# Time Poverty and Hidden Hunger: Food Delivery Riders in Nanjing, China

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## Abstract

The rapid expansion of platform-based food delivery has made gig-economy riders essential actors in urban food provisioning, even as they contend with long working hours and substantial employment precarity. To date, there has been limited research on riders' own food security and household dietary diversity. This paper examines both the direct and indirect mechanisms through which their work hours influence dietary outcomes using data from a 2024 survey of migrant food-delivery riders in Nanjing, China. The paper shows that time poverty associated with long work hours directly diminishes dietary diversity by constraining the time available for other activities, including food acquisition and preparation. However, it also indirectly enhances dietary diversity by raising household income. Because the detrimental time-related effect surpasses the positive income effect, the overall impact of extended work hours is a reduction in household dietary diversity. Therefore, the paper deepens understanding of the nutritional consequences of structural time poverty in the precarious gig economy and provides the first evidence from China on the pathways linking delivery work to household dietary diversity.



## Keywords

Migration, food security, time allocation, dietary diversity, food delivery, China

## Suggested Citation

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## Cover Image

Food-delivery riders wait for order pickup in Chongqing, China, on January 4, 2025. Photo credit: Cynthia Lee/Alamy

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## Introduction

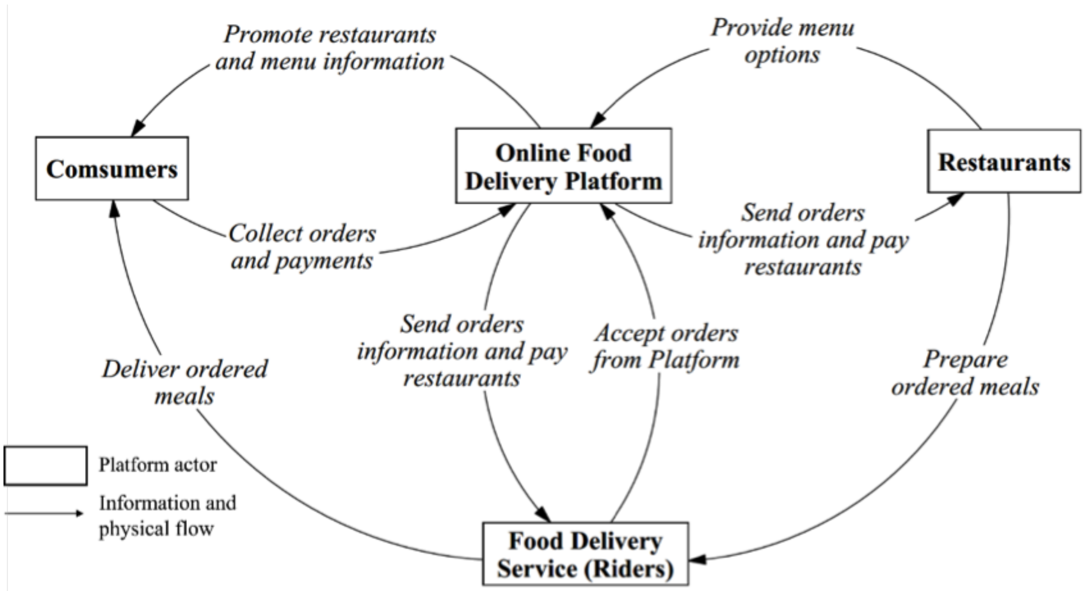
Driven by the rise of digital labour platforms, flexible employment models, and new technologies, the gig economy has expanded rapidly worldwide in recent years, particularly in countries with low entry barriers and large labour supplies such as China (ILO, 2021; Li et al., 2020). Within the broader gig economy, the food delivery sector, including both grocery delivery and ready-to-eat meal delivery, has been one of the fastest-growing segments, signalling a fundamental shift in the urban food system landscape as consumers increasingly favour on-demand, app-based home delivery over traditional dine-in restaurants (Mahmuda et al., 2020; Meemken et al., 2022). This shift to online food ordering has been further accelerated by the COVID-19 pandemic, driven by lockdowns and social distancing measures implemented across cities worldwide (Ahuja et al., 2021; Poon & Tung, 2024). Food delivery platforms contributed greatly to urban food systems and food security during the pandemic (Amicarelli et al., 2021; Wang et al., 2022). For example, a 2022 multi-country study conducted in Australia, Canada, Mexico, the UK, and the US found that 58% of adults used online retail and delivery platforms, while 36% ordered meals online from restaurants (Bennett et al., 2025). Consumers satisfied with their online food-ordering experiences have likely continued using these services post-pandemic (Sharma et al., 2023). Researchers predict that revenues in the food-delivery industry will continue to grow at an estimated rate of 9.3% in the coming years (Melián-González, 2022).

Accompanying the shift towards online food ordering has been the exponential growth of popular food delivery companies, such as DoorDash and Uber Eats, as well as in China, Meituan and Ele.me. Their intense competition has driven down prices and further bolstered the sector's growth. With policy support, these online food delivery platforms have become a key force in ensuring the resilience and efficiency of food supply chains in the post-pandemic era (Yu et al., 2022). By integrating AI, algorithms, the internet, fintech, instant communication, and geolocation technologies, these platforms collect consumer orders through apps and pass them to restaurants and delivery riders (also known as electric scooter or motorbike couriers), thereby facilitating a new power dynamic among the three groups (Figure 1). In this new hierarchical power structure, on the one hand, delivery riders arguably gain freedom from flexible working hours (Yu et al., 2022). On the other hand, the platforms are at the core of the power structure, exerting control over all informational and financial exchanges in the ecosystem (Li & Qi, 2022). This shift towards online food delivery services is not only transforming consumer practices but also reshaping the urban food environment, generating new forms of labour demand and posing new challenges for development policies (Chen & Sun, 2023; Talamini et al., 2022; Zheng & Wu, 2022).

China has emerged as both the fastest growing and the largest food delivery market worldwide, leading in sales volume, user base, and total revenue (Xinhua Net, 2025). The scale of the sector in China is reflected in several indicators: over 10 million people had worked as delivery riders and over 540 million people used food delivery apps in 2023; an estimated 56,000 online food orders were delivered every minute in 2025; and the largest company Meituan alone had around 150 million orders on July 12 in 2025 (Jiang, 2025; Xinhua Net, 2025). The enormous size is perpetuated by various socioeconomic changes such as financialization of the platform economy, rapid urbanization, the wide adoption of cellphone and mobile payment system, and changing consumer expectations, habits and trust (Ahuja et al., 2021; Dai et al., 2024; Qi et al., 2024; Poon & Tung, 2024; Reddy & Aradhya, 2020).

Studies in various geographical contexts show both the economic opportunities and the challenges that the gig economy platforms have brought to their workers. The experiences of food delivery riders, who are typically young, male,

**Figure 1: Online Food Delivery Schematic**




*Source: Figure created with assistance of ChatGPT 5.2.*

and of migrant background, revolve around key themes such as earning, orders, tips, flexible schedules, apps, and customers that provide economic opportunities (Saydam et al., 2024). Because a large share of delivery riders are migrants, the job offers a crucial and accessible income-generating opportunity that is otherwise restricted by limited access to formal employment and, in the context of urban China, household registration (*hukou*) barriers (Tang & Hao, 2023). However, researchers have highlighted what they call the "illusion of freedom", where the flexibility and freedom of work promised by platforms masks the algorithmic control that compels workers to maintain punctuality and speed (Li & Jiang, 2022; Wang et al., 2021). Additional challenges facing delivery riders highlighted in existing studies include a lack of social protection, intense competition, and downward pressure on wages (Alauddin et al., 2025). Precarious employment conditions, health vulnerabilities, and lack of welfare measures are also emphasized (Parwez, 2023).

While research on the labour conditions of food-delivery workers and how they contribute to or undermine urban food security continues to grow, far less attention has been paid to their own food security (Hwang et al., 2024; Jia et al., 2022). This is particularly true for migrant food delivery riders in China, despite it having the largest food delivery economy in the world. This gap can obscure the fact that they may themselves struggle to access adequate, nutritious food for various reasons, resulting in what we call the "hidden hunger," which remains largely unrecognized. In fact, a study in Brazil found that food delivery workers, especially those on bicycles, often experience hunger and food insecurity both at work and at home due to low pay and a lack of support from the platform (Daufenback et al., 2025). A review of risk factors and injuries affecting food delivery riders by McKinlay et al. (2022) mentions that the time-pressured work conditions of food delivery also impact workers' eating patterns. Research in Korea found that gig workers were significantly more likely than general workers to eat fewer than three meals per day (Kim et al., 2023). These findings align with those from China, which show that long working hours, intense algorithmic pressure, and tight delivery schedules contribute to irregular meal timing, skipped meals, and reliance on convenience or low-cost foods (Li & Jiang, 2022; Wang et al., 2021).

These studies highlight the significant challenges food delivery riders face in maintaining adequate, healthy diets, but tend to reduce the multidimensional issue of "food security" to a narrow issue of irregular meal timing, and do not examine diet quality more broadly. As a result, the literature offers limited insight into workers' dietary diversity, a key but underexplored dimension of food security that extends beyond meal timing alone, even though irregular meal timing and skipped meals do imply potential compromises in dietary diversity. Moreover, few studies have conducted statistical analyses examining the relationship between food delivery riders' working hours and their household food insecurity. To the best of our knowledge, the limited literature has neither identified the net effect of working hours on food security nor investigated whether working hours exert both positive and negative (i.e., dual) impacts through different pathways.

To address these gaps, this paper analyzes the potential mechanisms linking food-delivery riders' working hours to their household food security and empirically evaluates these relationships using data from a thematic survey of migrant food-delivery riders in Nanjing, China. The City of Nanjing itself is in the east of the country, roughly 300 km northwest of Shanghai and about one hour away by high-speed train. Nanjing's advanced economic status has created favourable conditions for the rapid development of the food delivery economy. Approximately 35% of households in an urban population of 8.4 million (Nanjing Bureau of Statistics, 2025) used a food delivery service in 2022 (Liang, 2023). According to one report, there are 11 major platform companies and about 23,400 takeaway riders in Nanjing, accounting for 2.3% of the total number of riders in China (Jiang & Zhou, 2025; Xu & Hong, 2022). Most food delivery riders are migrants, and three-quarters are from rural areas (Li, 2019).

The first section of the paper analyzes the connections between working hours and food security, with particular attention to dietary diversity. Building on this conceptual foundation, the next section presents a survey of delivery riders conducted by the authors in Nanjing in 2024, outlining the data-collection methods and the variables used in the statistical analysis. The following section presents the survey findings and results of the data analysis, and the paper concludes by discussing the policy implications of the results.

## Conceptual Framework

This section of the paper develops a conceptual framework linking working hours and food security. In particular, we draw on studies that distinguish between paid and unpaid work and offer useful insights into how different forms of time poverty can affect household food security (Martey & Koomson, 2025). An empirical study of the linkage between time poverty and household food insecurity in Ghana identifies the dual effects of time use: unpaid work-induced time poverty increases food insecurity, while paid work-induced time poverty reduces it (Martey & Koomson, 2025). They argue that income and its associated asset accumulation are potential mediating factors, since paid and unpaid work have different impacts on household income, thereby producing opposite effects on food insecurity. The results of this analysis reveal both positive and negative effects of work hours on household dietary diversity.

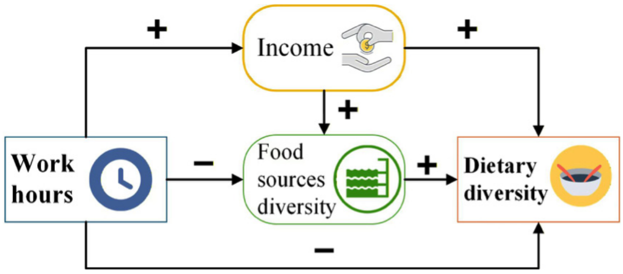
Although longer work hours raise income, which in turn can enhance dietary diversity, the overall net effect is still negative because longer hours reduce the time riders can devote to household food acquisition and preparation. Thus, this study confirms the two-sided nature of the impact of income-generating work hours on household dietary diversity. A study conducted in the US found that the time households spend on food-related activities, such as eating and food preparation, is negatively associated with income (Berning et al., 2023). While time poverty induced by unpaid work significantly contributes to household food insecurity, time poverty induced by paid work can also potentially reduce household food security. This is because a household member's working hours can affect the time available for other responsibilities, including food-related tasks. This pattern echoes broader research on time poverty, which shows that women typically face greater time constraints because they perform most unpaid domestic and caregiving work, while men's time poverty is primarily shaped by paid employment (Rodgers, 2023).

Food-related tasks are commonly categorized as unpaid work, which can be further divided into food-related and non-food-related activities. An increase in time allocated to paid work reduces the time available for unpaid work, thereby decreasing the time available for food-related tasks. Researchers have noted that the heavy time demands of food preparation may discourage individuals from preparing meals (Miller et al., 2023). For working individuals, highly time-demanding work may result in time poverty (Chaudhuri et al., 2021), which in turn influences both individual and household food security (Rao & Raju, 2020). For instance, time poverty reduces women's personal time and thus negatively affects both their own eating practices and those of other family members. Therefore, an increase in work hours can reduce the time available for food-related activities such as meal planning, food shopping, cooking, and eating. Food-related activities can also be grouped into shopping and non-shopping aspects.

Figure 2 illustrates the pathways through which working hours influence household dietary diversity. Working hours can directly impact household dietary diversity through income generation as well as various food-related activities such as planning, cooking, eating, and clean-up. An increase in working hours can reduce the time allocated to these activities which, in turn, can decrease dietary diversity. This "direct" path is labelled *working hours —› dietary diversity*. From a modelling perspective, the "direct" path from working hours to dietary diversity represents a reduced-form relationship that incorporates unobserved mediating mechanisms. Because the survey did not collect detailed data on household time use devoted to these activities, this intermediate mechanism could not be explicitly modelled. The pathway *working hours —› time spent on non-shopping food activities —› dietary diversity* is therefore represented empirically as a direct effect of working hours on dietary diversity, capturing the net influence of unobserved time constraints on household dietary outcomes. Besides the "direct" impact, three indirect pathways through "food sources diversity" and "income" can exist.

Additionally, longer working hours can reduce time allocated to food shopping, which, in turn, diminishes food source diversity and, consequently, dietary diversity. This constitutes an indirect food source diversity pathway labelled *working hours —› food source diversity —› dietary diversity.* An increase in working hours typically translates into greater household income, which is generally associated with lower household food insecurity and improved dietary diversity (Benfica & Kilic, 2016; Nord, 2014; Singh et al., 2020; Zhong et al., 2018). This suggests a third income pathway of *working hours —› household income —› dietary diversity*. Moreover, an increase in household income can also influence its food purchasing patterns, which in turn affect dietary diversity (French et al., 2010). Therefore, a fourth pathway can be identified: *working hours —› household income —› food source diversity —› dietary diversity.*

**Figure 2: Relationship between Working Hours and Dietary Diversity**



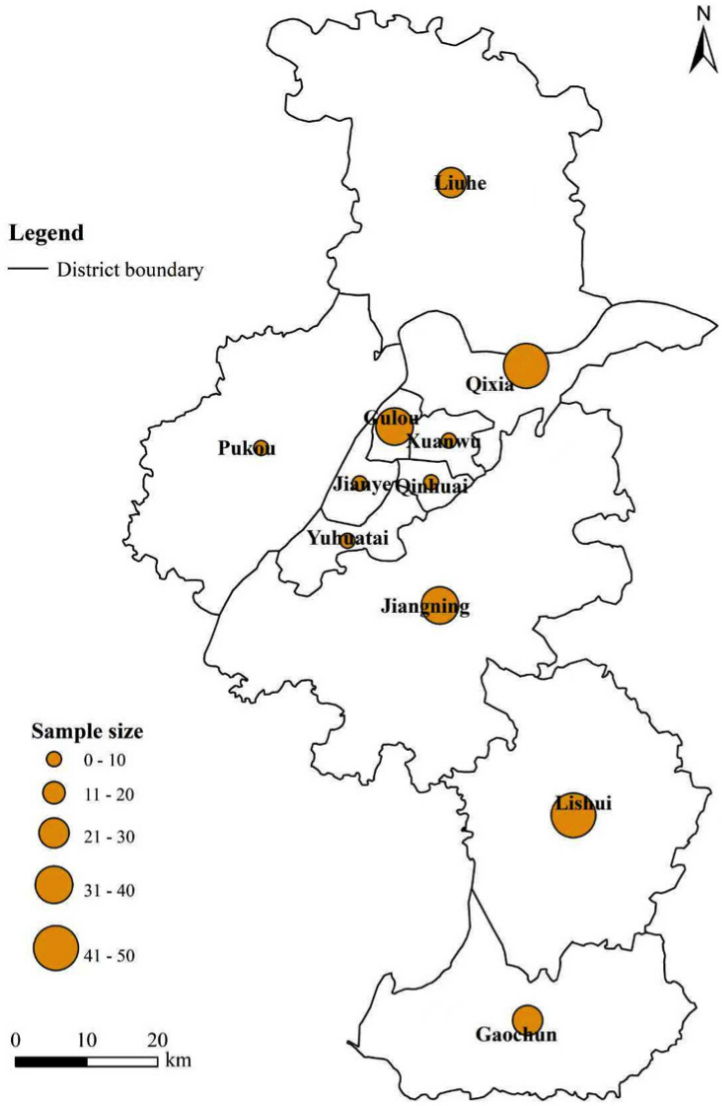

Food security and dietary diversity reflect the combined effects of both time and income constraints, so the net effect of working hours depends on the balance between its positive and negative impacts on household dietary diversity (Aguiar & Hurst, 2005). As illustrated in Figure 2, the four potential pathways linking delivery workers' working hours to their household dietary diversity may involve both negative and positive effects. Although food delivery riders often work long hours, whether this ultimately increases or decreases dietary diversity depends on whether the positive mechanisms outweigh the negative ones.

# Methodology

This paper is based on data from a survey in Nanjing City implemented in September and October, 2024. The survey was administered by trained university students using an online survey platform. All respondents were migrants from other prefectures or from the rural areas of Nanjing. A three-step approach was used to locate and interview migrant food delivery riders in the city. First, 100 residential communities were randomly selected. Second, commercial centres and delivery rider rest stations near each community were identified. Finally, encounter-based sampling was used to recruit respondents in these locations. Migrant delivery riders willing to complete the questionnaire immediately were interviewed on-site. Others registered their information and filled out an electronic version later, with phone numbers used for identity verification. In total, 281 valid samples were obtained. Table 1 shows the distribution of the sample by city district, and Figure 3 shows the spatial distribution across the city.

| Table 1: Migrant Delivery Rider Sample by District | | |
|---|---|---|
| **District** | **No.** | **%** |
| Jiangning | 48 | 17.1 |
| Qixia | 45 | 16.0 |
| Lishui | 41 | 14.6 |
| Liuhe | 29 | 10.3 |
| Gaochun | 28 | 10.0 |
| Gulou | 23 | 8.2 |
| Qinhuai | 10 | 3.6 |
| Xuanwu | 10 | 3.6 |
| Pukou | 9 | 3.2 |
| Yuhuaitai | 6 | 2.1 |
| Jianye | 4 | 1.4 |
| No location data | 28 | 10.0 |
| Total | 281 | 100.0 |

**Figure 3: Distribution of Surveyed Food Delivery Riders in Nanjing**



## Profile of Migrant Food Delivery Riders

The sex ratio of the respondents was highly imbalanced, with 97% of the respondents being men and only 3% women. The age distribution of surveyed delivery riders reveals that the 19-24 cohort formed the largest demographic segment at 28%. Other groups showed gradually decreasing proportions: 25–29-year-olds accounted for 23%, followed by 30–34-year-olds at 22% (Figure 4). Cumulatively, delivery riders aged 35 and under represented three-quarters of all survey respondents. A marked decline appeared in older age brackets. The 35-39 age group accounted for 14%, with progressively smaller percentages in subsequent decades: 40–44-year-olds accounted for 7%, and 45–57-year-olds accounted for only 6%.

There was significant variation in the educational background of the delivery rider workforce (Figure 5). Respondents ranged from those with primary school, junior high school, and senior high school education to those with junior college, university, or even master's or doctoral degrees. However, the top three educational levels were senior high school, junior high school, and junior college, accounting for 44%, 26%, and 18% of respondents, respectively. Those with only a primary school education made up about 2% of the respondents. Overall, delivery riders with education levels below university accounted for nearly 90% of respondents, while those with university or higher education accounted for only 10%.

Most riders lived either alone (27%) or in three-person households (25%) (Figure 6). Additionally, four-person households accounted for 17%, two-person households for 15%, and five-person households for 9% (Figure 6). Few respondents lived in households of six or more people. Overall, 56% of the riders were members of nuclear families (56%), followed by male-centred families (28%), and extended families (13%). Female-centred households were almost negligible.

**Figure 4: Age Group Distribution of Delivery Riders**

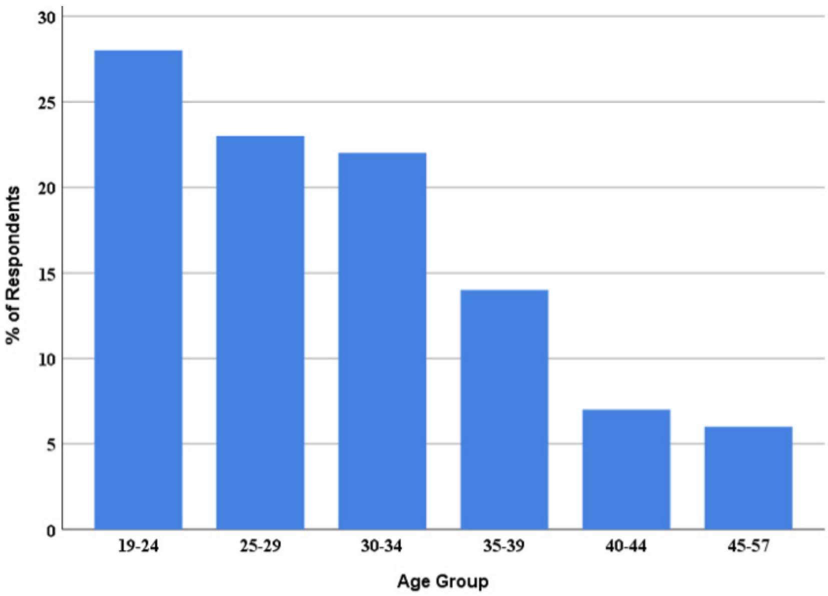



**Figure 5: Education Level of Delivery Riders**

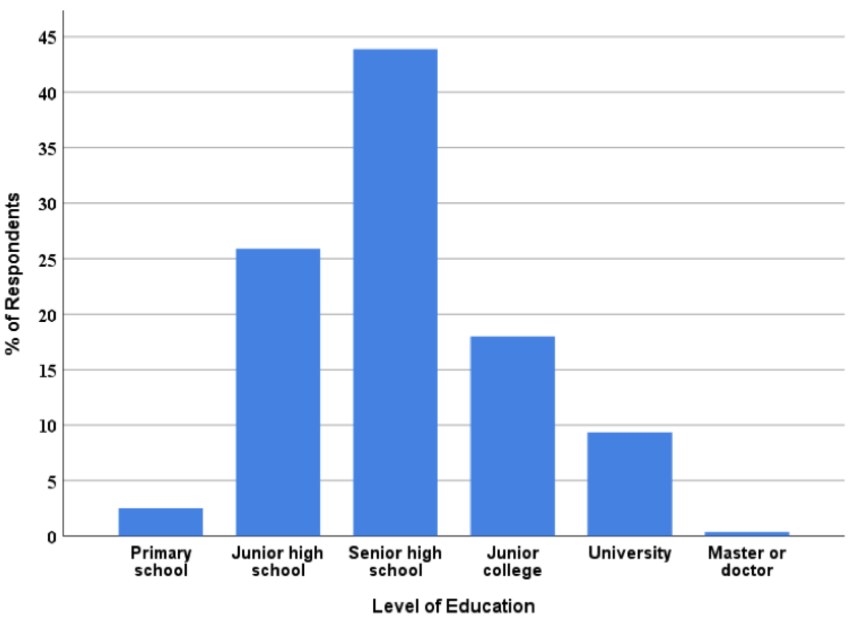
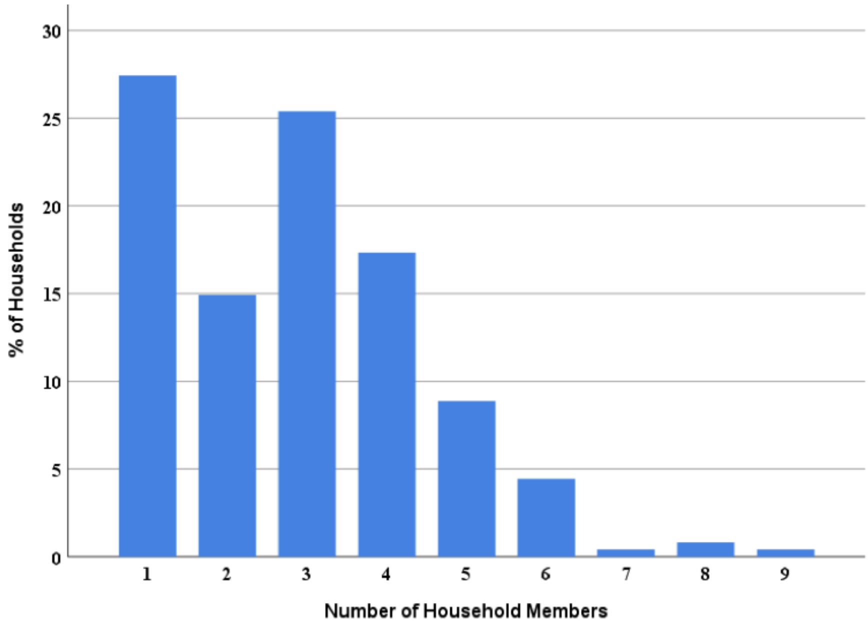


**Figure 6: Household Size among Delivery Riders**




On their migration origins and status, 40% of respondents were born in urban areas of other provinces, while 20% were born in rural areas of other provinces. Additionally, 27% of respondents were from other urban or rural areas within Jiangsu Province (excluding Nanjing). This shows that most delivery riders working in Nanjing were born outside the city, with a sizable portion coming from provinces outside Jiangsu. Only a small proportion of respondents, about 13%, were born within the urban or rural areas of Nanjing itself. However, when comparing delivery riders from outside Nanjing, those from urban areas (56%) outnumbered those from rural areas (31%). This data highlights that the delivery rider workforce in Nanjing is predominantly composed of individuals from other regions, particularly urban areas outside the province.

Almost 77% of the respondents reported not having a Nanjing *hukou* (household registration status). In Nanjing, having a *hukou* gives residents access to the city's comprehensive resources, including employment opportunities, social security, education, and healthcare. In contrast, non-local individuals without a Nanjing *hukou* face greater challenges in accessing these high-quality urban resources. This disparity highlights the structural barriers faced by migrant workers, such as delivery riders, in securing equal access to essential services and opportunities in the city.

## Study Variables

### Dependent Variable

The HDDS was used to assess the dietary diversity of migrant food delivery riders' households (Leroy et al., 2015; Swindale and Bilinsky, 2006). Migrant riders were asked to identify the food items consumed in their households in the previous 24 hours. The HDDS categorizes these items into 12 food groups: (a) cereals, (b) root and tubers, (c) vegetables, (d) fruits, (e) meat, poultry, offal, (f) eggs, (g) fish and seafood, (h) pulses/legumes/nuts, (i) milk and milk products, (J) oil/fats, (k) sugar/honey, and (l) miscellaneous, yielding a score for each household ranging from 0 to 12. (Swindale and Bilinsky, 2006). The variable *hdds* represents the HDDS and served as the dependent variable in the analysis, treated as a count outcome.

### Independent Variables

(a) *Working hours:* Two questions were posed to collect information on the working hours of migrant food delivery riders:

- "How many hours a day did you work as a rider in the last month?"
- "How many days in the last month did you work as a rider?"

Three independent variables measuring riders' working hours were then generated. The variable *dayhour* captures their daily working hours, while *monthday* reflects the number of days they worked in the previous month. The variable *monthhour*, reflecting the total working hours in a typical month, was then generated by multiplying the variables *dayhour* and *monthday*. To assess their level of satisfaction or dissatisfaction with their working hours, the riders were asked: "How satisfied are you with your working hours" with five response options: 1 = dissatisfied, 2 = relatively dissatisfied, 3 = neutral, 4 = relatively satisfied, and 5 = satisfied. These time-use attitudes are captured by the variable *timeusesatis*.

(b) *Income:* Income plays a fundamental role in a household's dietary diversity, and higher income is widely associated with higher food variety (Thiele & Weiss, 2003). The variable *income100* represents the previous month's income of the riders, and the coefficient of the variable is expected to be positive when the HDDS is used as the dependent variable.

(c) ***Food sources:*** Food source diversity is often positively associated with the dietary diversity of mothers and children within a household (O'Malley et al., 2025). In China, the number of food stores is positively associated with the Chinese Food Pagoda Score in rural China (an indicator of food consumption diversity) (Huang & Tian, 2019). Information on food sourcing was collected through the question: "How did your household obtain food in the past six months?". The variable *nsoureces* represents the number of different sources from which a household obtained its food, and the questionnaire listed 26 possible options including supermarket chains, wet markets, small fresh food supermarkets, and vegetable grocery stores (outside of the wet markets). In addition, the number of food sources is commonly positively associated with the amount of time available for food shopping. Because longer working hours could reduce the time riders have to purchase food from multiple sources, month-hour is expected to have a negative coefficient with *nsoureces*. In contrast, higher income could enhance a households' ability to access a wide range of food outlets, so it is reasonable to hypothesize a positive coefficient between *income100* and *nsoureces*.

(d) ***Household size:*** Household size is an important factor influencing household dietary diversity (Berning et al., 2023). Some empirical studies confirm a positive relationship between household size and dietary diversity (Thiele & Weiss, 2003). Others show a negative relation between household size and dietary diversity, especially in low-income countries or regions, suggesting that an increase in household size decreases household dietary diversity (Obayelu & Osho, 2020). The variable *householdsize* represents the number of people in the household. Since Nanjing City is a relatively high-income region, it is expected to have a positive coefficient between *householdsize* and *hdds*. In addition, household size can influence the number of food sources, as larger households have a greater demand for food and are likely to make more trips to food outlets and visit different stores to fulfill more diverse needs (Bawa & Ghosh, 1999). Larger household size could be associated with a larger number of food sources. Therefore, we hypothesize a positive coefficient between *householdsize* and *nsoureces*.

Table 2 provides summary descriptive statistics for the variables used in this study and reveals substantial variation in both HDDS and working hours. The HDDS ranges from a minimum of 1 to a maximum of 12, while daily working hours vary from as few as 2 hours to as many as 18 hours. Monthly income from delivery service work also shows notable variation, ranging from CNY400 (~USD57) to CNY15,000 (~USD2,134).

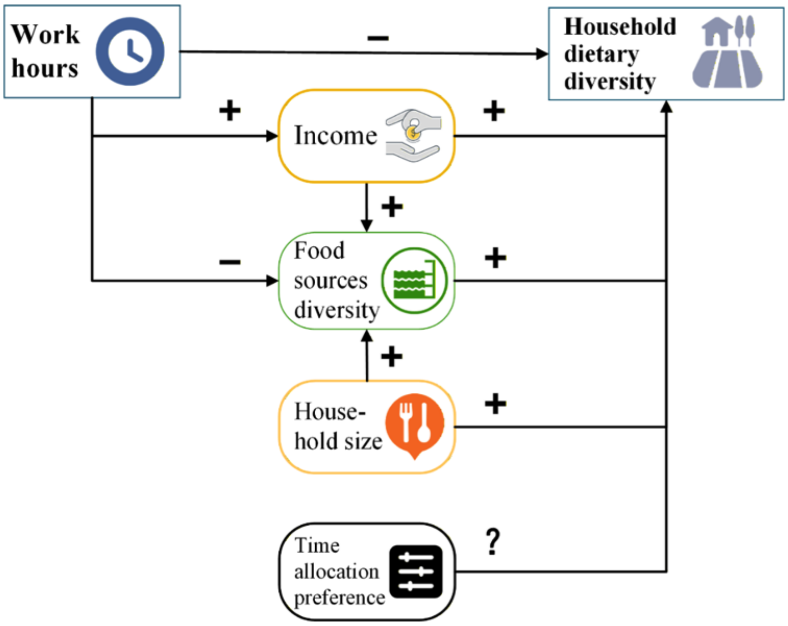
*Regression models:* As discussed above, there are several potential pathways for delivery riders' working hours to impact their household dietary diversity. This study therefore, employed the path analysis based on the Generalized Structural Equation Modeling (GSEM) approach and Stata (StataCorp LLC, 2023). The Poisson regression model is suitable, as the dependent variable *hdds* is a variable of count outcome (Long & Freese, 2001). The Poisson regression model includes the variables *monthhour*, *timeusesatis*, *nsoureces*, *income100*, and *householdsize*. When regression models were estimated, two means were used for the variable *timeusesatis*. Besides treating *timeusesatis* as one variable, the category 1 = dissatisfied was treated as the reference group, and four dummy variables were generated based on *timeusesatis*, including *relativelydis*, *neutral*, *relativelysat*, and *satisfied*, corresponding to the response options 2 = relatively dissatisfied, 3 = neutral", 4 = relatively satisfied, and 5 = satisfied, respectively. Figure 7 shows several potential indirect pathways, including:

(a) *monthhour —› income100 —› hdds* reflecting the mechanism through which migrant riders' working hours influence household dietary diversity via changes in income. As the variable *income100* is a continuous variable, the path of *monthhour —› income100* is a linear regression equation. The path of *monthhour —› income100 —› hdds* is a

Table 2: The Definition and Descriptive Statistics of Variables Used in the Study

| **Variable** | **Definition, type and range** | **N** | **Mean** | **Std. dev.** | **Min** | **Max** |
|---|---|---|---|---|---|---|
| *hdds* | Household dietary diversity, count, 0-12 | 271 | 4.89 | 3.35 | 1 | 12 |
| *monthhour* | Work hours a month, continuous | 251 | 258.42 | 74.20 | 18 | 540 |
| *dayhour* | Work hours a day, continuous, 0-24 | 259 | 9.49 | 2.19 | 2 | 18 |
| *monthday* | Work days a month, continuous, 0-31 | 257 | 26.99 | 4.24 | 2 | 31 |
| *income100* | Income from delivery rider work, one hundred yuan, continuous | 236 | 61.18 | 26.78 | 4 | 150 |
| *timeusesatis* | Time use attitude, ordered, 1-5 | 269 | 3.06 | 1.10 | 1 | 5 |
| *dissatisfied* | dissatisfied with work hours, binary, 0 or 1 | 269 | 0.14 | 0.35 | 0 | 1 |
| *relativelydis* | relatively dissatisfied with work hours, binary, 0 or 1 | 269 | 0.11 | 0.31 | 0 | 1 |
| *neutral* | neutral with work hours, binary, 0 or 1 | 269 | 0.37 | 0.48 | 0 | 1 |
| *relativelysat* | relatively satisfied with work hours, binary, 0 or 1 | 269 | 0.32 | 0.47 | 0 | 1 |
| *satisfied* | satisfied with work hours, binary, 0 or 1 | 269 | 0.06 | 0.24 | 0 | 1 |
| *nsoureces* | the number of sources obtaining food, continuous, 0-26 | 252 | 3.56 | 2.63 | 1 | 12 |
| *householdsize* | Household size, continuous | 242 | 2.87 | 1.63 | 1 | 9 |

Figure 7: Potential Paths between Variables




combined model that has a linear regression equation and one Poisson regression equation, with the continuous outcome variable *income100* also being an explanatory variable in the Poisson equation.

(b) *monthhour —› nsources —› hdds,* reflecting the path through which working hours affect household dietary diversity by affecting the number of food sources available to the household. This path is a combined model with two Poisson regression equations.

(c) *monthhour —› income100 —› nsources —› hdds* reflecting a more complex mechanism in which working hours affect income, which in turn influences the diversity of food sources and ultimately household dietary diversity. This path is a combined model with one linear regression equation and two Poisson regression equations.

(d) *householdsize —› nsources —› hdds* reflecting the path in which household size may influence dietary diversity indirectly through its effect on the number of food sources used by the household. This path is a combined model which has two Poisson regression equations, with the Poisson response variable *nsources* also being an explanatory variable in the another Poisson equation with variable as *hdds* Poisson response variable.

Two main limitations of the methodology can be identified. First, it is exploratory in nature because conducting a random sampling of migrant food delivery riders is nearly impossible. Riders are a highly mobile and hard-to-reach population. It is also challenging to access data from platform companies for probability-based sampling. As a result, although the survey provides valuable insights, its findings should be interpreted with caution. Second, the survey was originally designed to investigate the food security status of migrant rider households and did not collect detailed information on the time use of all their household members. Household diet quality is shaped not only by an individual's time use but also by the collective time resources of the household (Liu et al., 2022). For this reason, household time use would have served as a better measure than an individual's time use for examining the relationship between time constraints and dietary outcomes. Future studies are needed to evaluate how the distribution of time across family members influences food access, preparation, and overall dietary diversity.

## Results

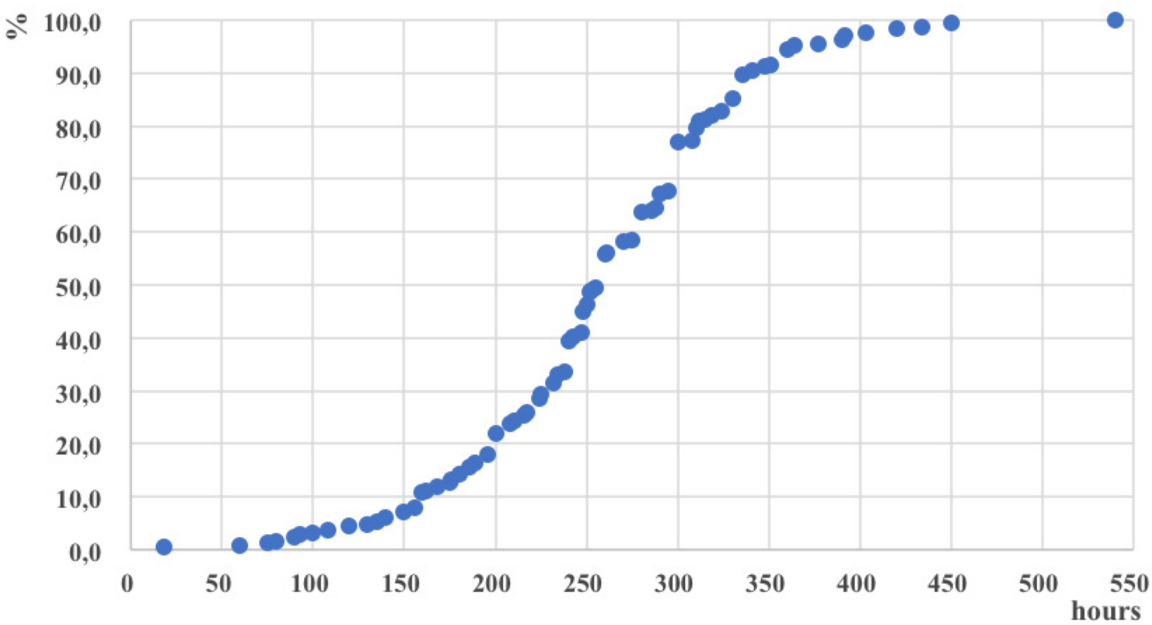
*Working hours and household dietary diversity:* Table 3 shows the distribution of the number of working days a month (*monthday*) and the number of working hours a day (*dayhour*). Over 85% of the migrant food delivery riders worked for 25 days or more per month. About 45% (10.51%+34.24%) of the riders had no rest day. Regarding daily working hours, more than half (56.37%) of the riders worked 10 hours or more per day, while approximately 12% worked less than 8 hours per day.

In China, the average number of working days per month is 21, and the standard working hours are 8 per day (MHRSSC, 2025). Thus, the standard monthly working hours are 168. However, only 12% of the food delivery riders surveyed had monthly working hours of less than 168. Figure 8 shows that over 80% of riders worked more than 200 hours per month, and approximately 10% reported monthly work hours above 336 hours, or twice the 168-hour standard. Also, 51% of riders worked for over 252 hours per month, or 1.5 times the 168-hour standard.

The mean HDDS of the migrant delivery riders' households was 4.89, which is significantly lower than the average HDDS of 7.39 for the entire urban population reported in a previous survey conducted in 2022-2023. The difference indicates that migrant rider households consumed, on average, food from 2.5 fewer categories. Moreover, almost half of the rider households had an HDDS of less than 3, while

| Table 3: Daily Work Hours and Monthly Work Days | | | | | |
|---|---|---|---|---|---|
| **dayhour** | **%** | **Cumulative %** | **monthday** | **%** | **Cumulative %** |
| 18.0 | 0.4 | 0.4 | 31.0 | 10.5 | 10.5 |
| 15.0 | 1.2 | 1.5 | 30.0 | 23.7 | 34.2 |
| 14.0 | 2.3 | 3.9 | 29.0 | 7.0 | 41.3 |
| 13.0 | 2.7 | 6.6 | 28.0 | 19.5 | 60.7 |
| 12.0 | 10.4 | 17.0 | 27.0 | 6.2 | 66.9 |
| 11.0 | 5.8 | 22.8 | 26.0 | 13.2 | 80.2 |
| 10.5 | 0.4 | 23.2 | 25.0 | 5.1 | 85.2 |
| 10.0 | 33.2 | 56.4 | 24.0 | 1.6 | 86.8 |
| 9.5 | 1.2 | 57.5 | 23.0 | 0.4 | 87.2 |
| 9.0 | 7.7 | 65.3 | 22.0 | 0.4 | 87.6 |
| 8.5 | 0.8 | 66.0 | 20.0 | 8.2 | 95.7 |
| 8.0 | 22.0 | 88.0 | 18.0 | 1.2 | 96.9 |
| 7.0 | 4.6 | 92.7 | 15.0 | 1.6 | 98.4 |
| 6.5 | 0.4 | 93.1 | 10.0 | 1.2 | 99.6 |
| ≤6.0 | 7.0 | 100.00 | 2.0 | 0.4 | 100.00 |

**Figure 8: Cumulative Monthly Work Hours**




only 5% of city-wide households fell below this threshold. Figure 9 further illustrates these disparities: about 70% of the migrant food delivery rider households had an HDDS below 5, compared with only 24% of the city-wide sample.

Figure 10 presents a scatter plot of migrant riders' monthly working hours and HDDS, along with a fitted non-linear trend line. The distribution suggests a non-linear relationship between working hours and dietary diversity. At lower to moderate levels of monthly working hours, increase in work hours are generally associated with higher HDDS. However, beyond a certain threshold, further increases in working hours correspond to declining HDDS. This inverted U-shaped pattern indicates that delivery riders' working hours may exert opposing effects on their HDDS, with potential income-related benefits at lower hour levels and time-constraint-related costs at higher hour levels.

*Model results:* In this analysis, two sets of models were estimated. In the first set, time allocation was treated as a nominal variable with five categories and four dummy variables. The corresponding models are presented as Model I-1 and Model I-2 (Table 4). The second set treated time allocation as an ordered variable, and the resulting models are presented as Model II-1 and Model II-2. The Bayesian Information Criterion (BIC) was used to evaluate models. Table 4 shows that Model II-1 had the smallest BIC value, meaning that it is preferable to the other three models.

Figure 9: Cumulative HDDS Scores of City-Wide and RIder Households

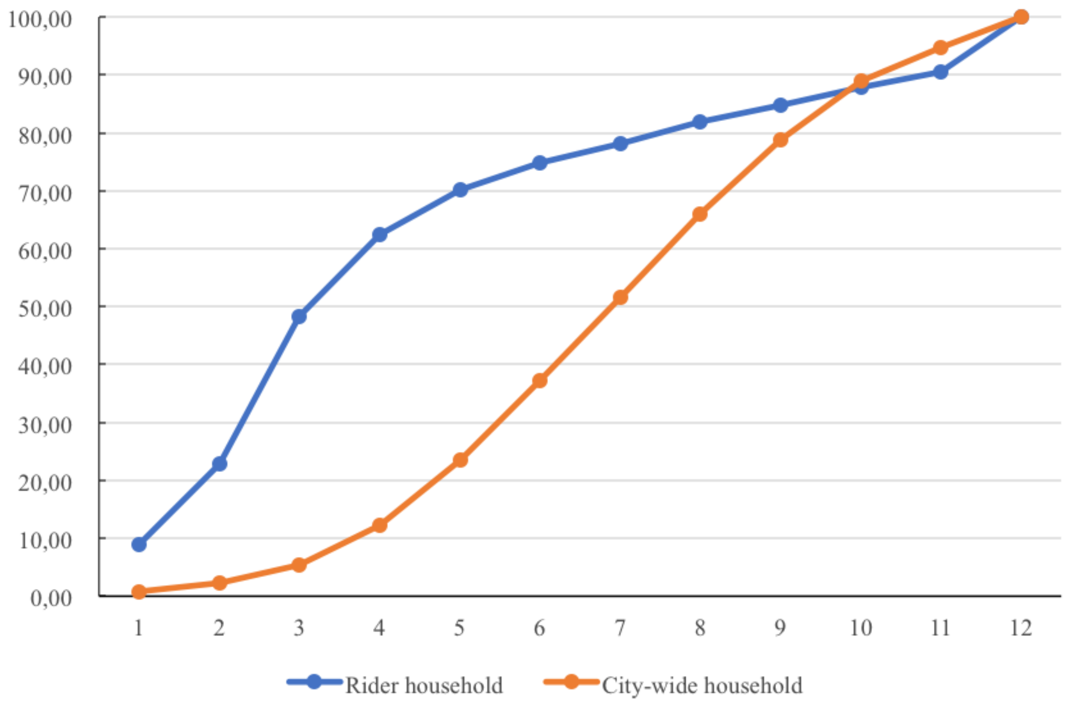



Figure 10: Migrant Riders' Work Hours and Household Dietary Diversity

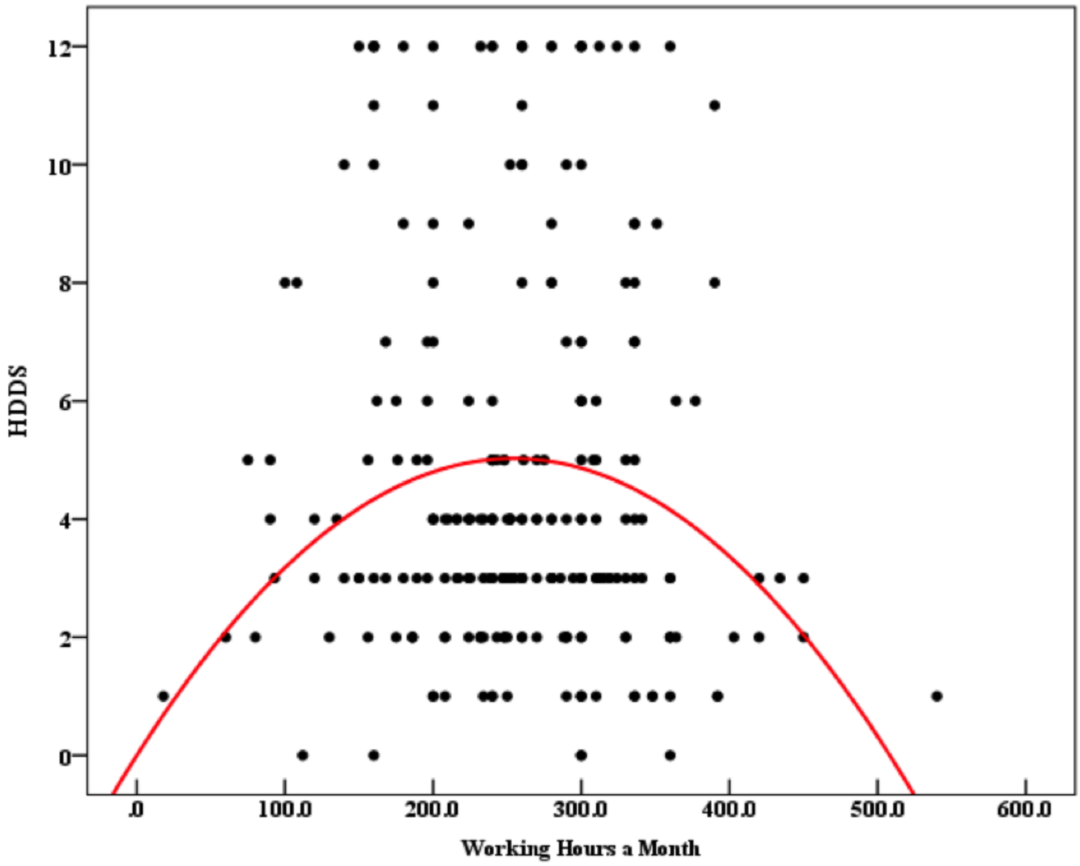


Table 4: Results of Generalized Structural Equation Models with HDDS as Dependent Variable

| **Variable** | **Model Ⅰ-1** | **Model Ⅰ-2** | **Model Ⅱ-1** | **Model Ⅱ-2** |
|---|---|---|---|---|
| *monthhour* | -0.0018*** | -0.0019*** | -0.0018*** | -0.0019*** |
| *income100* | 0.0031** | 0.0027** | 0.0032** | 0.0030** |
| *timeusesatis* | | | -0.2046*** | -0.1970*** |
| *relativelydis* | -0.2266** | -0.2139** | | |
| *neutral* | -0.4225*** | -0.4205*** | | |
| *relativelysat* | -0.7259*** | -0.7290*** | | |
| *satisfied* | -0.3516* | -0.3498** | | |
| *nsoureces* | 0.0985*** | 0.1025*** | 0.0993*** | 0.1035*** |
| *householdsize* | 0.0218 | | 0.0221 | |
| *constant* | 1.7989*** | 1.8778*** | 1.9592*** | 2.0211*** |
| *income100* | | | | |
| *monthhour* | 0.1057*** | 0.1057*** | 0.1057*** | 0.1057*** |
| *constant* | 33.6048*** | 33.6048*** | 33.6048*** | 33.6048*** |
| *nsoureces* | | | | |
| *householdsize* | 0.1101*** | 0.1186*** | 0.1101*** | 0.1186*** |
| *monthhour* | -0.0002 | | -0.0002 | |
| *income100* | -0.0002 | | -0.0002 | |
| *constant* | 1.0044*** | 0.9331*** | 1.0044*** | 0.9331*** |
| N | 226 | 254 | 226 | 254 |
| Log likelihood | -1902.3800 | -2014.6510 | -1906.7830 | -2020.5560 |
| AIC | 3836.7600 | 4055.3020 | 3839.5660 | 4061.1120 |
| BIC | 3891.4890 | 4101.2870 | 3884.0330 | 4096.4850 |

*Note: *, ** and *** represent significant at 10%, 5% and 1% level, respectively.*

In Model Ⅱ-1, the coefficients for some variables are statistically significant when *hdds* is the dependent variable and work hours (*monthhour*), income (*income100*), time allocation (*timeusesatis*), and food sources diversity (*nsoureces*) are the independent variables. Although the coefficient for household size (*householdsize*) is not statistically significant, it becomes significant when the number of sources (*nsoureces*) is treated as an endogenous variable. A further test was conducted to examine whether householdsize has a mediating effect on the variable hdds through the variable nsoureces, using the command nlcom in STATA which tests whether indirect effects exist, and calculates the coefficients of any indirect effects. The test results indicated that two indirect pathways are statistically significant out of the four potential paths proposed in Figure 4:

- *monthhour —› income100 —› hdds* path. The coefficient is 0.0003, significant at the 5% level, indicating that working hours influence household dietary diversity through their effect on income.

- *householdsize —› nsources —› hdds* path.The coefficient is 0.0109, significant at the 1% level, suggesting that larger household size increases the number of food sources used, thereby enhancing dietary diversity.

The remaining pathways have indirect effect coefficients that are not statistically significant.The coefficient of the *monthhour —› income100 —› hdds* path is 0.0003 and the coefficient of variable *monthhour* is -0.0018. There were no statistically significant coefficients of the other two paths *monthhour —› nsources —› hdds* and *monthhour —› income100 —› nsources —› hdds*

A further test was conducted to examine whether householdsize has a mediating effect on the variable hdds through the variable nsoureces, using the command nlcom in STATA, which tests whether indirect effects exist, and calculates the coefficients of any indirect effects. The test results indicated that two indirect pathways are statistically significant out of the four potential paths proposed in Figure 4:

- *monthhour —› income100 —› hdds* path. The coefficient is 0.0003 with significance at the 5% level, indicating that working hours influence household dietary diversity through their effect on income.

- *householdsize —› nsources —› hdds* path.The coefficient is 0.0109 with significance at the 1% level, suggesting that larger household size increases the number of food sources used, which in turn enhances dietary diversity.

The remaining pathways have indirect effect coefficients that are not statistically significant.  The coefficient of the *monthhour —› income100 —› hdds* path is 0.0003 and the coefficient of variable *monthhour* is -0.0018. There were no statistically significant coefficients of the other two paths *monthhour —› nsources —› hdds* and *monthhour —› income100 —› nsources —› hdds*

Therefore, the paths *monthhour —› income100 —› hdds* and *monthhour —› hdds* determine the net effect of the influence of work hours on household dietary diversity. The net effect of working hours on household dietary diversity is determined by the sum of the indirect coefficients across the two paths, yielding a combined effect of -0.0015. This result indicates that the overall impact of work hours on household dietary diversity remains negative, despite a small positive indirect effect of longer working hours on HDDS via higher income. In other words, an increase in migrant food delivery riders' working hours ultimately reduces their household dietary diversity.

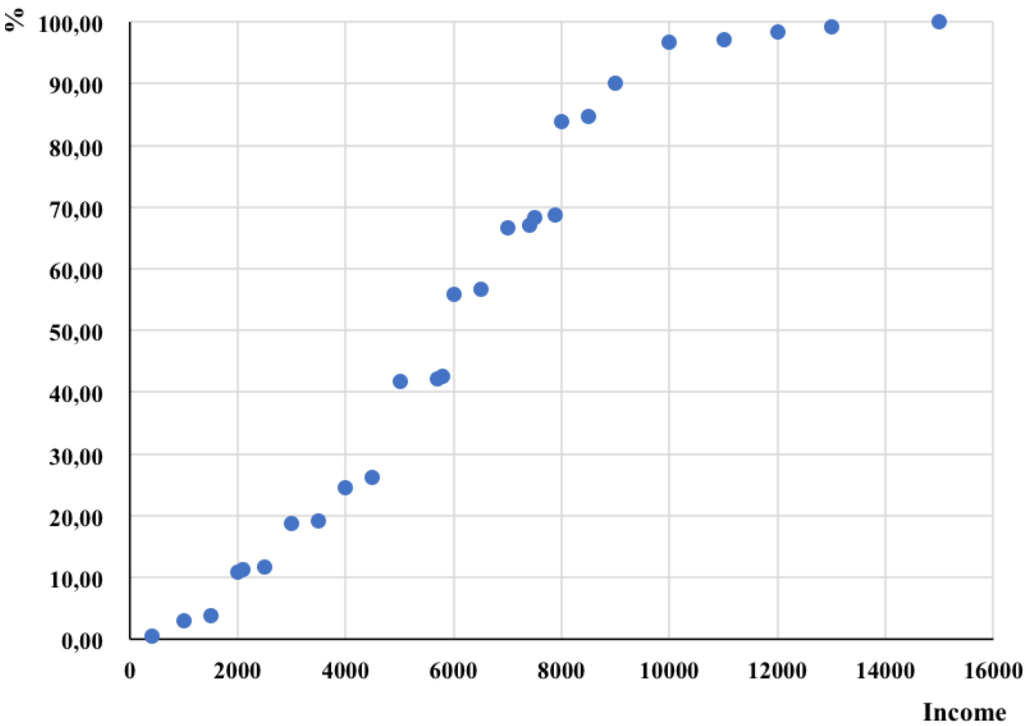
The impact on the HDDS is also measurable. An hour's increase in daily work (or 30 hours total per month) decreases the expected HDDS by a factor of 0.9560 or 4.4%. A 20-hour increase reduces the expected HDDS by 0.9704, or 2.96%. And a 10-hour increase decreases the expected HDDS by a factor of 0.9851 or 1.49%. For riders with monthly work hours exceeding 336 hours (80 hours above the mean), the expected HDDS is 11% lower than the mean of 4.89. The model also estimates that households with standard work hours have an expected HDDS approximately 15% higher than the migrant riders' average.

Migrant rider work hours are positively correlated with income, as indicated by the positive coefficient for monthhour, with income100 as the mediator variable (Table 4). At the same time, the household composition of riders suggests that working hours are likely to have a strong influence on the time available for food-related activities. This is because the majority of riders live in small households (Figure 6). Specifically, 27.1%, 15.0%, 25.5% and 17.4% of riders lived in households with one, two, three, and four members, respectively. Overall, 68% of the riders live in households of no more than three persons, and 85% lived in households of no more than four persons. In single-person households, the rider's working hours directly determine the total time available for food-related activities. Even in two-person households, the rider's working hours are highly influential in shaping household's time allocation for food-related activities. It is thus possible that while longer work hours increase income, they may simultaneously reduce the time a household has available to devote to food-related activities. If this is the case, then although increased income from longer work hours boosts dietary diversity, the gain may be insufficient to offset the negative effect on dietary diversity from reduced time spent on food-related activities. As a result, the overall impact of longer work hours is a decline in household dietary diversity.

*Time allocation and dietary diversity:* The model shows that time allocation is another important determinant of household dietary diversity. The coefficient of variable *timeusesatis* is statistically significant at the 1% level. The variable *timeusesatis* is an ordered variable, meaning that a higher value indicates working more hours for income earning, whereas a lower value indicates more time spent on other activities such as housework or leisure. The significant coefficient for variable *timeusesatis* indicates that households in which the migrant delivery rider worked longer work hours exhibited higher levels of household dietary diversity.

*Income and dietary diversity:* Income from food delivery work is a significant contributor to increasing household dietary diversity. The highest earnings from the delivery service were CNY15,000 (USD2,112), far more than the average wage of rural migrant workers in 2024 (CNY4,961 (USD698) (National Bureau of Statistics, 2025). The mean monthly

**Figure 11: Cumulative Percentage of Monthly Income**



income from delivery riding was CNY6,118 (~USD861), which is also higher than the average wage of rural migrant workers and roughly equal to the monthly disposable income per capita of middle-income households in Nanjing in 2023 (CNY6156) (Nanjing Bureau of Statistics, 2025). Almost 60% of the migrant food delivery riders earn more than their rural counterparts (Figure 11). The coefficient of variable *income100* is 0.0032 (Model II-1), which is significant at the 5%-level. This means that a unit (100 yuan) increase in a migrant rider's income increases the expected HDDS by a factor of 1.0032, or by 0.32%. A ten-unit increase in a migrant rider's income increases the expected HDDS by a factor of 1.0325 or 3.25%.

*Household size and dietary diversity:* The coefficient for *householdsize* is not statistically significant when hdds is treated as the dependent variable, indicating no significant direct effect of household size on household dietary diversity. However, the coefficient of variable *householdsize* is statistically significant when variable *nsoureces* is treated as a mediator. The coefficient of variable *nsoureces* is also statistically significant when variable *hdds* is treated as the dependent variable. The coefficient for the path *householdsize —› nsources —› hdds* is significant, suggesting a statistically meaningful indirect effect. As a result, this relationship can be interpreted as a case of complete mediation (Hair et al., 2021). The indirect effect coefficient of 0.0109 suggests that, for every additional household member, the expected HDDS increases by a factor of 1.0110 through its influence on the number of food sources used.

*Diversity of food sources and dietary diversity:* Household dietary diversity is commonly positively associated with market food diversity (O'Malley et al., 2025). In the urban context, retail food diversity plays a vital role in determining household and individual-level dietary diversity (Chege et al., 2021; Hülsen et al., 2024). A single market or shop cannot provide all the food items to meet consumers' demand, so consumers commonly use multiple sources to meet their various food needs. The significant coefficient of the variable *nsoureces* aligns with the literature on the relationship between the food environment and diet quality, which argues that the food environment is another major determinant of dietary diversity (Hülsen et al., 2024). In Model II-1, the estimated coefficient for the variable *nsoureces* is 0.0993 and is significant at the 1%-level. This means that for each added food source, the expected HDDS increases by a factor of 1.1044 or10.44%.

In contrast to the negative net effect of longer work hours on HDDS, increases in food-source diversity and household size were associated with higher HDDS. In other words, while longer work hours reduce household dietary diversity, greater access to diverse food sources and larger household size has positive overall effects. This suggests potential avenues for intervention, such as improving the local food environment by increasing the density and accessibility of food retail outlets. This could help offset the negative effects of long work hours. Likewise, policies that facilitate family co-residence for migrant riders could, by increasing household size, indirectly enhance household dietary diversity.

*Meal skipping and dietary diversity:* A key reason for reduced dietary diversity among the riders is meal skipping. About 38% of riders skipped and 34% skipped lunch in the previous six months. The main reasons for skipping breakfast included habit (79%), having more time for rest (79%), being too busy to eat (49%), and having more time for work (44%) (Table 5). Among the riders who skipped lunch, 45% wanted time to rest, 44% were too busy to eat, and 38% said it gave them more time to work. Only a few of those who skipped meals said they did so to save money or because food was inaccessible, suggesting that unaffordability and inaccessibility are not the main reasons for skipping meals. Instead, time constraints emerged as the key factor driving riders to forego breakfast and lunch.

Table 5: Reasons for Skipping Meals

| Reasons | Skips breakfast | | Skips lunch | |
|---|---|---|---|---|
| | No. | % | No. | % |
| Dietary habits | 85 | 78.7 | 8 | 8.3 |
| Have more time to rest | 82 | 75.9 | 43 | 44.8 |
| Too busy and forget to eat | 53 | 49.1 | 42 | 43.8 |
| More time for working | 48 | 44.4 | 36 | 37.5 |
| Save energy | 12 | 11.1 | 9 | 9.4 |
| Save money | 10 | 9.3 | 10. | 10.4 |
| Unable to obtain satisfactory food | 4 | 3.7 | 5 | 5.2 |
| Avoid conflict with schedules of other household members | 3 | 2.8 | 2 | 2.1 |
| Health considerations | 0 | 0.0 | 1 | 1.0 |
| Total | 108 | | 96 | |

## Conclusion

The rapid expansion of the food-delivery sector and the essential role of migrant riders in sustaining urban food security highlight the need to understand their work habits and own food security, topics that have attracted remarkably little research attention to date. To address this gap, this paper analyzes household dietary diversity among migrant food-delivery riders in China and shows that increased workload exerts a contradictory influence on dietary outcomes. Longer working hours raise household income, thereby enhancing dietary diversity. Yet they simultaneously reduce the time available for other activities, such as food acquisition, preparation, and consumption, thereby reducing dietary diversity. In Nanjing, the negative time-related effect outweighs the positive income effect, resulting in an overall decline in HDDS as work hours increase. Quantitatively, we conclude that increases of 30, 20, and 10 hours in monthly work hours are associated with 4.4%, 2.9%, and 1.5% declines in expected HDDS, respectively. Given that more than 88% of migrant riders work for more than the standard monthly work hours, the nutritional costs of long work hours are substantial.

To our knowledge, this is the first study in China that moves beyond descriptive accounts of delivery riders' food insecurity to examine the causal linkages between working hours and household dietary quality. This critical, yet largely overlooked, negative consequence of platform-based labour conditions is too consequential to be disregarded in discussions about the gig-economy. This analysis identifies two significant indirect effects: a pathway through income, in which longer work hours modestly increase household dietary diversity via higher earnings, and a pathway through food-source diversity, in which larger household size facilitates access to a broader range of food outlets, thereby improving dietary diversity. However, the study also reveals that the positive income pathway is insufficient to offset the negative direct effect of long work hours on dietary diversity, driven by the time constraints that reduce riders' ability to acquire and prepare diverse foods. Both the descriptive statistics and the regression analysis also show that time scarcity, rather than access or affordability alone, is the central channel through which long work hours reduce the household dietary quality of food delivery riders.

Given that the time poverty driving food insecurity among migrant food-delivery riders is a fundamentally structural constraint, this research identifies several policy pathways to address these systemic barriers. First, the results highlight the importance of enhancing the urban food environment, such as by increasing the density and accessibility of affordable food retail outlets, to reduce the time constraints riders face in obtaining diverse foods. Second, policies that remove barriers to migrant workers' access to services such as childcare, schooling, and housing support would make it more feasible for their families to join them in cities and, in turn, enhance household dietary diversity and food security. Third, at the institutional level, platform companies can help alleviate time pressure by adjusting algorithmic delivery scheduling, including offering protected meal breaks within shifts. Municipal governments could also encourage platforms to designate rest zones with basic amenities such as microwaves, drinking water, and healthy food options, to help riders access food more efficiently. These three measures could help mitigate the negative dietary consequences associated with long work hours.

This paper represents a contribution to broader debates on employment precarity in the rapidly developing platform-based delivery economy. The negative net effect of long work hours on household dietary diversity demonstrates that time poverty is a central dimension of employment precarity for delivery riders, which is compounded by other structural vulnerabilities such as algorithmic control, unstable earnings, and limited social protection. The finding that most migrant riders work exceptionally long hours reflects not individual choice, but the structural pressures embedded in the platform economy. Therefore, addressing the nutritional challenge facing delivery workers requires food-environment and household-support interventions, as well as broader labour protections that address the underlying precarious conditions of platform-based work.

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