Job Conditions and Workers' Wellbeing in the New Economy: A Comparison of Food Delivery and Retail Workers in China

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Abstract

This study examines the differential impacts of various working conditions on the mental and physical health of low-wage workers in two types of occupations–food delivery and retail–in China. Online survey data of 686 respondents, collected through snowball sampling, is utilized for this study. Using OLS regression models, my analysis shows that food delivery workers consistently reported a higher level of physical fatigue and worse health compared to retail workers. Further analysis indicates that the lack of fixed eating times, late-night working hours, and greater encounters with customer complaints and physical attacks explain food delivery workers' worse health outcomes than retail workers. Interestingly, income and the level of fluctuation in income account for little of the mental health differences between workers of the two occupations. Taken together, findings from this research suggest changing working conditions in the new economy contribute to heightened physical and mental health risks for food delivery workers. These results underscore the need for policy interventions that address occupational health disparities within emerging labor sectors.

Introduction

The US economy experienced dramatic changes since the 1970s. In the past, the industrial and manufacturing sectors were in the dominant positions in the US labor market. However, with the gradual outsourcing of the labor force to overseas factories, the domestic industries tilt to produce services instead of products. With such a transition, the gig economy begins to capture a share of the US labor market. The gig economy, in this research paper, refers to the economy that comprises short-term independent freelance workers (Kuhn, 2016) who provide the requested service given by on-demand companies and are compensated for the jobs (Dunn, 2018). The gig work exhibits rapid growth. There were 57 million freelance workers in 2019, contributing to 5% of the U.S. Gross Domestic Product (Rodriguez, 2021). The COVID-19 pandemic has once again given a boost to the gig economy, skyrocketing the demand for gig services, such as home delivery services. Individuals who lose jobs also turn to gig work (Rodriguez, 2021). According to a statistical report, there were around 3 million new workers in the gig economy during the pandemic (Garin, 2023). Within the gig economy, prior literature has drawn attention to the health situation of gig workers. The research conducted by Rodriguez indicates a strong correlation between the working conditions of gig workers and cardiovascular risk (Rodriguez, 2021). Precarity, including unpredictable and unstable working schedules, as one of the working conditions of gig workers, is shown to be strongly associated with psychological distress, poor sleep quality, and unhappiness (Schneider, 2018). The relatively low wages earned by gig workers also reveal a positive relationship with poor health outcomes (Schneider, 2018). Additionally, these gig workers are usually vulnerable to working injuries and lack of medical care due to the unofficial labor contract signed with the company.

Scholars have explored the operational dynamics and structural underpinnings of food delivery work, examining how companies leverage new technologies to exploit labor and undermine workers' rights. Others have focused on the health and safety challenges inherent in the food delivery sector. However, among the various influencing factors, there is still no comprehensive and structured analysis of the degree of importance of these factors, and researchers do not build connections between the algorithm system and the health consequences. Additionally, instead of simply examining food delivery workers, this study employs a comparative methodology that compares the health situation of food delivery workers and retail workers. Many studies that only examine food delivery workers would find it hard to tell whether it is the way the food delivery industry operates or generally the overall low-paid workers. Using a comparison, it is more visualized to see the influence of the unique characteristics of food delivery workers' working environment on their health. Thus, this study aims to connect these operational frameworks to resultant health outcomes, visualizing and quantifying to what extent and specifically which is the most influencing factor within this new type of working mechanism that affects the health condition and social network relationship of food delivery workers, compared to retail workers.

Gig Economy in China

Similar to the labor structure in the United States, the gig economy in China also contains a large amount of freelancers in the low-wage labor markets. The workers in these two countries are commonly classified as self-employed without signing labor contracts (International Labour Office, 2020). In the United States, if the number of self-employed workers continues to grow, the majority of workers will be in such status by 2027 and over 92 percent of the platform workers in China are self-employed (International Labour Office, 2020). Other than the similar classification of workers to avoid extra costs for employers in these two countries, Chinese companies have developed some more exploitative and strict management algorithms and strategies to supervise platform workers, which will be discussed in the following sections. Because of the different social and economic contexts, the impact of algorithms and company management on platform workers in the two countries will be different. In the following sections, the unique manipulation of algorithms in China will be discussed.

Within the Chinese gig economy, the fastest-growing digital labor platform is the "location-based platform", which includes the ride-hailing service platform and the food delivery service platform (International Labour Office, 2020).

The rise of the platform economy has catalyzed the merging of online food delivery services, creating a novel paradigm for labor organizations in China. The unemployment tide caused by the pandemic has attracted a large proportion of individuals to the food delivery market. The advertisement of high wages, low level of entry barrier, schedule flexibility, and simple job contents are the main driving forces that attract workers. As reported by the All-China Federation of Trade Union, the total number of food delivery workers will be over 13 million by the end of 2023. With the increasing popularity and prosperity of the food delivery industry, the working situation and the management of these food delivery workers have been brought to the public. Prior research indicates food delivery workers experience stress, anxiety, and physical injuries during work. According to research conducted in Shanghai, 46% of the participants reported anxiety symptoms, and 18% reported depression symptoms (Peng, 2022). In research on delivery drivers, over 95% of them reported a high fatigue level and experienced frequent occupational stress in their daily lives (Lin, 2021). The negative impacts have been further exacerbated after the outbreak of the pandemic, leading to increasing health risks, a larger economic burden, and stricter governmental regulations. Given such a phenomenon, scholars try to delve into the real culprit behind it. Bérastégui summarizes the factors that influence psychological health into three dimensions: physical and social isolation, algorithmic management and digital surveillance, and work transience and boundaryless careers.

In this research, I build upon the work of previous investigators who have identified a range of influencing factors. I categorize these factors into three major sections: The exploitation of online algorithms, the outdoor working environment, and social isolation and unequal treatment, which are the factors that this study aims to analyze using the linear regression model. The objective is to determine the relative significance and different impacts of these factors on the food delivery workers' physical fatigue level and mental health situation.

The following sections will introduce the two major types of working mechanisms of food delivery workers and describe how the company uses the online operational system to manage and control these delivery workers. Additionally, the literature on the relationship between food delivery jobs and the health effects and the operation of online algorithms will be summarized. Finally, an outline and structure of this research paper will be provided.

Exploitation of Online Algorithm

The food delivery workers are mainly divided into two types: crowdsource workers ("Zhongbao") and specialized full-time workers. The Crowdsource workers, by its name, are independent contractors who enjoy some freedom to decide when and where to work (Chan, 2021). They are able to refuse orders assigned by the systems and do not need to wear uniforms. These workers usually obtain a high level of autonomy. The specialized full-time riders are directly employed by the platform and are directly under its management. To maintain the number of contractors working and make them work more hours, although the platform cannot directly force or ask these workers to work for a longer time, the platform indirectly achieves this by using the online algorithm. Subsidies are an important method. The platform will often set up incentives or subsidies to attract riders to take orders. Those subsidies usually occur on high-temperature or rainy days, during lunch rush hours, late nights, and on weekends. The rewards are cumulative, and to get the highest bonus, delivery workers need to spend a longer time working. According to a survey conducted in Beijing in 2021, among 300 delivery workers in cities across China, about 40% said they had not had a day off in a month. Long hours and low pay are issues still facing the industry today (Kawakami, 2024). Therefore, data-driven game-based tactics (rankings, rating) are used to monitor workers and “encourage workers to willingly engage in their own exploitation” (Huang, 2023). Such control of the algorithm is possibly one contributing factor to the health situation of food delivery workers.

Other than the required long working hours, to maximize the time capital, the company sets strict delivery times for food delivery workers. The data suggests that the average delivery time for food delivery orders across the industry in 2019 was 10 minutes less per order than it was three years ago (Liu, 2022). The consequences of late arrival are immense: half of the wage for that order will be deducted, or workers face the risk of receiving complaints or bad reviews from customers, both of which could pose a serious threat to their jobs (Jiang, 2021). Thus, food delivery workers frequently sustain worries and anxiety while sending orders because of the strict and limited time requirement imposed by the platform. Such long-lasting anxiety can contribute to the worse mental health situation of these workers. Chen also found out that the time pressure imposed on food delivery workers has a positive relationship with mental stress during work (Chen, 2023).

A following side effect of the time pressure is the increasing number of risky behaviors. In order to arrive on time, these workers have no choice but to ignore the traffic regulations. One worker said in an interview, “When there are more than five orders, they should go into ‘death mode,’ which means ignoring all traffic rules, but this inevitably leads to tickets and fines, and even safety concerns (Liu & Friedman, 2021). It is worth mentioning that since crowdsource workers sign labor contracts with the labor agency instead of the major employee, these workers cannot obtain basic labor rights and compensation when they get injured or encounter emergencies. Of the four cases of labor dispute about “LePao” riders, none of them were found in the court that the two sides “exist in the labor relationship” (Yin, 2021). The increasing economic burden of medical fees and the inability to afford them worsen the physical and mental health situation.

Combined, the various techniques the platform used exhibit more stringent but invisible control over these workers and more imbalance of power control to exploit these workers in order to maximize the time capital. Although the platform uses an online algorithm to extend daily working hours, the workers still experience a high level of precarity and unpredictable working schedules due to the characteristics of this occupation. The salary is counted on a task-by-task basis, and the number of orders they can have is largely dependent on external factors, such as weather, traffic, the algorithm designed by the platform, and the number of food delivery workers working that day. With that in mind, the research conducted at Harvard concludes that unstable and unpredictable work schedules are associated with poor physical and mental health outcomes through the "pathway of sleep" and other forms, such as lack of exercise, obesity, smoking, and the effect of the unpredictability is even stronger than that of wages (Schneider, 2019). Therefore, in this case, delivery workers' autonomy, followed by irregular working schedules, makes them more prone to high levels of fatigue and other mental health problems brought on by work than other gig workers who usually have fixed working arrangements.

Working Environment

Prior research in the field of workers' mental health has found a significant correlation between the working environment and adverse mental health outcomes. These findings underscore the pronounced mental health challenges experienced by food delivery workers, largely attributable to their working conditions.

Due to the job characteristics of food delivery workers, they mostly spend their working hours outdoors and doing physical labor. Long-time exposure to UV light, extreme weather conditions, traffic accidents, and heavy lifting make them more vulnerable to the heightened risks of physical and occupational hazards, which in turn are closely associated with symptoms of stress and depression (Tran, 2022). More than mental influence, physical damage is also prevailing. A report published in 2022 said that the fatality rate among food delivery workers was 36 deaths per 100,0000 workers per year (Mayorquin, 2024).

Additionally, in the aforementioned section, these workers often work at times when they should be off, such as meal times and bedtime. With no fixed and regular working space, there are no basic facilities provided for these workers, such as restrooms and a place to rest. Therefore, in China, it is common to see those workers sitting in the street or sleeping on their tiny, crowded electric bikes.

Social isolation and unequal treatment

Since food delivery workers manage or complete their work individually, they need help getting in contact with other colleagues. A collaborative working community is necessary for delivery workers to obtain support or socialize with their colleagues. Even though workers experience physical isolation, they do not escape from the competition with coworkers. The unique algorithm of "grabbing order" turns the colleagues into competitors, increasing mental pressure and restraining the opportunity to have support. The "grabbing order" operates in a way that many delivery workers will try to accept one order at the same time, and the one who is the first to notice this new order will get the order. Although workers are in different physical spaces, they compete in the same virtual space, "resulting in a silent but intense fight" (Li, 2022). Grabbing a profitable and easy-to-deliver order is a huge success, which means they can earn more money but spend less time. Such an order-grabbing mechanism induces fierce competition among food delivery workers and invisibly increases their pressure and anxiety.

In addition, the public categorizes food delivery workers as a low-skilled labor force with little respect and support. According to a video posted on Weibo, when the blogger tried to enter a shopping mall in Beijing with his delivery uniform, he was turned away, and the security guard said, ‘You can't get in wearing the delivery uniform.’ (Shen, 2021). Many neighborhoods in China also prevent food delivery workers from entering the neighborhood, or the delivery worker can only enter from the back door. In some office buildings, delivery workers may only use designated elevators and must be separated from those working in the office building. So during peak ordering times, you can see an empty elevator with no one lined up next to it and a long line of delivery people waiting to get on the elevator. Such intended social segregation undoubtedly puts the delivery person in an inferior social position, presenting an inequality of power structure.

Retail workers

Retail workers are the group of workers who are employed by an offline business and engaged in the sale of products in a fixed working environment. Retail workers and food delivery workers both belong to working-class jobs with low pay and sometimes without health care benefits (Kenton, 2021). Low pay, erratic working schedules, and monotonous working tasks largely influence retail workers’ mental and physical health while working. Additionally, the development of e-commerce largely changes buying habits across China and poses a threat to supermarkets in terms of price and convenience. Retail workers who work in supermarkets experience the flow of unemployment with no compensation and, therefore, endure a high level of precarity and unpredictability in their working positions. The Suning and Carrefour China closed down in 2022, but the company had not made payments to workers' social security or housing provident funds or given the proper amount of compensation according to the labor contract (China Labor Bulletin, 2023). Retail workers who work in supermarkets or small businesses have fixed incomes and working hours each week, and they sign official labor contracts with the employees directly. However, the strict regulations impose inadequate and unequal working policies for these workers. Walmart China implemented a “comprehensive working hours system,” allowing the company to adjust the working hours based on needs and reduce the overtime and other benefits of retail workers (China Labor Bulletin, 2023). Retail workers and food delivery workers in the low-wage labor market both experience unequal treatment and imbalanced power dynamics that continue to exploit their basic labor rights. Research is now needed to investigate both these two groups of workers’ working situations and improve their working conditions.

Data and Methods

The dataset for the analysis comes from the self-reported survey completed by participants working in the food delivery and retail sectors. Two distinct online surveys, specifically tailored to food delivery and retail workers, were designed and spread via a professional survey and questionnaire platform known as "Wenjuanxing" in China.

While retail workers typically operate within structured environments characterized by fixed working schedules and physical spaces, food delivery workers contend with a different set of working conditions. Despite these disparities, both cohorts share similar levels of educational attainment and skill sets, rendering them comparable subjects for analysis.

Since the retail industry includes various forms of retail workers, in this study, I narrowed down the focus and only collected data from retail workers in the service sector, mainly staff from large supermarkets and pharmacies.

Thus, the comparison is needed here as the different operational logic in these two different labor fields leads to different physical and mental health outcomes, allowing us to identify which aspects of the labor mechanism will lead to a larger impact.

	Food Delivery Workers	*Retail Workers*
Fixed income per month	X	√
Fixed working schedule	X	√
Indoor working environment	X	√
With colleagues presented while working	X	√
Requirement on punctuality	√	X
Labor contract with employees	X	√

Table 1. Food delivery workers vs. Retail Workers

Snowball sampling was used to collect survey data. I placed online orders and directly invited the delivery workers to participate in the survey in Chengdu and Hangzhou. Many of these workers were part of small group chats with other food delivery workers on social media platforms, and then I asked them to disseminate the survey among their colleagues. For retail workers, I contacted the managers of a chain supermarket in Tianjin province and a chain pharmacy named "Tianxing Jian" in Chengdu province. These managers assisted in distributing the questionnaires to their employees and encouraged them to share the survey within their networks. Since snowball sampling was used, I set the range of the survey collection to be all provinces in China.

The snowball sampling process commenced on January 5, 2024, and concluded on February 5, 2024. A cash incentive of ¥20 was provided to each respondent upon completing the questionnaire. The online survey was responded in Mandarin and subsequently translated into English. In total, 326 valid responses from food delivery workers and 360 from retail workers were collected, predominantly from the provinces of Chengdu and Hangzhou in China.

The analysis has two main outcomes: the work-related fatigue score and the general mental health score for food delivery and retail workers. To evaluate the extent of the fatigue, I incorporated Schwartz's Fatigue Assessment Inventory (FAI) and the Fatigue self-evaluation system designed for couriers in China by Lin (Lin, 80). With five response categories, 17 questions are included, such as “At work, I feel mentally exhausted,” or “Everything I do at work requires a great deal of effort,” or “After a day at work, I find it hard to recover my energy.” Valid answers to these 17 questions were converted into a numeric variable running from 1 (the least frequent of experiencing such symptom) to 5 (the most frequent of experiencing such symptom) by recoding “Never” as 1, “Rarely” as 2, “Sometimes” as 3, “Often” as 4, and “Always” as 5, and then summing up to take the mean (Cronbach’s alpha=0.91). General mental health well-being was evaluated using the Chinese version of the Burnout Assessment Tool (BAT-C), using 5-point scale answers as well. The items in BAT-C include the evaluation of exhaustion, mental distance, cognitive impairment, and emotional impairment. I similarly coded all the items in the same direction, with a higher value indicating worse mental health, and then averaged the responses to construct the variable (Cronbach’s alpha=0.89).

In the dataset, I first created a dummy variable to differentiate food delivery workers from retail workers, along with their responses to the survey. Our major research question is which work conditions account for the differences in work-related fatigue and mental health between these two types of workers. To answer this question, based on the prior literature review, I created a series of possible predictors concerning work schedules (working hours, working flexibility, and late night shifts), work environment (rest location, rest time, and eating time), employer demand (required meetings), and customer interactions (attacks, and complaints). The variables that indicate income and income fluctuation are also included because some of the work-related stress could be caused by the instability of income.

Working-environment factors

The working-environment factors comprise factors of the work type (delivery or retail), fixed eating time during work, time to nap during work, frequency of late night working, work hours per day, fixed rest location during work, and fluctuation in Income. Fixed eating time and rest location are treated as dummy variables, with 1 corresponding to Yes and 0 corresponding to No. The frequency of late-night work specifically refers to the frequency per month for these workers to work from 10 pm to 5 am at night. This variable was categorized into five groups: Never, Rarely, Sometimes, Often, and Always. Fluctuation in income measures the difference in income per month among these workers. This variable was divided into five groups as well; a difference of less than ¥500 per month, a difference of ¥500- ¥1000 per month, a difference of ¥1000- ¥1500 per month, a difference of ¥1500- ¥2000 per month, a difference of more than ¥2000.

Employer-demand factors

As employer-demand factors, I used survey questions that are related to the employers' instructions and requirements for workers, including the rotated shifts arranged by employers and the required meetings before work every day. The rotated shifts arranged by employers specifically mean that workers need to follow the company's arrangement of working hours. The required meeting before work refers to whether workers need to attend a meeting organized by employers before going to work. These two variables are regarded as binary questions where 1 corresponds to Yes and 0 corresponds to No.

Interpersonal factors

Interpersonal factors take the factors related to socialization into consideration, such as customer complaint frequency and frequency of language attacks/physical attacks encountered. Customer complaint frequency is the frequency of complaints received by customers per month. The responses to these two questions are also categorized into 5 groups: Never, Rarely, Sometimes, Often, and Always.

Our model also controls for a series of variables that could shape mental health outcomes, including age, education, gender, number of children at home, number of elders to support, marital status, and Hukou Status. Age was classified into five categories: below 18, 18-30 years, 31-40 years, 41-50 years, and 51-60 years. Education level was also divided into five groups: less than high school diploma, high school diploma or equivalent, junior college, bachelor's degree, master degree or above. The number of children to raise is divided into four groups ranging from 0 to 3. The number of elders to support ranges from 0 to 4 and above. Hukou status refers to the workers' original place of domicile. It is classified as either an agricultural account or a non-agricultural account. Income was divided into five categories: below 3000, 3000-5000, 5000-7000, 7000-10000, 10000, and above.

Table 2 Socio-demographic characterstics of food delivery and retail workers

Variables	Food delivery workers		Retail workers	
	N	%	N	%
Gender				
Male	295	90.49	87	24.17
Female	31	9.51	273	75.83
Age groups				
Below 18	8	2.45	24	6.67
18-30	180	55.21	179	49.72
31-40	106	32.52	94	26.11
41-50	25	7.67	51	14.17
51-60	7	2.14	12	3.34
Educational Level				
Less than high school diploma	94	29	54	15
High school diploma or equivalent	145	44.48	84	23.33
Junior college	62	19.02	136	37.78
Bachelor's degree	20	6.13	85	23.61
Master degree or above	5	1.53	1	0.28
Martial Status				
Married	116	35.58	177	49.17
Single	201	61.66	172	47.78
Others	9	2.76	11	3.06
Place of domicile				
Agriculture account	258	79.14	233	64.72
Non-agriculture account	68	20.86	127	35.28
Number of children				
0	209	64.11	183	50.83
1	69	21.17	105	29.17
2	42	12.88	66	18.33
3 or above	6	1.84	6	1.67
Elder to support				
0	78	23.93	107	29.72
1	37	11.35	29	8.06
2	149	45.71	125	34.72
3	24	7.36	30	8.33
4 or above	38	11.66	69	19.17

Table 2 Socio-demographic characteristics of food delivery and retail workers

Prior to implementing the OLS regression model, the correlation matrix for all independent variables was calculated to assess multicollinearity. Variables exhibiting a high correlation coefficient (greater than 0.8) were combined to mitigate multicollinearity concerns. In this study, the correlation coefficients for the independent variables range from -0.594 to 0.523, indicating a low to moderate level of correlation. This range suggests that the variables do not exhibit strong collinearity, implying that each independent variable uniquely contributes to explaining the variability in the dependent variable without significant redundancy.

	Work Hours/Day	Late Night Working	Time to Nap during Work	Fixed Eating Time during Work	Income level	Income flucutation level	Fixed Rest Location during Work	Customer Complaint Freq	Language Attack/Physical Attack Encountered Freq	Rotate Shifts Arranged by Employers	Required Meeting Before Work Everyday
Work Hours/Day	1.000										
Late Night Working	0.155	1.000									
Time to Nap during Work	-0.158	-0.074	1.000								
Fixed Eating Time during Work	-0.044	-0.176	0.146	1.000							
Income level	0.363	0.095	0.045	0.087	1.000						
Income flucutation level	0.254	0.212	0.029	-0.017	0.327	1.000					
Fixed Rest Location during Work	0.037	0.232	-0.176	-0.334	-0.013	0.011	1.000				
Customer Complaint Freq	0.079	0.189	-0.078	-0.233	0.052	0.170	0.124	1.000			
Language Attack/Physical Attack Encountered Freq	0.024	0.166	-0.006	-0.189	-0.019	0.084	0.137	0.411	1.000		
Rotate Shifts Arranged by Employers	0.327	-0.060	-0.021	0.143	0.259	0.129	-0.146	-0.013	-0.060	1.000	
Required Meeting Before Work Everyday	0.064	-0.140	0.021	0.215	-0.100	-0.042	-0.272	-0.102	-0.051	0.404	1.000

Table 4. Correlation matrix of independent variables

Analytic strategy

Ordinary least squares (OLS) regression models are employed for the analysis. . Given a dataset with observations (x_i, y_i), where x_i are the predictors and y_i are the response variables, the linear relationship can be expressed as:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$$

Here, β_0 and β_1 are unknown regression coefficients, and ϵ_i represent the $n \times 1$ vector of errors. By adding additional independent variables each time, I calculate the percentage change in the dependent variable and get the final conclusion of which independent variable is more important.

Results

Table 5 presents the OLS regression modeling predicting the fatigue scores of workers.

Table 5. OLS Regressions of Work Related Fatigue Score

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Delivery work (ref. = Retail work	0.342**	0.340**	0.194**	0.194**	0.189**	0.135+	0.137+
	(0.049)	(0.069)	(0.070)	(0.071)	(0.071)	(0.071)	(0.071)
Gender		-0.033	-0.094	-0.111+	-0.113+	-0.106	-0.096
		(0.066)	(0.065)	(0.065)	(0.065)	(0.064)	(0.064)
Hukou		-0.024	-0.040	-0.043	-0.044	-0.038	-0.036
		(0.056)	(0.054)	(0.054)	(0.054)	(0.053)	(0.053)
Age		0.018	0.015	0.014	0.012	0.020	0.015
		(0.035)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Number of elder to support		0.045*	0.035+	0.035+	0.035+	0.026	0.026
		(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Number of children to raise		-0.090**	-0.096**	-0.101**	-0.107**	-0.113**	-0.110**
		(0.038)	(0.037)	(0.037)	(0.037)	(0.036)	(0.036)
Marital status (ref = divorced)							
Marital status: Married		0.116	0.110	0.102	0.091	0.094	0.099
		(0.148)	(0.142)	(0.142)	(0.142)	(0.139)	(0.139)
Marital status: Single		0.044	0.032	0.023	0.011	0.009	0.014
		(0.146)	(0.140)	(0.140)	(0.140)	(0.138)	(0.138)
Education level (ref = master degree and above)							
Less than high school diploma		-0.051	-0.069	-0.036	-0.003	-0.022	-0.008
		(0.266)	(0.255)	(0.255)	(0.256)	(0.252)	(0.252)
High school diploma or equivalent		-0.088	-0.091	-0.055	-0.021	-0.059	-0.047
		(0.264)	(0.253)	(0.254)	(0.254)	(0.250)	(0.251)
Junior college		-0.092	-0.071	-0.039	-0.007	-0.034	-0.025
		(0.265)	(0.255)	(0.255)	(0.256)	(0.252)	(0.252)
Bachelor's degree		0.003	-0.015	0.009	0.040	0.024	0.035
		(0.269)	(0.259)	(0.259)	(0.259)	(0.255)	(0.255)
Work Hours/Day			0.047	0.037	0.037	0.031	0.036
			(0.031)	(0.032)	(0.032)	(0.032)	(0.032)
Late Night Working			0.146**	0.136**	0.132**	0.113**	0.111**
			(0.026)	(0.027)	(0.027)	(0.026)	(0.027)
Time to Nap during Work			-0.006	-0.010	-0.020	-0.007	-0.012
			(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Fixed Eating Time during Work			-0.230**	-0.226**	-0.200**	-0.145**	-0.141*
			(0.052)	(0.052)	(0.055)	(0.055)	(0.055)
Income level				0.0001	0.001	0.001	-0.001
				(0.025)	(0.025)	(0.025)	(0.025)
Income flucutation level				0.048+	0.049+	0.038	0.041
				(0.027)	(0.027)	(0.026)	(0.026)
Fixed Rest Location during Work					0.086+	0.082	0.057
					(0.053)	(0.052)	(0.054)
Customer Complaint Freq						0.147**	0.145**
						(0.037)	(0.037)
Language Attack/Physical Attack Encountered Freq						0.056	0.059
						(0.038)	(0.038)
Rotate Shifts Arranged by Employers							0.001
							(0.063)
Required Meeting Before Work Everyday							-0.092+
							(0.051)
Constant	1.595**	1.599**	1.518**	1.481**	1.311**	1.118**	1.176**
	(0.033)	(0.304)	(0.306)	(0.306)	(0.324)	(0.321)	(0.328)

Notes: +p < 0.1, *p < .05; **p < .01 (two-tailed tes

Table 5. OLS Regression of Work-Related Fatigue Score

Model 1 indicates a significant difference in fatigue scores between food delivery workers and retail workers. food delivery workers reported a significantly higher level of physical fatigue. Model 2 incorporated sociodemographic variables, including age, gender, place of domicile, number of children to raise, number of elders to support, marital status, and educational level. In model 2, adding the sociodemographic variables does not affect the gap in fatigue between retail and delivery workers since 0.58% is very close to 0.

Model 3 introduces four work-environment-related variables. Workers who had longer working hours reported a fatigue score of 0.047 points higher for each additional hour worked per day than those without such hours. Workers with longer late-night working hours tend to have a fatigue score that is 0.146 points higher than those workers with fewer late-night working hours. Workers who have less time to nap during work reported a fatigue score that is 0.006 higher than those with more time to nap during work. Similarly, workers without fixed eating time during work show a fatigue score that is 0.23 points higher than those with such hours. Among these statements, the latter two, which are related to late-night working hours and fixed eating time, are statistically significant, highlighting their essential association with fatigue levels. In this model, retail workers reported a lower level of fatigue than delivery workers compared to Model 2, indicating that these work-environment factors significantly explain the fatigue differences.

In Model 4, income and income fluctuation levels are added. Workers with higher incomes showed a fatigue level of 0.0001 points higher than those with lower incomes, indicating a very weak effect of income on the difference between the fatigue scores. Workers with more income fluctuation per month reported a fatigue score that is 0.048 points higher than those with less income fluctuation. The statistical significance of late-night working and fixed eating time persists. In this model, with two more variables added, retail workers still reported a lower level of fatigue than delivery workers, which indicates little effect of income and income fluctuation on the difference in the decline among food delivery and retail workers.

Model 5 includes the variable for having a fixed rest location during work. Workers with fixed rest locations during work reported a fatigue level that is 0.086 higher than those without a fixed rest location. Retail workers reported a fatigue level that is 0.0258 points lower than that of delivery workers compared to Model 4, while late-night working and fixed eating time remain statistically significant.

In Model 6, the customer-related variables are added, which are the customer complaint frequency and the frequency of experiencing language or physical attacks. Workers who encounter a higher frequency of customer complaints indicate a fatigue level that is 0.147 points higher than those with a lower frequency of customer complaints. Retail workers reported a fatigue level that is 0.2858 points lower than that of delivery workers compared to Model 5, and the p-value increases slightly, falling between 0.1 and 0.05. The variables of late-night working and fixed eating time continue to be statistically significant.

In Model 7, the two variables related to the employer's requirement are added. Retail workers reported a fatigue level that is 0.0148 points lower than that of delivery workers compared to Model 6. This means that rotating shifts and required meetings before work are more prevalent in retail work than in food delivery work. The variable "Customer Complaint Frequency," "Late Night Working," and "Fixed Eating Time" all retain their statistical significance, with p-values smaller than 0.05.

Across Model 1 to Model 7, retail workers continuously report a lower fatigue score than the food delivery workers but experience a slight increase in Model 7. After calculating the percentage drop, I observed that the transition from Model 2 to Model 3 led to the largest difference in fatigue levels between food delivery workers and retail workers, which is a difference of 0.4294 points. The large difference suggests that a significant portion of the mental health disparity between food delivery and retail workers is explained by these four work condition variables. This implies that these work conditions are major factors contributing to the mental health differences observed between the two groups.

Table 6 presents the OLS regression model predicting work-related mental health scores. The sequence of variables added from Model 1 to Model 7 mirrors that of the prior analysis on fatigue levels.

Table 6. OLS Regressions of Work Related Mental Health Score

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Delivery work (ref. = Retail work	0.214**	0.311**	0.212**	0.214**	0.209**	0.156*	0.163*
	(0.052)	(0.074)	(0.075)	(0.076)	(0.076)	(0.075)	(0.076)
Gender		-0.026	-0.065	-0.081	-0.082	-0.067	-0.057
		(0.071)	(0.069)	(0.070)	(0.070)	(0.068)	(0.068)
Hukou		-0.008	-0.022	-0.024	-0.026	-0.021	-0.019
		(0.059)	(0.058)	(0.058)	(0.057)	(0.056)	(0.056)
Age		0.031	0.036	0.036	0.033	0.039	0.036
		(0.037)	(0.036)	(0.036)	(0.036)	(0.035)	(0.035)
Number of elder to support		0.037+	0.032	0.032	0.032	0.019	0.019
		(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)
Number of children to raise		-0.062	-0.076+	-0.081*	-0.087*	-0.091*	-0.089*
		(0.040)	(0.039)	(0.039)	(0.039)	(0.038)	(0.039)
Marital status (ref = divorced)							
Marital status: Married		0.318*	0.304*	0.295+	0.284+	0.284+	0.289+
		(0.157)	(0.152)	(0.152)	(0.152)	(0.148)	(0.148)
Marital status: Single		0.244	0.217	0.206	0.194	0.192	0.197
		(0.156)	(0.151)	(0.151)	(0.194	(0.146)	(0.146)
Education level (ref = master degree and above)							
Less than high school diploma		0.136	0.169	0.200	0.236	0.262	0.281
		(0.282)	(0.273)	(0.274)	(0.274)	(0.268)	(0.268)
High school diploma or equivalent		0.134	0.177	0.212	0.274)	0.248	0.267
		(0.280)	(0.271)	(0.272)	(0.272)	(0.266)	(0.266)
Junior college		0.174	0.235	0.264	0.299	0.317	0.333
		(0.282)	(0.273)	(0.273)	(0.274)	(0.267)	(0.268)
Bachelor's degree		0.263	0.294	0.316	0.350	0.381	0.397
		(0.286)	(0.277)	(0.277)	(0.278)	(0.271)	(0.271)
Work Hours/Day			-0.018	-0.026	-0.025	-0.033	-0.032
			(0.033)	(0.035)	(0.035)	(0.034)	(0.034)
Late Night Working			0.156**	0.147**	0.143**	0.114**	0.114**
			(0.028)	(0.028)	(0.029)	(0.028)	(0.028)
Time to Nap during Work			-0.056+	-0.059*	-0.051+	-0.058*	-0.061*
			(0.029)	(0.029)	(0.029)	(0.028)	(0.028)
Fixed Eating Time during Work			-0.175**	-0.170**	-0.142*	-0.076	-0.072
			(0.056)	(0.056)	(0.058)	(0.058)	(0.058)
Income level				-0.007	-0.006	-0.006	-0.009
				(0.027)	(0.027)	(0.026)	(0.027)
Income flucutation level				0.051+	0.052+	0.042	0.045
				(0.029)	(0.029)	(0.028)	(0.028)
Fixed Rest Location during Work					0.093	0.090	0.069
					(0.057)	(0.055)	(0.057)
Customer Complaint Freq						0.116**	0.115**
						(0.039)	(0.039)
Language Attack/Physical Attack Encountered Freq						0.158**	0.161**
						(0.040)	(0.040)
Rotate Shifts Arranged by Employers							0.036
							(0.067)
Required Meeting Before Work Everyday							-0.086
							(0.054)
Constant	1.554**	1.379**	1.070**	1.316**	0.850*	0.546	0.564
	(0.033)	(0.297)	(0.328)	(0.299)	(0.347)	(0.341)	(0.348)

Notes: +p < 0.1, *p < .05; **p < .01 (two-tailed tests)

Table 6. OLS Regression of Work-Related Mental Health Score

Model 1 only shows the difference between the food delivery workers and the retail workers in that the food delivery workers reported a work-related mental health level that is 0.214 points higher than that of retail workers. Transitioning to Model 2, which incorporates seven sociodemographic variables, increases the difference between food delivery workers and retail workers by 0.4532 points. Such a large difference in mental health scores suggests that these sociodemographic variables (age, gender, place of domicile, number of children to raise, number of elders to support, marital status, and educational level) exhibit an effect on work-related mental health. This large difference suggests that these sociodemographic factors were previously masking the full impact of job type on mental health scores.

In Model 3, work-environment-related variables are introduced. Among these variables, "Late-night working hours" and "Fixed eating time" are statistically significant, underscoring their crucial association with mental health scores. Retail workers reported a work-related mental health level that is 0.3183 points lower than that of delivery workers compared to Model 2.

Model 4 adds income-related variables, leading to a 0.214 points difference between the food delivery and retail workers, indicating that these income-related factors also obscure the full effect of job type on mental health. "Late-night working hours" and "Fixed eating time" continue to be statistically significant.

In Model 5, the inclusion of the variable of "Fixed rest place during work" results in a 0.0239 points difference between the food delivery and retail workers while "Late-night working hours" and "Fixed eating time" remain statistically significant.

Model 6 introduces customer-related variables: "Customer Complaint Frequency" and "Language Attack/Physical Attack Encountered Frequency." The result indicates that encountering a higher frequency of customer complaints and language attacks is correlated with worse work-related mental health situations. After adding these two variables, retail workers reported a work-related mental health level that is 0.2536 points lower than that of delivery workers. In this model, having fixed eating time does not have a significant correlation with mental health scores.

In Model 7, the difference between food delivery workers and retail workers is 0.0448 points higher than in the previous model. In this model, “Time to nap during work” and “Late-night working hours” are statistically significant, but “Fixed eating time” does not retain its statistical significance. Additionally, “Customer Complaint Frequency” and “Language Attack/Physical Attack Encountered Frequency” continue to be statistically significant.

Conclusion

Based on the analysis using the OLS regression model on the physical fatigue level and general mental health of food delivery workers and retail workers separately, this research draws some new insights into the contributing workplace factors to health outcomes. With little prior research on the comparison between retail workers and food delivery workers, current data reveals that food delivery workers faced harsher working conditions compared to their retail counterparts, which provoked the following negative impacts on the mental health situation and fatigue brought by work. This effect, while pronounced in initial models, diminishes slightly with the inclusion of sociodemographic variables and other work-related factors, suggesting that job type alone does not fully capture the underlying dynamics of health disparities. Further models show the effect of other variables on the health situation.

In two models, with the inclusion of work-environment-related variables, the coefficient of “Job type” experienced the most significant decline, which suggests that these variables significantly account for the difference in both fatigue scores and mental health scores between food delivery and retail workers. This suggests that irregular eating times, higher frequency of late-night working, less time to nap or take lunch breaks, and prolonged working hours per day significantly worsen the physical and mental health of food delivery workers. The consistent statistical significance of “Fixed Eating Time” and “Late Night Working” across various models underscores their crucial association with health scores. Fixed eating times have a protective effect, as regular breaks and meal times reduce work-related stress, anxiety, and fatigue. This finding aligns with prior research that highlights the importance of a regular working schedule for retail workers, emphasizing regularity and predictability in the labor market.

On the other hand, frequent customer complaints, frequent language, and physical attacks by customers exhibit a meaningful and strong relationship with the mental health scores for both food delivery and retail workers. With a higher frequency of customer complaints and attacks, the health challenges are exacerbated. Behind the significant impact of customer complaints on workers' mental and physical health is the regulation and control of the company. In the aforementioned literature, the bad reviews from customers lead to serious consequences for food delivery workers, such as reduced wages and decreased ranking in the platform algorithm, which leads to further disadvantaged positions in accepting orders. Customer reviews and experiences play a crucial role in pay or job evaluation criteria for both food delivery and retail workers, making customer complaints significantly detrimental to their mental and physical health.

One limitation of this research is the relatively small sample and its implication for generalizability. The sample size for each labor group is approximately 300, which may limit the reliability and precision of the conclusions and patterns observed. Furthermore, the samples were drawn mainly from two provinces in China. The varying stages of economic development and socioeconomic contexts across different provinces may produce differing outcomes. Therefore, an increasing number of samples and a more targeted sample population are necessary to enhance the precision and reliability of the findings.

In Tables 5 and 6, the analysis shows that working conditions ultimately explain about half of the differences in fatigue and mental health between food delivery workers and retail workers (between Models 2 to 7). While this highlights the significant impact of working conditions, it also suggests that other factors contribute to these differences. The social support systems available to these workers might differ. Food delivery workers, who typically work independently, may lack the camaraderie and support that retail workers, who work in team environments, might experience. This lack of social support can contribute to feelings of isolation and mental health challenges. Also individual characteristics such as age, education level, and personal coping mechanisms could also play a role in these differences.

This research contributes significantly to the evolving dialogue on occupational health, particularly in understanding how the online algorithm and the gig economy influence worker well-being. By recognizing the particular challenges faced by food delivery and retail workers, targeted interventions can be developed to enhance both their mental and physical well-being, ultimately leading to more sustainable and productive work conditions.

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