4.5.2 Differences by Education

By education, the on-call coefficient is 0.364 among workers with higher education and 0.505 among those without higher education, with both estimates significant at the 1% level. The results indicate a stronger psychological association among workers with lower educational attainment. Higher education is often associated with stronger occupational choice, bargaining power, and job autonomy, which may provide workers with more resources to manage on-call demands. By contrast, lower-educated workers are more likely to occupy jobs with less autonomy and greater replaceability, making the requirement to “remain available” more likely to operate as a unilateral organizational demand on their time and therefore to entail greater psychological costs.

4.5.3 Differences by Age

The age pattern is distinctly nonlinear. The coefficient is largest among workers younger than 25 (0.703), compared with 0.394 among those aged 25–55 and 0.528 among those older than 55. All three estimates are positive, with the association particularly pronounced among the youngest workers. This pattern may reflect differences across career stages. Younger workers are typically at the stage of labor-market entry and early career accumulation, when work boundaries are less settled, performance-signaling pressures are stronger, and bargaining power is weaker, making immediate responsiveness harder to refuse. Middle-aged workers may have greater experience and job control, whereas older workers may face additional constraints related to recovery capacity and health vulnerability when exposed to nonstandard work periods and constant responsiveness.

4.5.4 Differences by Social Ties

With respect to social ties, the on-call coefficient is 0.610 among workers with weaker social ties and 0.366 among those with stronger social ties, with both estimates significant at the 1% level. The stronger association among workers with fewer social resources is consistent with a social-support buffering mechanism: stronger social ties may provide emotional support, information, and assistance with everyday stress, thereby mitigating the psychological impact of constant availability. When social support is weaker, workers may be more likely to bear alone the pressures created by work intruding into nonwork time. Overall, the heterogeneity results indicate that the psychological costs

of on-call work are not evenly distributed, but are more concentrated among workers with weaker social support, fewer educational resources, and more vulnerable career-stage boundaries.

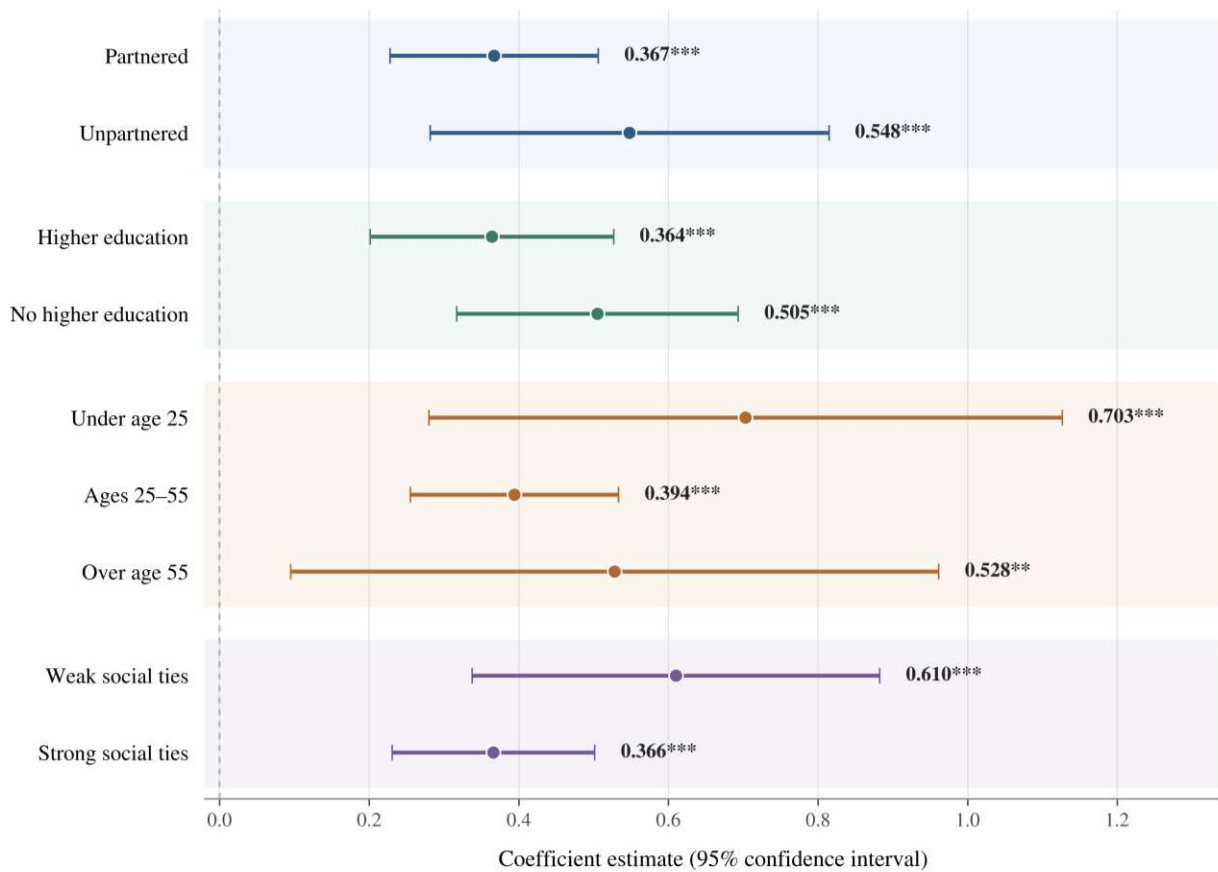


Figure 1. Subgroup Estimates of the Association between On-Call Work and Psychological Distress

Note: Points represent the subgroup regression coefficients on on-call work, and horizontal lines indicate 95% confidence intervals. Partner groups are defined by whether respondents are married or cohabiting; education groups are defined by whether respondents have received higher education; age is divided into under 25, 25–55, and over 55; and social-tie groups are based on self-rated interpersonal relations. Formal tests of between-group coefficient differences were also conducted, and the relevant differences are statistically significant. The figure is used solely to present the subgroup point estimates and confidence intervals more concisely and intuitively.

4.6 Further Results and Boundary Conditions

If on-call work simply represented a generally “low-welfare job,” it should reduce most measures of subjective well-being. Table 6 shows that the pattern is more complex: on-call work is significantly and positively associated with happiness, life satisfaction, and confidence in the future; it is weakly negatively associated with subjective job quality and weakly positively associated with overall job satisfaction. This apparently contradictory combination helps define the scope of the main conclusion.

CES-D measures the frequency of depressive affect and related symptoms over the previous week and is therefore closer to a measure of recent psychological distress. Happiness, life satisfaction, and confidence in the future reflect broader cognitive evaluations and may simultaneously be shaped by income, occupational status, employment opportunities, and family resources. Because on-call jobs are associated with higher income and stronger labor-market

attachment, it is entirely possible for workers to experience greater recent psychological distress while not evaluating their life or future more negatively overall. In other words, the results identify a specific psychological cost of constant availability rather than a uniform decline across all dimensions of subjective well-being.

These boundary results also caution against extrapolating the CES-D findings into a claim that on-call workers are generally less happy with life. A more precise conclusion is that, conditional on a range of individual and job characteristics, on-call work is associated with greater recent psychological distress; at the same time, economic returns and other occupational benefits may sustain relatively favorable evaluations on some broader subjective well-being measures.

Table 6. Further Results: Other Subjective Well-Being and Job-Evaluation Outcomes

Variable	Happiness	Life satisfaction	Confidence in the future	Subjective job quality	Overall job satisfaction
On-call work	0.165*** (0.034)	0.087*** (0.015)	0.110*** (0.015)	-0.023* (0.012)	0.026* (0.014)
Observations	14,814	14,817	14,813	14,819	14,819
R ²	0.112	0.119	0.097	0.149	0.087
Controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes

Note: All models control for individual and household characteristics, job characteristics, weekly working hours, night work, weekend work, labor income, year fixed effects, and province fixed effects; standard errors are clustered at the individual level. Because the directions of the results differ across outcomes, these estimates should be interpreted as a boundary analysis rather than as repeated confirmation of a single “welfare loss” conclusion.

5 Occupational AI Exposure and Constant Availability

The development of artificial intelligence may change not only how workers perform tasks but also the boundary between work and nonwork time. This possibility is especially relevant for workers who must remain constantly available. Occupations characterized by greater digitalization and AI exposure often have stronger information-transfer and remote-response capacities, making it easier for work to extend into nights, weekends, and other nonstandard periods. At the same time, AI-related technologies may change the time, methods, and resources required to complete tasks, so the same availability requirement may carry different psychological costs across occupations. Building on the preceding analysis of the overall consequences of on-call work, this section examines whether occupational AI exposure moderates its psychological and temporal consequences.

AI exposure is measured at the occupational level. This approach follows the central logic of the occupational-exposure literature, which assesses potential technological exposure by matching AI capabilities to the tasks or ability requirements embedded in occupations. The AI Occupational Exposure (AIOE) measure developed by Felten, Raj, and Seamans (2021), for example, links advances in AI applications to occupational abilities, while more recent generative-AI measures evaluate the correspondence between occupational tasks and large-language-model capabilities (Eloundou et al., 2024; Gmyrek et al., 2025). Following this approach, the occupational AI-exposure score is matched to the occupation information in the survey and standardized, with higher values indicating greater potential exposure. Importantly, this measure captures occupational technological exposure rather than workers' actual use of AI. The analysis should therefore be interpreted as heterogeneity across technological contexts, not as an estimate of the effect of individual AI adoption.

5.1 AI Exposure and the Psychological Cost of Constant Availability

Table 7 examines whether occupational AI exposure changes the relationship between constant availability and psychological distress. The coefficient on on-call work remains positive and statistically significant throughout, whereas the interaction between on-call work and AI exposure is negative and statistically significant. The interaction coefficient is -0.103 in Column (2) and becomes -0.123 after realized working-time measures are added in Column (3), while remaining statistically significant. Thus, although constant availability is generally associated with greater psychological distress, this psychological penalty is weaker in more AI-exposed occupations, and the difference is not readily explained by variation in realized working time.

Table 7. Occupational AI Exposure and the Psychological Cost of Constant Availability

	(1)	(2)	(3)
Variable	CES-D	CES-D	CES-D
On-call work	0.425*** (0.060)	0.467*** (0.064)	0.402*** (0.065)
AI exposure	-0.223*** (0.029)	-0.174*** (0.039)	-0.097** (0.040)
On-call work $\times$ AI exposure		-0.103** (0.052)	-0.123** (0.052)
Working-time controls	No	No	Yes
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	15,266	15,266	15,266
R ²	0.098	0.098	0.105

*Note: AI exposure is standardized at the occupational level. Robust standard errors clustered at the individual level are reported in parentheses. All specifications include the controls and fixed effects indicated in the table. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

5.2 AI Exposure and the Temporal Consequences of Constant Availability

Table 8 further examines whether occupational AI exposure changes the temporal consequences of constant availability. Panel A shows that on-call work is significantly associated with longer weekly hours and more frequent night and weekend work. Panel B indicates that the interaction between on-call work and AI exposure is not statistically significant for weekly hours but is positive and significant for both night and weekend work. In more AI-exposed occupations, constant availability therefore appears primarily as a stronger extension of work into nonstandard periods rather than as a further increase in total weekly hours.

This result contrasts with the preceding finding for psychological distress: higher occupational AI exposure strengthens the encroachment of on-call work into nights and weekends while weakening its psychological penalty. Temporal intrusion alone may therefore be insufficient to explain the psychological burden associated with constant availability; the nature of that intrusion may also differ across occupational contexts.

One possible interpretation is that more AI-exposed occupations tend to involve greater digital connectivity, information processing, and remote-response capacity. Increases in night or weekend work may therefore not imply an equivalent increase in physical recall, continuous overtime, or loss of control. Some nonstandard-hours work may take the form of brief replies, remote processing, information retrieval, or task coordination. Although such activities blur temporal boundaries, their psychological burden per episode may differ from that of conventional overtime.

A second possibility is that AI-related technologies change how workers respond to job demands. Even when constant availability remains, intelligent tools may reduce the response costs of some information-processing, communication, and routine tasks. Work interruptions could consequently become more frequent while requiring less time or cognitive effort per interruption. More frequent boundary crossings would not then necessarily translate proportionately into greater psychological strain.

These explanations remain possible mechanisms inferred from the observed pattern rather than directly tested channels. The data do not reveal workers' actual use of AI, the specific form of response tasks, or their degree of work autonomy; the results therefore do not establish that AI itself has a buffering effect. More cautiously, they suggest that occupational AI exposure may change the form of constant availability, making it more likely to involve dispersed digital responses during nonstandard hours. The translation of such temporal intrusion into psychological distress may be weaker than under long, continuous, or rigid overtime arrangements.

Table 8. Constant Availability, AI Exposure, and Working-Time Consequences

Panel A. On-Call Work and Working-Time Consequences			
Variable	Weekly hours	Night work	Weekend work
On-call work	1.922*** (0.273)	0.654*** (0.036)	0.314*** (0.025)
Observations	14,819	14,819	14,819
R ²	0.148	0.057	0.161
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Panel B. AI Exposure and the Temporal Consequences of Constant Availability			
	(1)	(2)	(3)
Variable	Weekly hours	Night work	Weekend work
On-call work	1.780*** (0.281)	0.651*** (0.035)	0.285*** (0.024)
AI exposure	-3.263*** (0.170)	-0.121*** (0.021)	-0.389*** (0.015)
On-call work × AI exposure	0.302	0.076***	0.095***
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	15,163	15,276	15,239
R ²	0.129	0.059	0.149

*Note: Panel A reports the overall working-time associations of on-call work. Panel B adds standardized occupational AI exposure and its interaction with on-call work. Robust standard errors clustered at the individual level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

6 Discussion

6.1 Main Findings

This study asks whether modern workers sell not only their working hours but also their availability. Using CFPS data from 2020 and 2022, the analysis yields four main findings.

First, on-call work is consistently associated with higher psychological distress. The association remains positive after extensive controls and becomes smaller but persists in the individual fixed-effects models, suggesting that it is not fully explained by observed characteristics or stable individual differences. Second, on-call work is associated with longer weekly hours and more frequent night and weekend work, yet these conventional working-time measures explain only a limited portion of the psychological-distress gap. This supports the distinction between actual working time and availability time. The latter captures the extent to which nominally nonwork time must remain reserved for potential job demands, interruptions, and uncertain calls to work. Third, on-call jobs are associated with higher labor income, but this economic premium does not offset the psychological cost. Moreover, the income effect becomes statistically insignificant in the individual fixed-effects models, suggesting that the cross-sectional premium may partly reflect differences in job level, skills, or organizational responsibility rather than an immediate wage gain from entering an on-call arrangement. Fourth, occupational AI exposure marks an important boundary condition: it is associated with a weaker psychological penalty of constant availability even as on-call work extends more strongly into nights and weekends. This contrast indicates that technological context may change how temporal intrusion translates into psychological strain.

6.2 Policy Implications

Working-time governance should extend beyond formally recorded hours to workers' actual discretion over nonwork time. For jobs requiring frequent availability, organizations should specify on-call periods, response expectations, and genuine emergency boundaries rather than treating continuous reachability as the default.

Rules governing after-hours communication are also important. Rather than prohibiting all communication outside regular hours, organizations can distinguish urgent from non-urgent matters, use delayed sending for routine messages, establish clear duty rotations, and avoid treating immediate response as an implicit performance criterion. Finally, compensation for constant availability should not rely solely on pay. Monetary rewards can be complemented by protected rest periods, backup-duty arrangements, and stronger recovery support, particularly where night work and repeated disruption of nonwork time are common.

6.3 Limitations and Directions for Future Research

Several limitations remain. First, on-call status is not randomly assigned. Although the analysis includes extensive controls and individual fixed effects, time-varying unobserved factors cannot be fully ruled out, so the results should not be interpreted as strict causal effects. Second, only the 2020 and 2022 CFPS waves are available

for the present analysis. The fixed-effects estimates therefore rely on a relatively limited number of workers who change on-call status, reducing statistical power. Longer panels or clearer institutional shocks would strengthen future identification. Third, the data do not directly measure psychological detachment, after-hours communication, sleep interruption, response deadlines, or perceived control over availability demands. Future studies could combine survey data with digital communication records or diary-based measures to examine these mechanisms more directly. Fourth, the occupational AI-exposure measure captures technological potential rather than workers' actual adoption or use of AI. The interaction estimates should accordingly be interpreted as differences across occupational contexts, not as causal effects of AI use.

Finally, different dimensions of subjective well-being do not necessarily move together. The additional results suggest that constant availability may coexist with both psychological pressure and certain perceived benefits. Future research could therefore adopt a broader multidimensional job-quality framework.

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