Risk tolerance, soft skills, and sectoral sorting: Lab-in-the-field experiments in urban India's dual informal labor market

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Abstract

Informal employment continues to dominate labor markets in developing economies, with digital platforms rapidly expanding the organization of low- to mid-skill service work. This coexistence raises an economic puzzle: what explains workers sorting into digital platform (gigs) versus traditional offline informal work, beyond differences in technology access and observed earnings? Little is known about how economic preferences, especially risk tolerance, and soft skills are distributed across digital platform and traditional offline informal workers, and whether these soft skills help explain why some informal workers engage in digital platform while others remain in traditional offline informal employment. We address this gap by using a lab-in-the-field experiment with informal service workers in urban India (dominantly male) by building on a post-sorting framework in which workers are already engaged in either digital platform (D) or traditional offline (T) work modes. We elicit incentivized measures of risk tolerance and selected soft skills, and collect harmonized information on perceived working conditions. Our results show substantial heterogeneity by age and work mode, such that younger T workers display higher risk tolerance than D workers, whereas older D workers are more likely to be risk-neutral or risk-averse. D workers also exhibit higher self-control and openness, but lower grit and conscientiousness, relative to T workers. These patterns are consistent with sorting in secondary labor markets based on heterogeneous trade-offs over income risk, flexibility, and community-based security, rather than simple adoption of new work technology. Our findings are best interpreted as applying to male urban informal service workers. Policies that seek to improve welfare in dual labor markets should combine platform expansion with risk-sharing and skill-building interventions and minimum standards for worker protection.

Keywords: Gigs, Digital economy, Informal labor, Soft skills, Risk preferences
JEL Codes: I15, I18, J16

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1 Introduction

The informal labor market encompasses workers operating outside regulated economic activities, thus lacking protection from formal labor laws and regulations (Aguilar and López Guerrero, 2020). These markets rely primarily on casual employment, kinship, or personal networks rather than formal contractual arrangements (International Labour Office, 2000). Particularly, for individuals who face barriers to formal employment because of limited education and skills, informal labor markets provide opportunity with flexibility and adaptability. At the same time, informal labor markets are often characterized by low productivity, weak governance, poverty, and income inequality (Yu and Ohnsorge, 2019). As a result, informal work (labor market) often fails to meet the ILOs "decent work" standards and is associated with persistent worker vulnerability (ILO, 2002). Despite its inherent risks, the informal labor market remains crucial, particularly in developing countries, where it manifests within small-scale enterprises and dominates 70–90% of total employment (ILO, 2002; Maloney, 2004). India is a prime example, with over 90% of its workforce informally employed in roles like street vending, domestic service, and subsistence agriculture.[1] In recent years, the growth of digital platforms in urban India has increasingly shifted informal workers to online work.[2] Platforms like UrbanClap (now Urban Company) facilitate connections between workers and clients, allowing services such as plumbing, cleaning, appliance repair, and delivery to be offered online.

The informal employment is often precarious for low- to mid-skill service workers in developing and emerging economies, yet the expansion of digital platforms has introduced a work mode that can offer higher earnings and more transparent task-based compensation (World Bank Group, 2023; OECD, 2024). However, platform work can still be risky along other margins. For example, demand can fluctuate daily, platform rules and ratings may change, and workers face deactivation and search or entry risks. Thus, in our context, "risk" encompasses not only wage volatility but also the income and employment uncertainty inherent in digital platform. This definition underpins our central question regarding worker sorting. Existing evidence suggests that, even within comparable jobs, workers economic and social preferences can vary systematically with the structure of day-to-day interactions and the way work is organized (Leibbrandt, 2012; Leibbrandt, Gneezy and List, 2013; Gneezy, Leibbrandt and List, 2016; Hernuryadin, Kotani and Saijo, 2020). This motivates us to understand whether behavioral heterogeneity extends to the dual structure of informal labor markets, such that digital platform systematically attracts workers with different risk tolerance and soft skills than traditional offline work? We focus on risk attitudes and soft skills because they are known to shape labor market outcomes. In addition, we particularly examine the role of age in these dynamics by investigating such differences and sorting mechanisms in different age groups, as extant literature suggests that risk preference is unstable and shows evidence of system-

[1] In this study, we define "informal workers as the workers who work in the informal or secondary sector of the labor market. https://www.ilo.org/resource/45-informal-economy-workers

[2] In this paper, "digital platform work (D)" refers to platform-mediated service work in which workers obtain tasks through an app-based marketplace (e.g., urban home services, ride-hailing, or delivery), and "traditional offline informal work (T)" refers to those who work offline through informal networks, such as taxi drivers, and delivery workers.

atic change over the life cycle (Schildberg-Hörisch, 2018). [3] To study how workers preferences and soft skills differ across pre-existing work modes, we use a lab-in-the-field design to elicit incentivized measures of risk tolerance and selected soft skills.

This research contributes to the existing literature in three ways. First, we address a critical gap by examining differences in risk tolerance across distinct work modes within the urban informal labor market. Prior research has largely focused on the difference in risk attitudes between formal and informal employment, but we provide novel evidence on heterogeneity within the informal sector, based on a structured experimental design with enhanced reliability of behavioral measures. Second, we provide new evidence on correlates of participation in digital platform. Our findings reveal that risk tolerance and soft skills, such as self-control, are significantly correlated with the likelihood of engaging in digital platform work, offering insight into the supply-side composition of workers. Third, the study highlights that workers prioritize job prospects and growth opportunities over other conditions, such as work-life balance. This has important implications for digital platform employers seeking to attract and retain low- to mid-skill informal workers by emphasizing skill development and career advancement. Notwithstanding these caveats, this study is composed of (99%) male workers; accordingly, our findings on behavioral sorting are best interpreted as applying specifically to the male segment of the low- to mid-skill urban informal labor market in India.[4]

The remainder of the paper is organized as follows. Section 2 (Theoretical Foundation) reviews the related literature and presents the conceptual framework. Section 3 (Experimental Design and Procedures) describes the experimental design and methodology. Section 4 (Results) reports the nonparametric and parametric results. Section 5 (Discussion and Conclusion) discusses the main findings and policy implications.

2 Theoretical foundation

2.1 Related work

We structure our literature review around two key areas: the sociodemographic determinants of economic preferences and soft skills, and the relationship between these factors and job choice, with a particular focus on the latter.

Socioeconomic preferences and soft skills are shaped by an interplay of macroeconomic conditions (Canale et al., 2018; Pickard, Dohmen and Van Landeghem, 2024), personal characteristics and even emotions (Campos-

[3] Our data were collected from workers who were already engaged in either digital-platform work or traditional offline informal work at the time of the study. Thus, our estimates compare pre-existing work modes and should be interpreted as associations consistent with sorting into platform work. This concern is common in the platform labor literature; see, e.g., Farrell and Greig (2016) and Hall and Krueger (2018).

[4] This reflects strong occupational segregation in urban Indias low- to mid-skill service work; men predominantly take up location-based platform jobs such as food delivery and ride-hailing/driving, while women are more concentrated in platform-mediated beauty, care, and domestic services. Barriers to womens participation in delivery or transport platform work include safety and harassment concerns in public-facing gigs, restrictive mobility norms and time constraints arising from unpaid care responsibilities, and entry requirements such as access to vehicles and licensing (Ghosh, Ramachandran and Zaidi, 2022; Fairwork, 2023)

Vazquez and Cuilty, 2014). Studies document sociodemographic differences in risk attitudes. For example, Obermeier and Schneider (2015) find that German students from lower socioeconomic backgrounds exhibit higher risk-taking than wealthier students. Some other studies in the field primarily focus on the gender gap in risk preference. Holden and Tilahun (2022), for instance, find that Ethiopian women exhibit greater loss aversion, attributing this partially to cultural norms. Andreoni et al. (2020) show the gender gap emerges during adolescence, with girls becoming more risk-averse than boys. Finally, Schildberg-Hörisch (2018) shows that risk attitudes change over an individual's life cycle, providing insights into the instability of preferences over time.

The interaction between risk preferences, soft skills, and environmental constraints is a more complex process in workers' decision-making. For instance, Bonan, Burlacu and Galliera (2023) find that children's cognitive skills significantly influence their level of prosocial behavior in dictator games, based on a lab-in-the-field experiment conducted in El Salvador. Risk preferences and individual traits, particularly soft skills, shape behaviors such as engagement in risky activities (e.g., risky jobs, smoking, or heavy drinking) (Anderson and Mellor, 2008) and predict life success (Heckman and Kautz, 2012). The choice of informal jobs reflects broader risk preferences and trade-offs. Generally, risk aversion is strongly linked to choosing formal jobs (Dong, 2017). For example, Falco (2014), using experimental methods in Ghana, finds that risk-averse individuals prefer salaried jobs for stability, while risk-tolerant individuals favor self-employment. Furthermore, the perceived working environment varies among workers and can affect their welfare. Existing literature finds evidence that challenges the homogenization of gig workers, showing that working experiences and outcomes vary systematically with personal motivations (Keith, Harms and Tay, 2019; Myhill, Richards and Sang, 2023). Hafeez, Gupta and Sprajcer (2022) investigate the psychological toll of gig work and find that these workers experience significantly higher stress levels than traditional employees, driven by income instability, lack of benefits, and unpredictable workloads. This stress is compounded by the absence of workplace protections.

Individual job choice involves a complex interplay of soft skills, risk preferences, and environmental conditions. While these factors influence decision-making and welfare, two crucial gaps remain in the context of the informal labor market's digital transformation. First, there is a lack of evidence on the variation of risk attitudes within the informal labor market itself. The digital economy has transformed informal employment, but it remains unclear whether risk attitudes differ systematically between digital platformand traditional offlineinformal workers, which is the key behavioral sorting mechanism we aim to test in this study. Second, although existing studies highlight the influence of individual factors and external conditions on the decision to enter informal work, the specific microdeterminants (beyond standard demographics) that affect an informal workers choice of a particular work mode (digital platformvs. traditional offline) are not well explored. Addressing these gaps is necessary to clarify how informal labor markets are being reshaped by digital platformwork for providing an empirical basis for policies and improving worker welfare and productivity.

2.2 Ex ante sorting in a dual informal labor market

To provide a theoretical foundation for our analysis, we draw on research on surveillance and algorithmic control in digital platformlabor markets (Keith, Harms and Tay, 2019; Kelishomi and Nisticò, 2024). These insights motivate our ex ante sorting framework, in which workers choose between digital platform (D) and traditional offline (T) work. Ex-ante sorting depends not only on income volatility but also on surveillance, bargaining uncertainty, and entry costs. In our setup, digital platform(D) work features structured intermediation and systematic monitoring. It has standardized service categories and uses posted prices or commission schedules, which reduce day-to-day bargaining and bargaining-related uncertainty relative to traditional offlineinformal markets (Bester, 1994). Nevertheless, this structure is defined by constant tracking of worker performance, utilization of customer ratings, and the application of penalties. Furthermore, the presence of deactivation threats imposes reputational and contractual risks that workers are unable to diversify such high-stakes risk (Hafeez, Gupta and Sprajcer, 2022). Finally, the digital platformwork (D) model places considerable behavioral demands on workers, requiring continuous interpersonal interaction, polite conduct, and strict adherence to customer expectations, which in turn rewards the non-cognitive soft skills.

The traditional offlineinformal work (T) provides a different environmental set of trade-offs for workers. This sector is primarily characterized by highly negotiated working conditions, as the work requires daily negotiations over both prices and specific working arrangements. While this leads to considerable income uncertainty as a consequence of daily negotiation (Desai and Purohit, 2004), such arrangements offer significant benefits. Specifically, workers enjoy greater autonomy in managing their work, ample opportunities for price negotiation with customers, and a crucial freedom from monitoring, as they experience relative liberation from direct surveillance by employers or customers.

Given this background, we consider a population of workers $i \in \{1,\dots,N\}$ who are engaged in one of two informal work modes: digital platform (D) or traditional offline (T). We assume switching across work modes is costly, implying limited mobility across sectors over the horizon relevant for our analysis.

The utility of worker i in sector $j \in \{D,T\}$ is given by:

$$U_{i,j} = \mu_j - c_j \; - \; \frac{1}{2}\rho_i\left(\sigma_j^2 + \tau_j^2\right) + \alpha A_j + \beta S_j,$$

where μ_j is expected income in sector j; c_j captures non-income costs/disutility (e.g., monitoring burden, compliance costs, or expected penalties/fees); σ_j^2 is income variance; τ_j^2 captures non-income uncertainty (e.g., bargaining uncertainty in T and rating/deactivation risk in D); ρ_i is worker i's coefficient of risk aversion; A_j denotes autonomy/flexibility; S_j denotes social security and community support; and α, β are preference weights on autonomy and security.

To enter the digital sector, a worker must incur a fixed entry cost F (e.g., smartphone access, digital literacy,

onboarding requirements, or adaptation costs to platform protocols). The entry condition is:

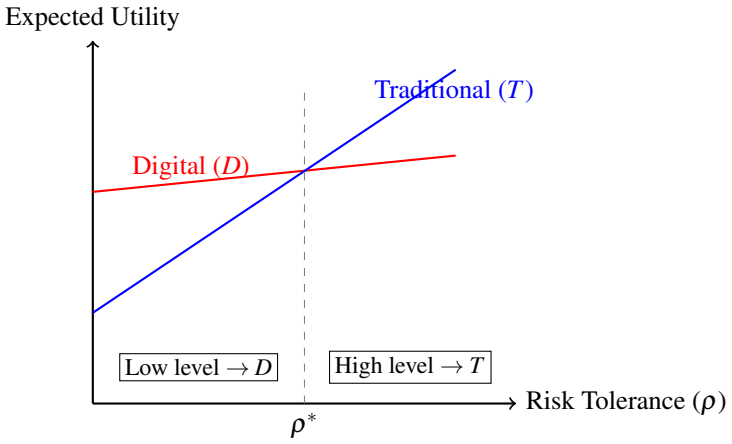
$$U_{i,D} - F > U_{i,T}.$$

Workers who do not satisfy this inequality remain in T, even if they would prefer D absent entry costs.

Given limited mobility, realized utility is:

$$U_i = \begin{cases} U_{i,D} - F, & \text{if } i \in D, \\ U_{i,T}, & \text{if } i \in T. \end{cases}$$

Figure 1: Utility-based sorting in dual informal labor markets.



Note: Digital platforms (D), traditional informal employment (T). The entry cost F creates a barrier that prevents some workers from accessing digital opportunities even when the potential utility in D is higher.

In this framework, digital platform work can reduce bargaining frictions through standardized terms and posted prices, lowering one source of uncertainty relative to traditional offline informal work. At the same time, digital platformwork (D) may introduce monitoring and enforcement risk, for example, rating penalties or deactivation, and impose behavioral demands that differentially reward soft skills such as self-control. In contrast, traditional offline informal work (T) often involves greater bargaining and income uncertainty but offers higher autonomy and flexibility. Fixed entry costs F into digital platform, including smartphone access, digital literacy, and compliance with platform protocols, can further limit participation, particularly among younger and liquidity-constrained workers.

2.3 Hypotheses and conceptual framework

In this section, we lay out the empirical questions and testable predictions that guide our analysis of work-mode heterogeneity within the informal sector. We focus on two related issues. First, we assess whether informal workers engaged in digital platform and traditional offline differ in economic preferences and soft skills. Second, we examine which worker characteristics and perceived working conditions are associated with participation in digital platform.

First, our empirical tests are differences across work modes, with our research question, "Do risk attitudes and soft skills differ between digital platformand traditional offlineinformal workers?" Rather than imposing it as a priori directional hypotheses, we treat these as empirical tests. These tests are motivated by the idea that the two work modes may attract different worker types and impose different job demands, but the net direction of differences is ambiguous ex ante.

Test 1 (Risk attitudes): We test whether risk attitudes differ systematically between digital platform and traditional offline workers, both overall and within age cohorts.

Test 2 (Soft skills): We test whether soft skills differ systematically between digital platform and traditional offline workers, both overall and within age cohorts.

We now turn to hypotheses regarding the worker characteristics associated with participation in digital platformwork. Here, our second research question is "What are the correlates of participation in digital platform?" Guided by the mechanisms discussed above, such as including standardized terms, monitoring and enforcement risk, and entry frictions, we formulate directional hypotheses as follows:

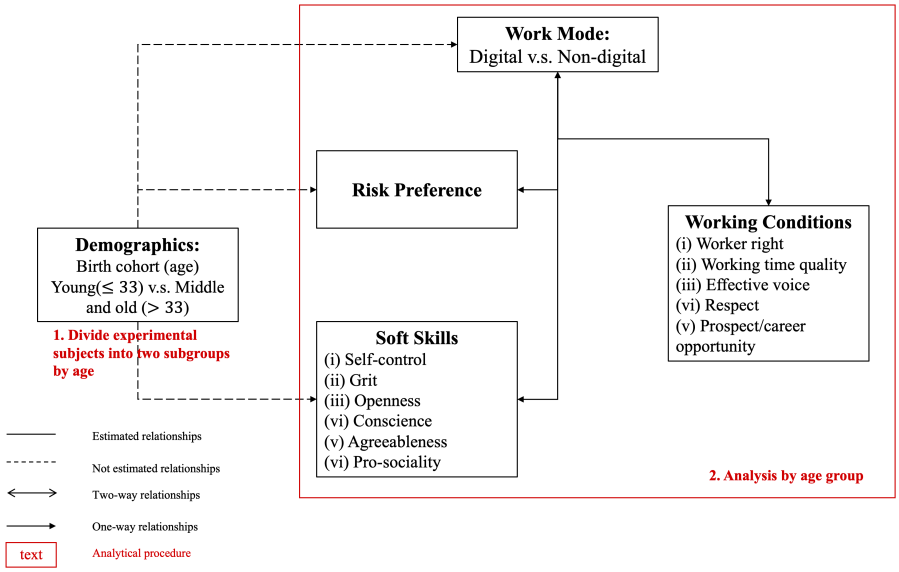
Hypothesis 1 (Risk tolerance and digital work): Higher risk tolerance is associated with a lower likelihood of engaging in digital platform, both overall and within age cohorts.

Hypothesis 2 (Soft skills and digital work): Higher levels of soft skills are associated with a higher likelihood of engaging in digital platform, both overall and within age cohorts.

Hypothesis 3 (Perceived working conditions): Better perceived working conditions are associated with a higher likelihood of engaging in digital platform, both overall and within age cohorts.

Our conceptual framework, illustrated in Figure 2, provides a roadmap for the analysis. It summarizes the relationships between risk attitudes, soft skills, perceived working conditions, and work-mode choice that we examine empirically. The framework has two objectives: (1) to assess differences in risk attitudes and soft skills between digital platform and traditional offline workers, and (2) to study how these soft skills and perceived working conditions correlate with participation in digital platform.

Figure 2: Conceptual framework



Note: The arrows indicate the direction of relationships, with solid lines representing relationships estimated in our main analysis, and dashed lines indicating unexamined relationships. The red text annotations outline our analytical procedures.

In the first phase of the analysis, we split the sample into two age cohorts: workers aged 33 or younger and workers older than 33.[5] This allows us to examine whether patterns differ by age, consistent with evidence that risk preferences vary over the life cycle (Schildberg-Hörisch, 2018). Furthermore, to enrich our interpretation of behavioral sorting, we draw on Campos-Vazquez and Cuilty (2014), who emphasize that self-selection into labor markets is often governed by non-expected-utility factors, such as reference dependence and loss aversion. Since younger and older workers likely operate with different reference points (e.g., due to differing liquidity constraints or accumulated assets), these insights suggest that the relationship between measured risk tolerance and platform participation may differor even reverseacross cohorts. We then compare risk attitudes and soft skills between digital platform and traditional offline workers within each cohort.

To study correlates of digital platform participation, we estimate a probit model:

$$\Pr(Digital_i = 1 \mid X_i) \;=\; \Phi\big(\alpha + \beta Risk_i + \mathbf{Skills}_i'\gamma + \mathbf{WorkCond}_i'\eta + \mathbf{Controls}_i'\lambda\big)\,,$$

Where $Digital_i$ equals 1 if worker i engages in digital platform and 0 otherwise; $Risk_i$ measures risk attitude; $\mathbf{Skills}_i$ is a vector of soft skills (self-control, grit, openness, conscientiousness, agreeableness and prosociality);

[5] We use 33 as the cutoff because it is the sample mean age (see Table 2). We use the sample mean age as a transparent cutoff that yields a relatively balanced split. In addition, this focus is highly contextually relevant to the Indian setting, where the gig economy is primarily powered by the youth demographic. Suryavanshi (2022) indicate that nearly two-thirds of gig workers are aged between 24 and 38. This concentration is particularly evident among platform workers, who tend to be better educated and younger than the general labor force, reflecting the economic dominance of India's 400-million-strong millennial population (Ramachandran and Raman, 2021). As robustness checks, we replicate the analysis using alternative cutoffs based on the median (50th percentile) of the age distribution and a 40-year threshold commonly used to distinguish younger from middle-aged populations. The main conclusions are unchanged (see Table A3, Table A4, and Table A5). Results using the 40-year cutoff should be interpreted with caution because the older subsample is smaller.

WorkCond$_i$ includes perceived working-condition indices (workers' rights, working-time quality, effective voice, respect, and prospects/career opportunities); and **Controls**$_i$ includes demographics and background characteristics (age, gender, education, marital status, household size, caste, occupation, household earners, years of work experience, and mental and physical health).[6]

3 Experimental design and procedures

3.1 Experimental setup

We conducted a lab-in-the-field experiment in September 2022, and accompanying survey with 400 informal service workers in New Delhi (NCT), comparing workers engaged in either digital platform or traditional offline.[7] We chose the National Capital Territory (NCT) of Delhi as the study site due to its diverse demographic composition and its large population of migrant informal workers who participate in Indias expanding low- to mid-skill, platform-mediated service economy.

The experiment elicited incentivized measures of risk attitudes and social preferences. Subjects completed three experimental tasks, such as a real-effort task (RET), a risky investment game (RIG), and a social value orientation (SVO) task, and a structured questionnaire capturing sociodemographic characteristics and soft skills. We did not have access to computer facilities or reliable internet connectivity in this field setup; therefore, all sessions were administered manually by the experimenter and trained research assistants. Subjects completed the tasks using pen and paper. The following subsections describe the design and implementation of each task and the construction of our key measures of risk attitudes, soft skills, and perceived working conditions.

Real-effort task (RET)

We begin with a real-effort task to measure baseline effort and attention under controlled conditions. Following established designs in the experimental economics literature (Gneezy and List, 2006; Falk and Ichino, 2006; Xie et al., 2022), subjects complete a zero-counting exercise in which they have three minutes to count the number of zeros (0s) in matrices of binary digits (0s and 1s). Subjects earn 100 points for each correct count. The task is intentionally simple and does not rely on specialized knowledge, so performance primarily reflects effort and sustained attention rather than domain-specific skills (Xie et al., 2022). We use performance in this task as a proxy for baseline effort/attention and include it as a control in robustness checks to ensure that our main patterns are not driven by differences in task engagement across work modes.

[6] Variable definitions are provided in Table A1.

[7] Although some respondents may hold multiple jobs, 96.74% report that their informal job is their primary source of income.

Risky investment game (RIG)

To elicit individual risk tolerance, we employ a risky investment game following Gneezy and Potters (1997) and Alan et al. (2017). At the start of the task, each participant receives an endowment of 10 tokens, where each token is worth 50 points (i.e., 500 points in total). The participant chooses how many tokens $x \in \{0, 1, \ldots, 10\}$ to invest in a risky option (the bowl) and keeps the remaining $10 - x$ tokens in a safe option.

After the investment decision is made, one chip is drawn from an opaque bag containing one white chip and one red chip, each drawn with equal probability ($p_{\text{white}} = p_{\text{red}} = 0.5$). If the white chip is drawn (good outcome), the invested tokens are tripled; if the red chip is drawn (bad outcome), the invested tokens are lost. Thus, the realized payoff (in points) is:

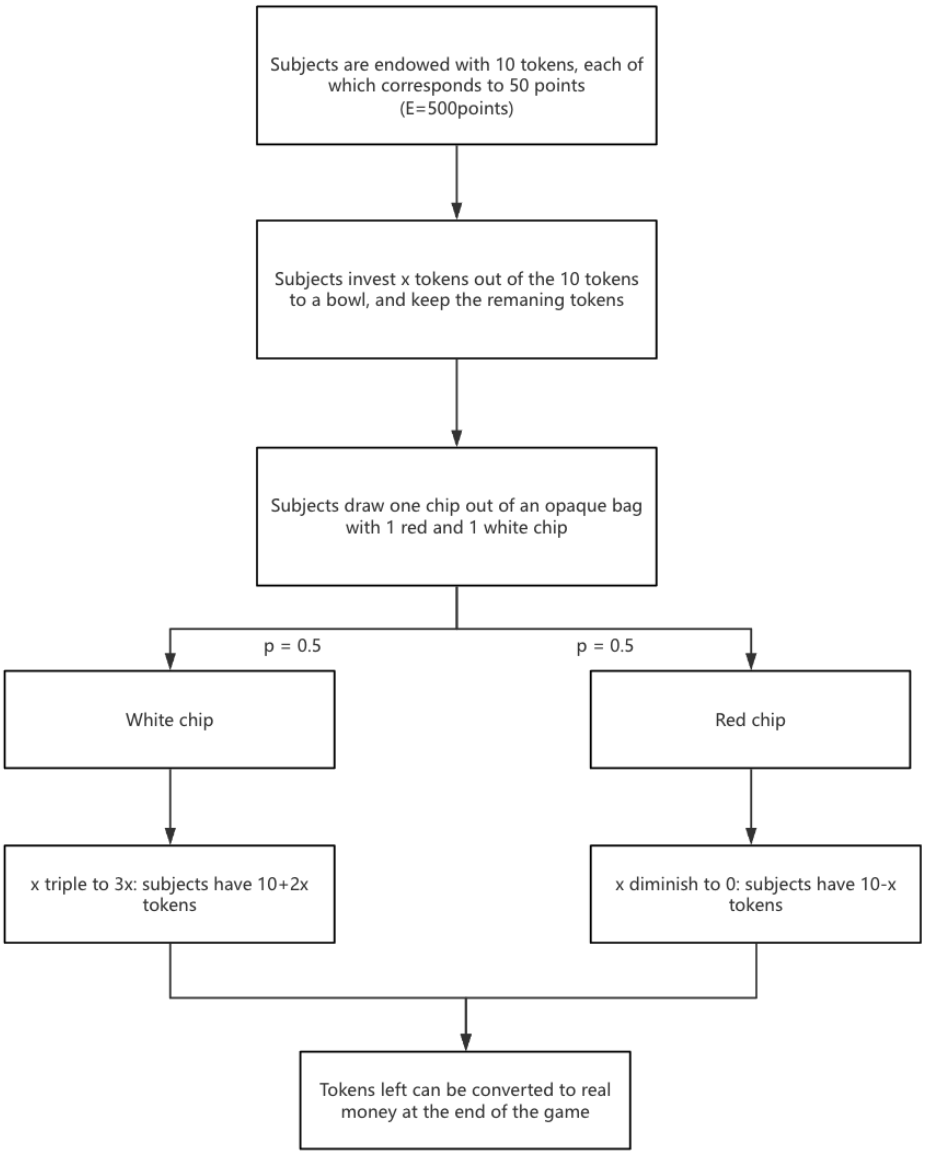
$$\pi(x) = \begin{cases} 50(10-x) + 150x = 500 + 100x, & \text{if white is drawn,} \\ 50(10-x) + 0 = 500 - 50x, & \text{if red is drawn.} \end{cases}$$

The expected payoff is therefore

$$\mathbb{E}[\pi(x)] = 0.5(500 + 100x) + 0.5(500 - 50x) = 500 + 25x.$$

Under risk neutrality, expected earnings are increasing in x, so a risk-neutral participant would invest the full endowment ($x = 10$). In contrast, risk-averse subjects will typically choose a smaller x. We therefore use the chosen investment level x as an incentivized measure of individual risk tolerance, with higher x indicating greater risk tolerance (and lower implied risk aversion). Figure 3 summarizes the procedure. We therefore use the chosen investment level x as an incentivized measure of the subject's risk tolerance, with a higher x indicating greater risk tolerance (and lower implied risk aversion).

Figure 3: Elicitation of risk tolerance



Soft skills

Soft skills shape decision-making and adaptability in work settings by helping individuals manage challenges, cooperate with others, and sustain effort toward long-term goals. In our study, we elicit prosociality using a Social Value Orientation (SVO) task and measure five additional soft skills, which include self-control, grit, openness, conscientiousness, and agreeableness, by using survey-based instruments.

Social Value Orientation (SVO) To measure social preferences, we use the Social Value Orientation (SVO) "slider method" following Murphy, Ackermann and Handgraaf (2011). The task consists of six primary items in which subjects choose one of nine allocations that jointly determine payoffs for themselves and for an anony-

mous other (see Figure 4). For each item, the subject indicates the most preferred allocation between "self" and "other" by marking the corresponding option on the response sheet.

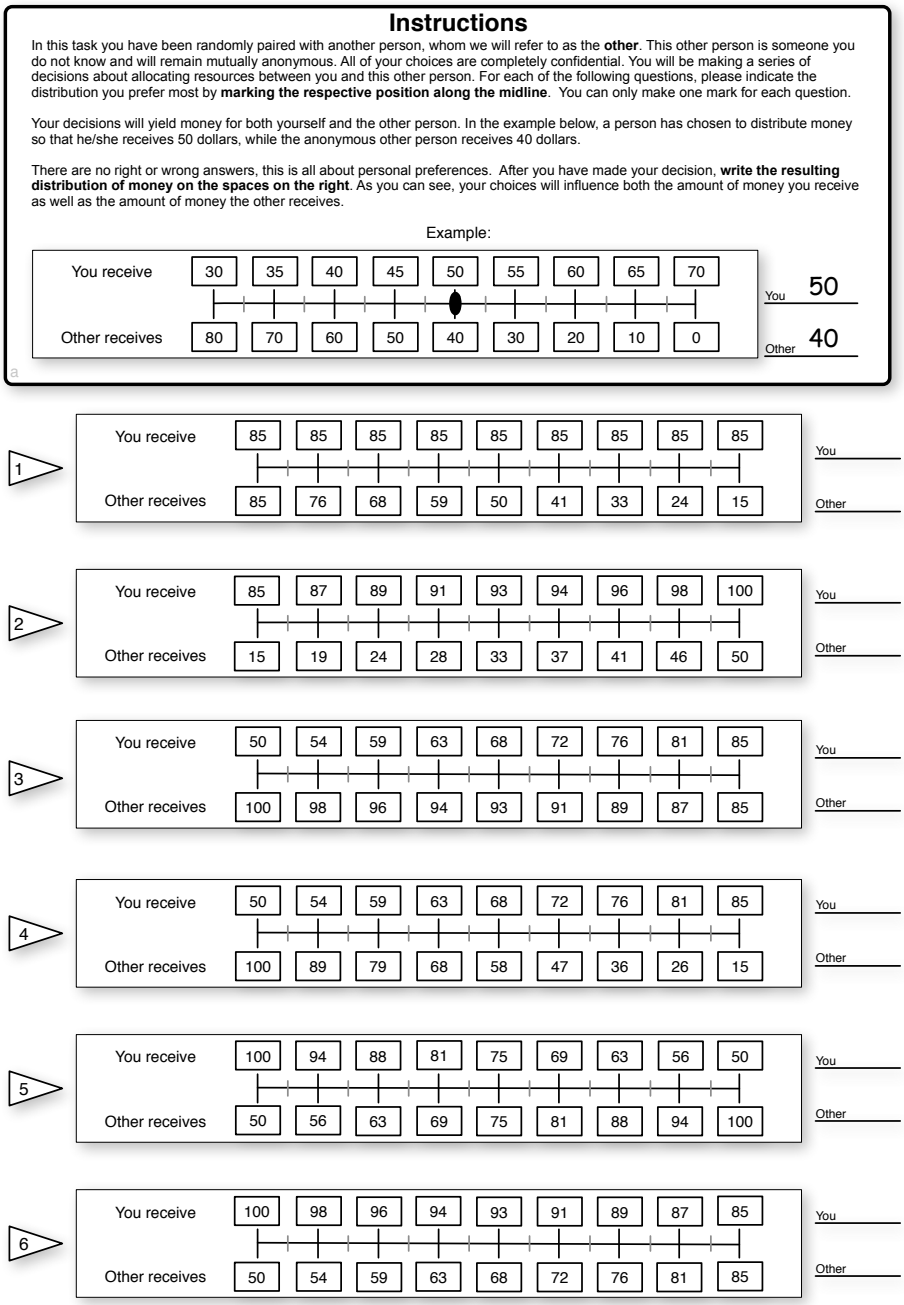
Let $\overline{A}_s$ denote the mean allocation to self and $\overline{A}_o$ denote the mean allocation to the other across the six items. Following Murphy, Ackermann and Handgraaf (2011), we compute the SVO angle as:

$$\text{SVO} = \arctan\left(\frac{\overline{A}_o - 50}{\overline{A}_s - 50}\right).$$

Based on the resulting angle, subjects are classified as: (i) altruistic if SVO $> 57.15^\circ$; (ii) prosocial if $22.45^\circ <$ SVO $< 57.15^\circ$; (iii) individualistic if $-12.04^\circ <$ SVO $< 22.45^\circ$; and (iv) competitive if SVO $< -12.04^\circ$. As is common in the literature, we additionally collapse these four categories into two types: altruistic and prosocial subjects are classified as *prosocial*, whereas individualistic and competitive subjects are classified as *proself* (Murphy, Ackermann and Handgraaf, 2011).

Subjects were informed that the units in the task are points and that more points translate into higher earnings (see Figure 4). Decisions were made privately and without communication. To determine payoffs, we randomly matched subjects into pairs after all decisions were completed. Each subject's payoff equals the sum of (i) the points assigned to "self" from the subject's own six choices and (ii) the points assigned to "other" from the matched partner's six choices. Points were converted to cash using a pre-announced exchange rate, yielding payments of up to 200 Indian rupees (approximately USD 2.5), with average earnings of about 100 rupees (approximately USD 1.0). We explained the random-matching procedure and the point-to-cash conversion rule to subjects before decisions were made.

Figure 4: Instructions for the "slider method" to measure social value orientation



Other soft skills We measure five additional soft skills, including self-control, grit, openness, conscientiousness, and agreeableness. We use quantified and validated psychometric instruments to support reliability and comparability across studies.

Self-control is a foundational skill that captures an individual's ability to regulate impulses, prioritize long-term goals over immediate gratification, and adapt behavior to situational demands (Maloney, Grawitch and Barber, 2012). We measure self-control using a 10-item Likert-scale questionnaire. Respondents rate statements such as "I resist distractions easily" on a scale from 1 (strongly disagree) to 5 (strongly agree), producing a total score ranging from 10 to 50. Higher scores indicate stronger self-regulatory capacity, which has been linked to academic achievement, prudent financial behavior, and health-related outcomes.

Grit reflects perseverance and sustained passion for long-term goals despite setbacks (Duckworth et al., 2007). We assess grit using an 8-item scale (e.g., "Setbacks do not discourage me"), with each item measured on a Likert scale and summed to generate a total score from 8 to 40. Higher values indicate greater perseverance and long-run commitment, which are particularly relevant for outcomes that require sustained effort and persistence.

Openness is a core trait in the Big Five framework and captures cognitive flexibility, creativity, and receptiveness to new experiences (John, Naumann and Soto, 2008). It is measured using standard survey items (e.g., "I enjoy exploring abstract ideas") that capture imagination and intellectual curiosity. Higher openness is commonly associated with comfort with novelty and tolerance for ambiguity, which may be relevant for adapting to new work processes and technologies.

Conscientiousness reflects organization, reliability, and self-discipline (John, Naumann and Soto, 2008). It is captured through items such as "I follow schedules strictly" and reflects goal-directed behavior and adherence to rules and norms. Higher conscientiousness has been linked to educational and labor-market success and may also predict compliance with structured work protocols.

Agreeableness measures interpersonal orientation toward cooperation, empathy, and conflict avoidance (John, Naumann and Soto, 2008). We measure agreeableness using standard items (e.g., "I trust others' intentions"), where higher scores indicate a stronger tendency toward prosocial and cooperative behavior. In work settings, agreeableness can shape collaboration and interactions with clients and peers.

For each scale, we construct an index by summing item responses (after applying any required reverse-coding), so that higher values consistently indicate a stronger level of the corresponding skill.

Working conditions and job quality

We construct indices of perceived working conditions to operationalize job quality along five facets commonly used in the "decent work" framework and related ILO-based measures (Charlesworth et al., 2014; Leschke and Watt, 2014). The five facets are: (i) workers' rights and social protection, (ii) working-time quality, (iii) effective voice, (iv) respect (including harassment and discrimination), and (v) prospects/career opportunities. Each index aggregates multiple survey items designed to capture the corresponding dimension; details are provided in Table A2.

A crucial distinction in the index construction lies in the framing of their underlying survey items, leading

to two types of indices with contrasting directional interpretations. The first group of indices are positively framed and they are built from survey items where a positive response or higher score inherently reflects a more favorable working condition or higher job quality. Consequently, for these indices, higher values directly indicate better job quality. In our study, these include: Workers' Rights and Social Protection, Effective Voice, and Prospects/Career Opportunities.

The second group of indices are reverse-coded and they include Working-Time Quality Index and Respect Index. These indices are constructed from survey items that are framed to capture adverse or undesirable working conditions (e.g., asking about the presence of long hours or exposure to harassment). Thus, for these indices, higher values indicate poorer working conditions or lower job quality. This distinction is vital for accurate interpretation, especially when comparing across different facets.

Scoring and aggregation: Each item is coded on a 0-100 scale. All the answers provided to each question are binary Yes or No and they are coded as *Yes* = 100 and *No* = 0. For example, for contract status, *Permanent* is coded as 100 (and less secure arrangements receive lower scores); for paid leave, *Yes* is coded as 100; and for overtime compensation, *Yes* is coded as 100. Within each facet, we compute the index as the unweighted average of its component items. For a facet with K items and item scores $q_k \in [0, 100]$, the index is:

$$JQI_d = \frac{1}{K} \sum_{k=1}^{K} q_k,$$

where d indexes the job-quality dimension. We then use these facet-level indices in the empirical analysis. For the positively framed indices, the higher the index value, the greater the job quality. As detailed above, for positively framed indices, larger values correspond to better job quality. Conversely, for reverse-coded indices, larger values correspond to worse job quality. [8]

Mental health

We measure mental health using the 12-item General Health Questionnaire (GHQ-12), a widely used screening instrument for psychological distress and common mental disorders (Goldberg et al., 1997). The GHQ-12 includes items on sleep quality, concentration, confidence, decision-making, resilience, and overall well-being. Each item is scored on a 5-point Likert scale (0–4), yielding a total score from 0 to 48, where lower values indicate better mental health.[9] A threshold of 12 is commonly used to indicate elevated risk of common mental disorders (Goldberg et al., 1997). For ease of interpretation, we rescale the GHQ-12 total to a 0-100 scale in the regressions. The measure exhibits good internal consistency in our sample (Cronbach's $\alpha = 0.74$).

[8] For analytical purposes where a uniform interpretation is desired (i.e., higher values always denoting better job quality), the reverse-coded indices can be transformed. In our descriptive analyses, we present the indices in their original coding to reflect the direct responses from survey participants.

[9] We follow the standard scoring rule in which higher GHQ-12 values reflect greater psychological distress.

Experimental procedures

The sessions were organized with the support of locally hired staff and trained research assistants, with the authors serving as the chief administrator. Subjects were contacted approximately one week in advance and invited to attend a scheduled session at a designated location. All sessions were conducted on weekends in centrally located halls with rooms large enough to accommodate group participation while maintaining privacy during decision-making. Our target population comprises low- to mid-skill informal service workers in New Delhi. To obtain balanced coverage across work modes and occupations, we used an occupation-stratified recruitment strategy. We first identified key service occupations with both platform-mediated and offline informal work opportunities (e.g., taxi/driver services, courier and delivery services, and related service jobs). Within each occupation, we recruited workers engaged in either app-based digital platform or non-app-based traditional offline informal work. Recruitment took place through local intermediaries and workplace access points (e.g., platform hubs/dispatch points, contractor networks, and offline market locations). Potential subjectsreceived brief invitation letters describing the study and session logistics. Individuals who expressed interest and provided informed consent were enrolled until occupational and work-mode quotas were met.

Eligibility criteria required that subjects(i) had been working in their current work mode for at least six months and (ii) were not simultaneously engaged in both digital platform and traditional offline in their primary informal job.[10] All subjectsreceived compensation for participation, including earnings from the incentivized tasks and a show-up payment, which contributed to an overall participation rate of approximately 80%. A pilot session was conducted before the main data collection to test instructions and implementation procedures and to make minor adjustments. Data collection commenced in September 2022. Our final sample was constructed to achieve approximately equal representation of digital platform and traditional offline workers across the selected occupations. Figure 5 summarizes the recruitment and sampling process, and Table 1 reports the resulting sample distribution.

[10] Subjects may hold additional secondary jobs, including formal employment; our restriction applies to the primary informal service job used to classify work mode.

Figure 5: Experimental procedure

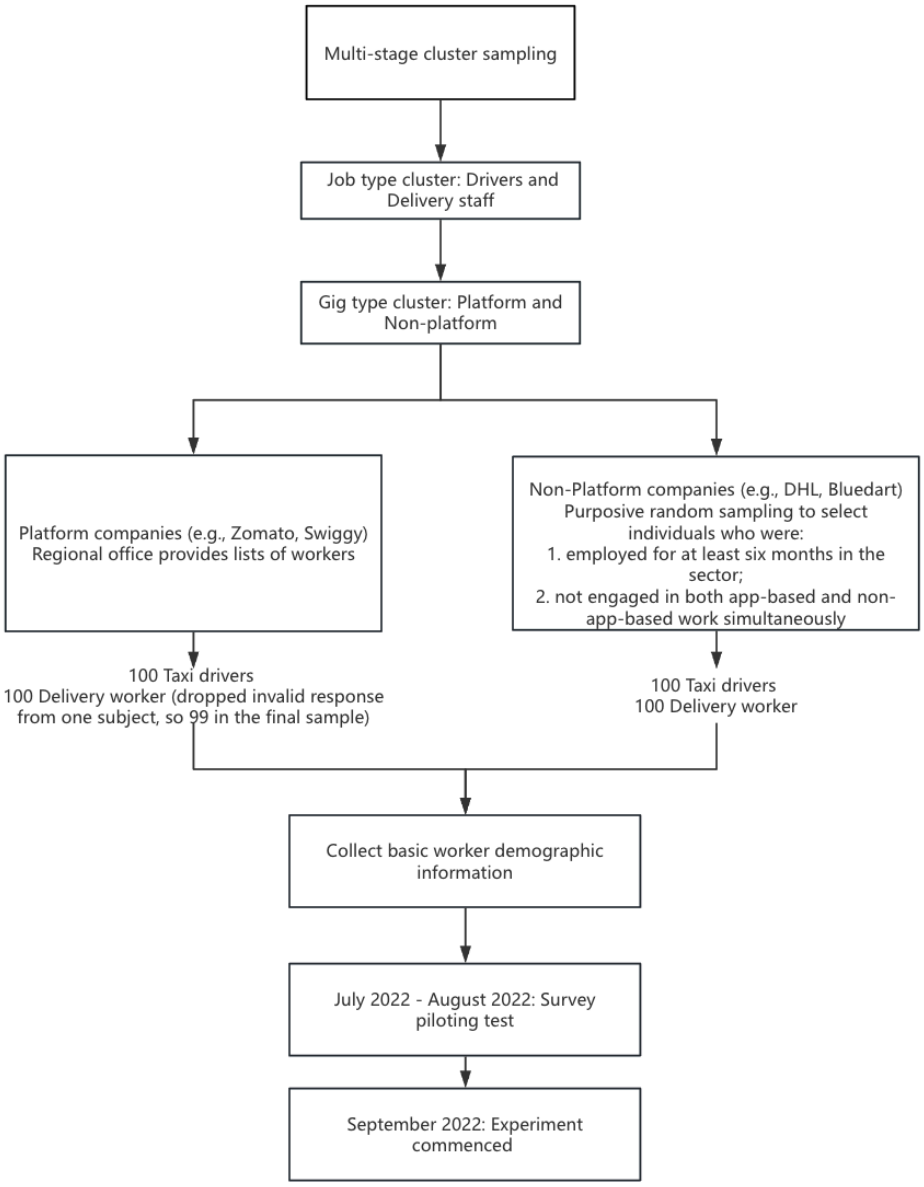


Table 1: Distribution of sampled digital platform and traditional offline informal workers (%) across various sectors.

Table 1: Distribution of traditional offline and digital platform service workers (%) across various sectors.

Traditional offline Services (T)			**Digital Platform Services (D)**		
Service Type	**Sample Size**	**% of Total Sample (400)**	**Service Type**	**Sample Size**	**% of Total Sample (400)**
Taxi services (other)	10	2.50%	Ola	16	4.00%
Private taxi service	90	22.50%	Ola/Uber	55	13.80%
			Uber	29	7.30%
Traditional Offline Taxi: Subtotal	*100*	*25.00%*	*Digital Platform Taxi: Subtotal*	*100*	*25.00%*
Bluedart/DHL/DTDC/Ecom Express	46	11.50%	Big Basket/Blinkit/Dunzo	25	6.30%
Restaurant Delivery/Ration Shop/Medical Store	54	13.50%	Swiggy	29	7.30%
			Zomato	46	11.50%
Traditional Offline Delivery: Subtotal	*100*	*25.00%*	*Digital Platform Delivery: Subtotal*	*100*	*25.00%*
Traditional Offline services: Total	**200**	**50.00%**	**Digital Platform services: Total**	**200**	**50.00%**

Upon arrival, subjects assembled in a common hall and received written instructions in their preferred language (Hindi or English). After all subjects were seated, the experimenter (the first author) provided a verbal explanation of the rules and procedures. To ensure anonymity and avoid identification by work mode or recruitment channel, each participant was assigned an identification number by drawing a chip from an opaque bag and was then directed by research assistants (RAs) to a seat.[11]

Each session included 18-24 subjects and lasted approximately 75-90 minutes. Tasks were completed individually and in a fixed sequence. We began with the real-effort task, followed by a short questionnaire module, then the risky investment game, and then the SVO task. Between tasks, we used brief questionnaires and debriefing prompts to reset attention and reduce spillovers across tasks. At the end of the session, subjects completed the remaining survey modules covering sociodemographic characteristics and soft skills. Throughout the session, RAs monitored progress, answered procedural questions, and ensured that subjects followed the instructions. Participant payments were based on the sum of points earned from (i) the real-effort task, (ii) the risky investment game, and (iii) the SVO task, plus a fixed participation fee. Total points were converted to Indian rupees using a pre-announced exchange rate and paid in cash at the end of the session. Average total compensation was approximately INR 1,000 (about USD 12).

[11] We administered short comprehension quizzes before each incentivized task. The session proceeded only after all subjects demonstrated understanding of the rules.

4 Results

In this section, we present the results that address the empirical questions and testable predictions outlined in section 2. We begin by describing the composition of our experimental sample. We then report descriptive comparisons and formal statistical tests for our first research question, whether risk attitudes and soft skills differ across work modes and age cohorts within the informal sector. Finally, we examine the association of participation in digital platform work and discuss the patterns consistent with sorting across work modes.

Table 2 reports summary statistics for the main outcomes and the demographic composition of the sample. On average, participants display moderate risk tolerance in the risky investment game, investing about 5 out of 10 tokens. A small share invests nothing (7.8%), while 8.8% invests the full endowment, consistent with risk-neutral or risk-loving behavior. Participants also exhibit moderate levels of selected soft skills, such as self-control and openness. The sample is predominantly young, with a mean age of 33 years. Almost all participants are male (99%), and the reported informal job is the primary source of income for the vast majority. Average educational attainment is approximately 10 years. The occupational composition is balanced by design, roughly half of the sample are taxi drivers, and half are delivery workers.

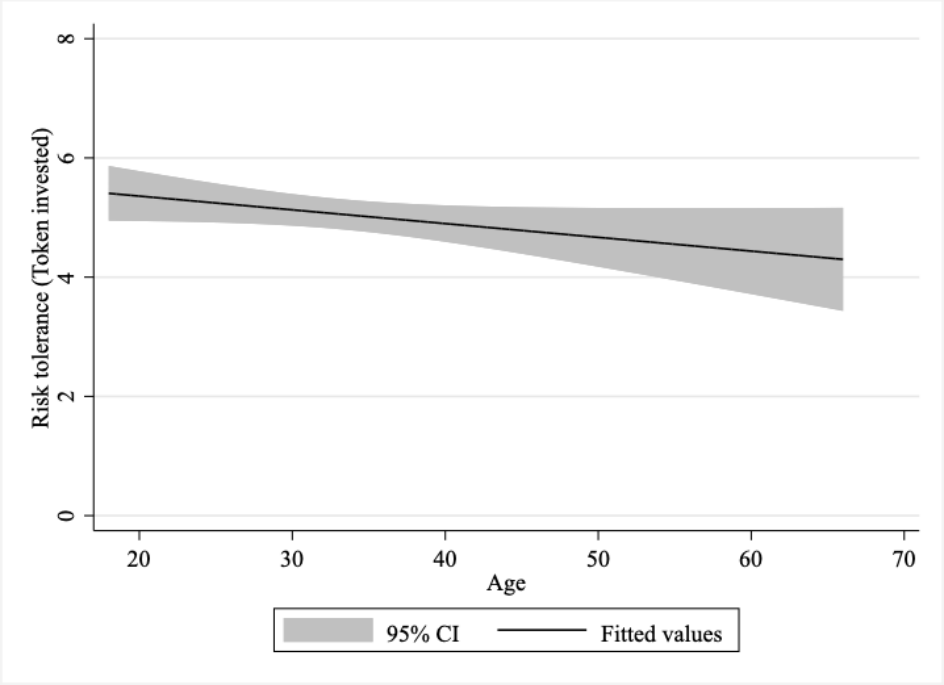
Table 2: Summary statistics

Variable	Obs	Mean	SD	Min	Max
Risk tolerance	399	5.055	2.58	0	10
No tolerance of risk	399	0.078	-	0	1
Risk neutral/seeking	399	0.088	-	0	1
Self-control	375	24.445	6.811	10	47
Grit	379	29.169	5.399	16	40
Openness	395	32.428	5.648	15	45
Conscience	398	36.141	5.243	21	45
Agreeableness	396	35.609	4.428	12	45
Pro-social	399	0.602	-	0	1
Digital work	399	0.499	-	0	1
Workers' rights and social protection	399	72.321	10.246	56.25	100
Working time quality index	399	39.536	25.222	0	100
Effective voice index	398	27.782	21.638	0	100
Respect Index	394	27.31	21.81	0	100
Prospect/Career opportunity Index	399	31.328	25.725	0	100
Age	399	33.201	10.067	18	66
Gender (Male=1)	399	0.99	-	0	1
Education	396	10.412	2.748	0	17
Married	399	0.682	0.466	0	1
Household size	399	5.386	2.346	1	22
General caste	399	0.877	-	0	1
Taxi driver	399	0.501	-	0	1
Earning family members	399	1.784	0.887	1	8
Family members with a regular job	399	1.647	0.484	0	2
GHQ Mental health index	399	35.318	19.509	0	100
GHQ physical health index	398	26.356	17.106	0	100

Note: The number of observations varies due to certain subjects not responding to specific questions. Additionally, we excluded one subject from the full sample who reported being 1 year old. For the variables for which standard deviations are not reported, these are binary variables that take a value of "1" if the respondent belongs to the indicated group (as specified by the variable name) and "0" otherwise. The detailed variable explanation can be found in Table A1.

Next, we examine the relationship between risk tolerance and age. Figure 6 shows a linear fit that indicates a negative association such that average risk tolerance declines with age. This pattern is consistent with evidence that risk-taking tends to decrease over the life cycle (Schildberg-Hörisch, 2018). Motivated by this relationship, we use the sample mean age (33 years) as the baseline cutoff for cohort comparisons in the subsequent analysis.

Figure 6: Risk tolerance and age



Note: This figure displays the relationship between age and risk tolerance, measured by the amount of tokens invested. The solid line represents the fitted values from a linear regression analysis, while the shaded area indicates the confidence interval around the fitted line.

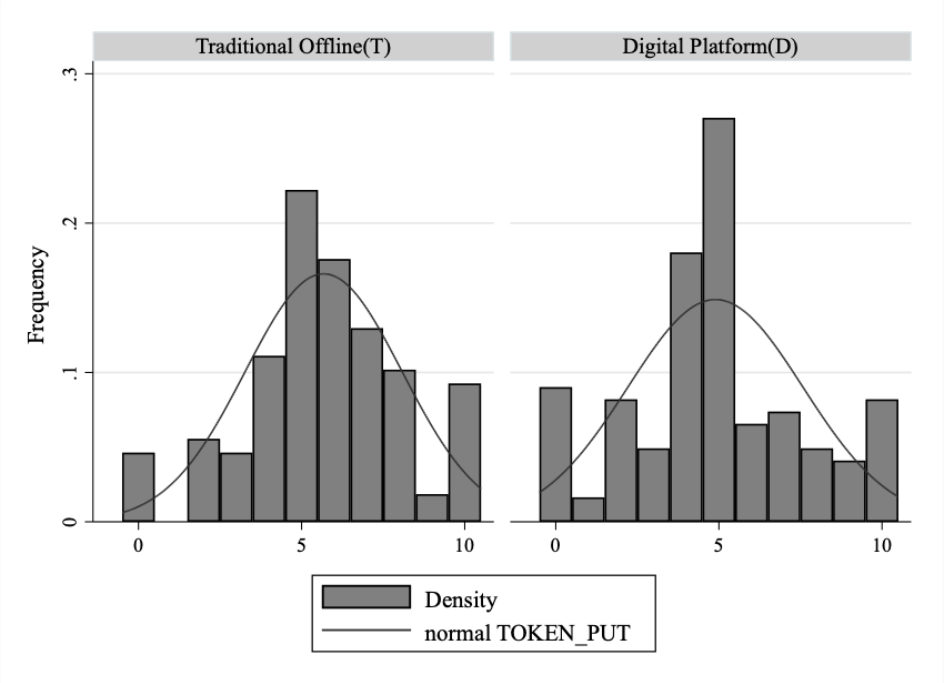
4.1 Difference in risk attitudes and soft skills

Here, we examine whether risk attitudes and soft skills differ between informal workers who perform comparable jobs but operate under different work modes, namely digital platform and traditional offline informal work. For each age cohort, we proceed in two steps. First, we present graphical comparisons of outcomes across work modes. Second, we report formal nonparametric tests of work-mode differences and complementary regressions that account for observable demographic characteristics.

Young age group

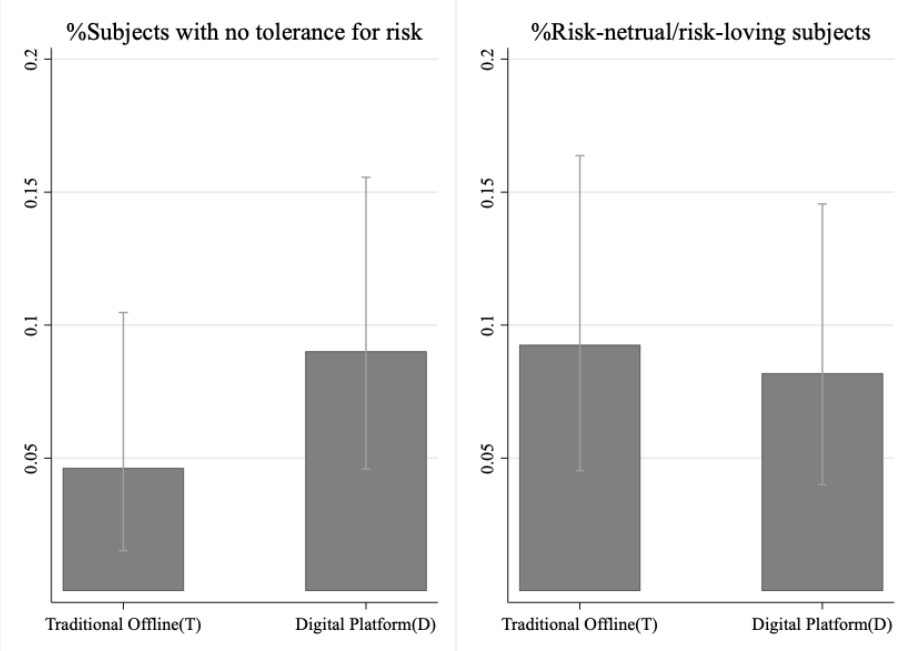
Figure 7 plots the distribution of token investments in the risky investment game for the young cohort, separately for traditional offline and digital platform workers. The distribution for young traditional offline workers places relatively more mass on higher investment levels, whereas the distribution for digital platform workers is more centered around an investment of five tokens. Figure 8 complements this evidence by reporting the shares of subjects making extreme choices such as investing zero tokens (no risk tolerance) or all ten tokens (risk-neutral/risk-seeking). Extreme choices are uncommon in both groups; however, a larger share of young traditional offline workers invests the full endowment and a smaller share invests zero, relative to young digital platform workers.

Figure 7: Histogram of token invested: Young age group



Note: This figure presents a histogram of the amount of tokens invested in RIG, which represents the frequency distribution of token investments, for traditional offline and digital platform workers in the young cohort.

Figure 8: Share of subjects with no tolerance of risk and risk-neutral/risk-seeking: Young cohort



Note: The height of each bar represents the mean proportion for each group. Confidence level is at 95%.

Table 3 reports two-sided tests of mean differences in risk tolerance and soft skills between the two groups,

digital platform and traditional offline workers in the young cohort.

The results indicate that young digital platform workers are, on average, significantly less risk-tolerant than their traditional offline counterparts (i.e., they invest fewer tokens in the risky investment game). Young digital platform workers also exhibit significantly higher self-control and openness, but significantly lower grit and conscientiousness; differences in agreeableness are weaker. Because the token-investment measure may be non-normally distributed, we additionally conduct a nonparametric Wilcoxon rank-sum test. The null hypothesis of the Wilcoxon test is that the distribution of token investments is the same for digital platform and traditional offline workers. We reject this null for the young cohort (p-value = 0.007), implying a statistically significant difference in risk tolerance across work modes.[12] Consistent with the t-test evidence, the Wilcoxon result indicates that young digital platform workers invest fewer tokens than young traditional offline workers, reflecting lower risk tolerance among young platform workers.

[12] Wilcoxon rank-sum test p-values for risk tolerance, no tolerance of risk, and risk-neutral/risk-seeking are 0.007, 0.193, and 0.776, respectively.

Table 3: Difference in risk tolerance and soft skills by worker type: Young age group

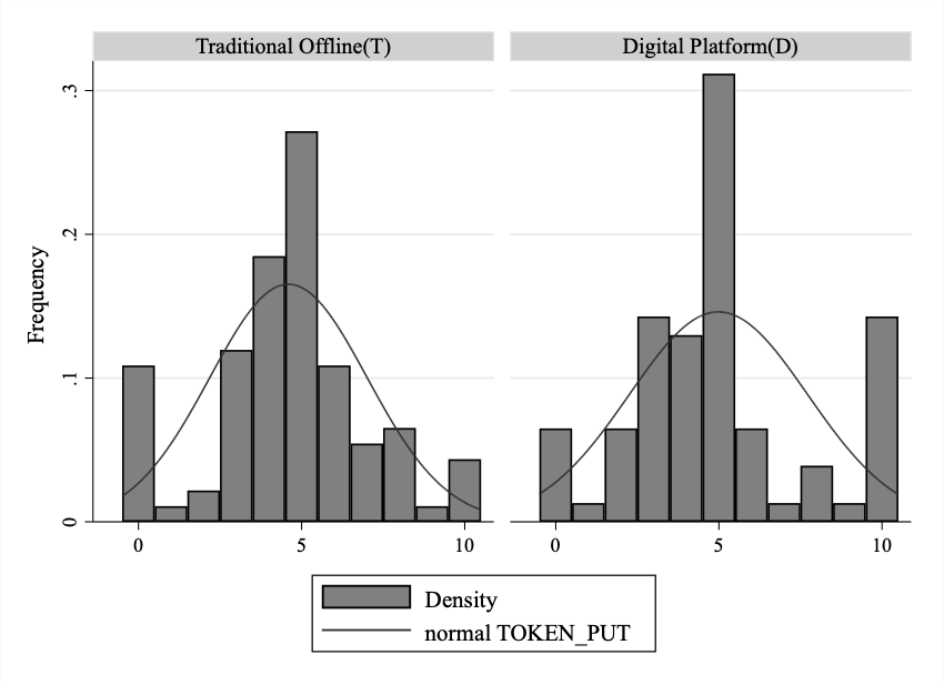
	(1)	(2)	(3)
Variable	Traditional offline (T)	Digital Platform (D)	Diff.
Risk tolerance	5.676	4.893	-1.211***
	(2.403)	(2.681)	(0.457)
No tolerance of risk	0.046	0.090	0.094*
	(0.211)	(0.288)	(0.052)
Risk neutral/seeking	0.093	0.082	-0.061
	(0.291)	(0.275)	(0.047)
Self-control	23.028	27.000	2.893***
	(7.000)	(5.696)	(1.042)
Grit	30.980	26.964	-3.686***
	(4.483)	(5.273)	(0.846)
Openness	32.124	33.579	1.984**
	(4.136)	(5.383)	(0.775)
Conscientiousness	37.159	34.057	-2.221***
	(4.261)	(5.672)	(0.799)
Agreeableness	35.639	34.372	-0.431
	(3.832)	(4.772)	(0.674)
Pro-social	0.537	0.582	0.089
	(0.501)	(0.495)	(0.076)
Observations	108	122	230

Note: Columns (1) and (2) report group means for traditional offline and digital platform workers, respectively (standard deviations in parentheses). Column (3) reports the difference in means between digital platform and traditional offline workers based on a two-sided t-test implemented via a linear regression of the outcome on a digital-work indicator and controls for individual characteristics (age, gender, educational attainment, marital status, household size, caste, occupation indicator for taxi driver, number of earning household members, number of household members with a regular job, and mental and physical health scores). Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Middle and old age group

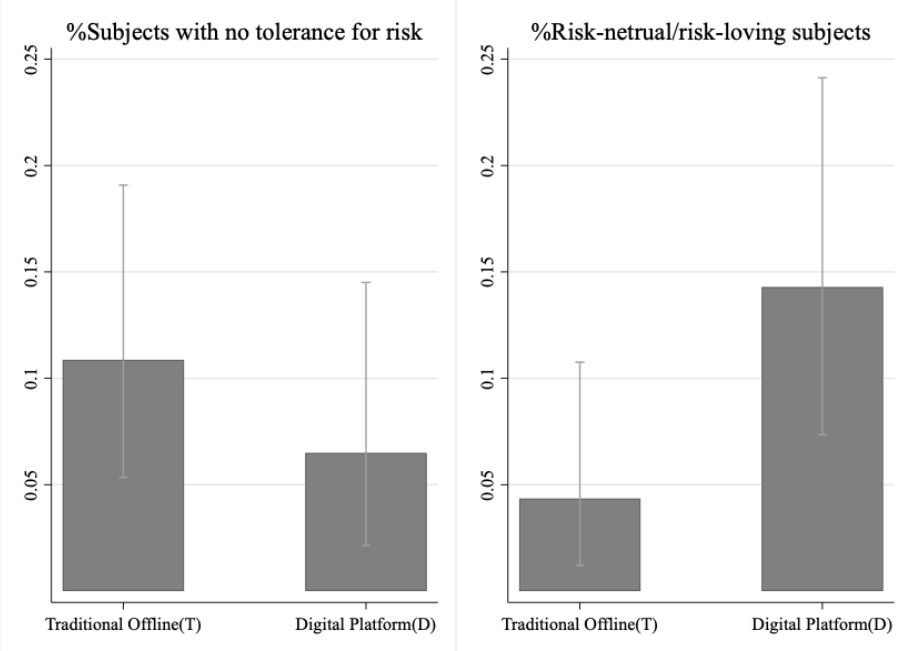
This subsection compares risk tolerance and soft skills between traditional offline and digital platform workers in the middle-to-older cohort. We first plot the distribution of token investments by work mode in Figure 9. We then report the shares of subjects making extreme choices, like investing zero tokens (no risk tolerance) or all ten tokens (risk-neutral/risk-seeking), as shown in Figure 10. For this cohort, the distributions of token investments for traditional offline and digital platform workers are broadly similar. As in the young cohort, extreme choices are uncommon; however, among workers older than 30, a slightly larger share of digital platform workers invests the full endowment and a smaller share invests zero relative to traditional offline workers.

Figure 9: Histogram of token invested: Middle and old age group



Note: This figure presents a histogram of the amount of tokens invested in RIG, which represents the frequency distribution of token investments, for traditional offline and digital platform workers in the older age group.

Figure 10: Share of risk-neutral/seeking subjects: Middle and old age group



Note: The height of each bar represents the mean proportion for each group. Confidence level is at 95%.

409 Table 4 reports two-sided tests of mean differences between digital platform and traditional offline workers

in the middle-to-older cohort. The t-test results show that the share of subjects classified as risk-neutral/risk-seeking (i.e., investing all ten tokens) is significantly higher among digital platform workers than among traditional offline workers. We corroborate this result using the Wilcoxon rank-sum test. Specifically, the Wilcoxon test rejects the null hypothesis that the distribution of the risk-neutral/risk-seeking indicator is identical across work modes (p-value = 0.046). In contrast, we do not reject equality of distributions for token investments (risk tolerance) or for the "no risk tolerance" indicator (p-values = 0.680 and 0.472, respectively). Turning to soft skills, digital platform workers in this cohort exhibit higher self-control and openness, but lower grit and conscientiousness, consistent with the patterns documented for the younger cohort.

Table 4: Difference in risk tolerance and soft skills by worker type: Middle and old age cohort

	(1)	(2)	(3)
Variable	Traditional offline (T)	Digital Platform (D)	Diff.
Risk tolerance	4.598	4.987	0.389
	(2.414)	(2.731)	(0.400)
No tolerance of risk	0.109	0.065	-0.044
	(0.313)	(0.248)	(0.043)
Risk neutral/seeking	0.043	0.143	0.099**
	(0.205)	(0.352)	(0.045)
Self-control	22.462	25.229	2.767**
	(7.054)	(6.521)	(1.074)
Grit	31.854	26.842	-5.012***
	(4.713)	(5.185)	(0.777)
Openness	29.935	34.013	4.078***
	(6.769)	(5.386)	(0.935)
Conscientiousness	38.707	34.961	-3.745***
	(4.500)	(5.001)	(0.738)
Agreeableness	36.538	36.421	-0.117
	(4.480)	(4.199)	(0.673)
Pro-social	0.685	0.623	-0.061
	(0.467)	(0.488)	(0.074)
Observations	92	77	169

Note: Columns (1) and (2) report group means for traditional offline and digital platform workers, respectively (standard deviations in parentheses). Column (3) reports the difference in means between digital platform and traditional offline workers based on a two-sided t-test implemented via a linear regression of the outcome on a digital-work indicator and controls for individual characteristics (age, gender, educational attainment, marital status, household size, caste, occupation indicator for taxi driver, number of earning household members, number of household members with a regular job, and mental and physical health scores). Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Overall, the evidence indicates systematic differences in risk attitudes and soft skills between digital plat-

form and traditional offline workers, and these differences vary by age cohort. Accordingly, we *reject* Test 1 and Test 2 (the empirical tests of no systematic differences in risk attitudes and soft skills across work modes).[13] For the young cohort, traditional offline workers exhibit higher risk tolerance than digital platform workers, as reflected in higher average token investments in the risky investment game. Among middle-to-older workers, average token investments do not differ significantly across work modes; however, the share of workers making the extreme "risk-neutral/risk-seeking" choice (investing all ten tokens) is higher among digital platform workers. Differences in soft skills are more stable across cohorts: digital platform workers tend to score higher on self-control and openness, but lower on grit and conscientiousness, relative to traditional offline workers. Taken together, these results are consistent with heterogeneity in preferences and soft skills across work modes within the informal sector, rather than a uniform worker type across digital and offline arrangements.

4.2 Risk tolerance, soft skills, working conditions, and job choice

Next, in this section, we examine the association for participation in digital platform to address our second research question, i.e., how are risk attitudes, soft skills, and perceived working conditions associated with work-mode choice among informal workers? We also analyze and evaluate Hypotheses 1-3, which posit that these individual characteristics and job attributes are systematically related to selection into digital platform. Our goal is to quantify these associations and assess which dimensions appear most closely linked to digital work participation.

Main results

Table 5 reports the probit estimates for the full sample (Columns 1–3), the young cohort (Columns 4–6), and the older cohort (Columns 7–9). Table 6 reports the corresponding marginal effects of risk tolerance, soft skills, and perceived working conditions on the probability of engaging in digital platform. Model fit improves as additional covariates are added in each panel. For the full sample, the Pseudo R^2 increases from 0.198 in Column (1) to 0.532 in Column (3). For the young cohort, it rises from 0.258 in Column (4) to 0.619 in Column (6). For the older cohort, it increases from 0.279 in Column (7) to 0.834 in Column (9). These patterns indicate that the expanded specifications capture a substantially larger share of the variation in work-mode participation across both the full sample and age subgroups.

[13] In section 2, we frame these as empirical tests rather than directional hypotheses.

Table 5: Predictors of participation in digital platformwork

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DV: $Digital_i$		All			Young			Old	
Risk Tolerance	-0.054*	-0.051	-0.081**	-0.106***	-0.130***	-0.252***	0.013	0.040	0.312***
	(0.030)	(0.035)	(0.040)	(0.041)	(0.049)	(0.067)	(0.047)	(0.055)	(0.115)
Self-Control		0.001	-0.010		0.034	0.027		0.000	0.049
		(0.017)	(0.020)		(0.025)	(0.034)		(0.028)	(0.046)
Grit		-0.079***	-0.087***		-0.045	-0.053		-0.145***	-0.417***
		(0.021)	(0.025)		(0.028)	(0.032)		(0.048)	(0.085)
Openness		0.044***	0.056***		0.056**	0.127***		0.038	0.089**
		(0.016)	(0.019)		(0.024)	(0.032)		(0.025)	(0.044)
Conscientiousness		-0.069***	-0.047*		-0.045*	-0.014		-0.137***	-0.143**
		(0.020)	(0.025)		(0.026)	(0.036)		(0.040)	(0.070)
Agreeableness		0.046**	0.034		0.014	-0.008		0.141***	0.185**
		(0.021)	(0.026)		(0.029)	(0.037)		(0.043)	(0.086)
Pro-Social Behavior		0.137	0.125		0.052	0.098		0.889**	2.918***
		(0.170)	(0.200)		(0.211)	(0.249)		(0.362)	(0.676)
Workers' Rights and Social Protection Index			0.015			-0.011			0.035*
			(0.010)			(0.014)			(0.021)
Working Time Quality Index			-0.027***			-0.046***			-0.081***
			(0.004)			(0.009)			(0.016)
Effective Voice Index			-0.021***			-0.007			-0.180***
			(0.006)			(0.010)			(0.039)
Respect Index			0.002			0.010			-0.049***
			(0.004)			(0.007)			(0.013)
Prospect/Career Opportunity Index			0.028***			0.042***			0.054***
			(0.004)			(0.008)			(0.015)
Observations	391	344	339	225	191	189	166	153	150
Pseudo R2	0.198	0.340	0.532	0.258	0.363	0.619	0.279	0.529	0.834
Individual Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: $Digital_i$ is an indicator for digital platform work (= 1) versus traditional offline informal work (= 0). The column title indicates the corresponding subgroup. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Individual controls include age, gender, education level, marital status, household size, caste, job, number of earning members in the family, number of family members with a regular job, years of work, mental health, and physical health status. The detailed variable explanation could be found in Table A1.

Table 5 reports probit estimates where the dependent variable equals 1 if the subject participates in digital platform work and 0 otherwise. The table presents results for the full sample, the young cohort, and the older cohort. The specifications are nested as the baseline model that includes risk tolerance, the next model adds soft skills, and the final model further includes perceived working-condition indices. Results in table 5 show that risk tolerance is negatively associated with digital participation in the full sample and strongly negative in the young cohort across specifications. In contrast, for the older cohort, risk tolerance becomes positively and significantly associated with digital participation with all the controls. Among soft skills, openness is consistently positively associated with digital participation in the full sample and among young workers (and remains positive for older

workers in the final model), whereas grit and conscientiousness are generally negatively associated, especially in the older cohort, where the magnitudes are large and precisely estimated. After adding working conditions, i.e., the 3rd model, such as prospects, career, and opportunities, show positive and significant results in all three panels (all, young, and old cohorts), while working-time quality gives negative, significant results in all three panels. Effective voice is also negative and significant in the full and older samples, and the respect index is negative and significant for older workers. Overall, the table shows that both soft skills and perceived job attributes are systematically related to digital platform participation, with particularly strong age heterogeneity in the association with risk tolerance.

Table 6: Marginal effects

	(1)	(2)	(3)
DV: $Digital_i$	**All**	**Young**	**Old**
Risk Tolerance	-0.015*	-0.037***	0.020**
	(-2.05)	(-4.56)	(2.78)
Self-Control	-0.002	0.004	0.003
	(-0.49)	(0.81)	(1.10)
Grit	-0.016***	-0.008	-0.026***
	(-3.58)	(-1.60)	(-5.06)
Openness	0.010**	0.019***	0.006*
	(3.11)	(4.95)	(2.18)
Conscientiousness	-0.009	-0.002	-0.009*
	(-1.93)	(-0.40)	(-2.17)
Agreeableness	0.006	-0.001	0.012*
	(1.32)	(-0.21)	(2.24)
Pro-social Behavior	0.023	0.014	0.184***
	(0.63)	(0.39)	(3.94)
Workers' Rights Index	0.003	-0.002	0.002
	(1.40)	(-0.77)	(1.70)
Working Time Quality Index	-0.005***	-0.007***	-0.005***
	(-6.73)	(-7.86)	(-5.25)
Effective Voice Index	-0.004***	-0.001	-0.011***
	(-4.23)	(-0.76)	(-4.57)
Respect Index	0.000	0.001	-0.003***
	(0.44)	(1.49)	(-4.15)
Prospect/Career Opportunity Index	0.005***	0.006***	0.003***
	(7.82)	(7.99)	(4.74)
Observations	339	189	150

Note: $Digital_i$ is an indicator for digital platform work (= 1) versus traditional offline informal work (= 0). Marginal effects from probit models. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 reports marginal effects from the fully specified probit models, separately for the full sample, the young cohort, and the older cohort. The marginal effect can be interpreted as the change in the predicted probability of participating in digital platform associated with a one-unit increase in the corresponding regressor,

holding other covariates fixed (Wooldridge, 2025). Risk tolerance exhibits pronounced heterogeneity by age group. In the full sample, a one-unit increase in risk tolerance is associated with a 1.5 percentage-point decrease in the probability of digital platform participation (-0.015, $p < 0.1$). Among young workers, the association is larger in magnitude: a one-unit increase in risk tolerance reduces the probability of digital platform participation by 3.7 percentage points (-0.037, $p < 0.001$). In contrast, among older workers, a one-unit increase in risk tolerance increases the probability of digital platform participation by 2.0 percentage points (0.020, $p < 0.05$). Overall, these estimates do not support a single, cohort-invariant relationship between risk tolerance and platform participation. We therefore reject Hypothesis 3 as stated and interpret the results as evidence of age-dependent selection into digital platform.

Soft skills influence digital platform work participation, and the measures have economically and statistically significant effects where these patterns vary by age cohort. In the full sample, grit is negative and precisely estimated as a one-unit increase in grit is associated with a 1.6 percentage-point lower probability of digital platform participation (-0.016, $p < 0.01$). Openness is positive: a one-unit increase is associated with a 1.0 percentage-point higher probability of digital platform participation (0.010, $p < 0.05$). For the young cohort, openness remains positive and larger in magnitude: a one-unit increase is associated with a 1.9 percentage-point increase in digital platform participation (0.019, $p < 0.01$), while other soft-skill effects are not precisely estimated. For the older cohort, grit remains negative (-0.026, $p < 0.01$) and openness remains positive (0.006, $p < 0.1$). In addition, agreeableness is weakly positive (0.012, $p < 0.1$), conscientiousness is weakly negative (-0.009, $p < 0.1$), and prosocial behavior has a large positive marginal effect (0.184, $p < 0.01$). Overall, these marginal effects support Hypothesis 4: openness is positively associated with participation in digital platform, with the strongest relationship among younger workers.

Perceived working conditions are also associated with participation in digital platform, and the relationships differ across indices. The Workers' Rights and Social Protection Index is not statistically significant in any demographic group, suggesting that informal workers may not prioritize workplace rights when choosing work mode. The Working Time Quality Index is negative in the full samples and the two age subsamples, as a one-unit increase in this index is associated with around 0.5 percentage-point lower probability of digital platform participation in the full sample (-0.005, $p < 0.01$), with similarly negative effects for the young and older cohorts. Because higher values of the Working Time Quality Index indicate *poorer* working-time quality (e.g., longer hours and weaker work-life balance), the negative marginal effect implies that worse working-time conditions are associated with a lower likelihood of digital platform participation (equivalently, better working-time quality is associated with a higher likelihood of digital platform participation). Effective voice is also negative in the full and older samples, with marginal effects of -0.004 ($p < 0.01$) and -0.011 ($p < 0.01$), respectively. The Respect Index is negative and significant for older workers (-0.003, $p < 0.01$). Since higher values of the Respect Index reflect *worse* treatment (e.g., harassment, discrimination, or threats), this estimate implies that

poorer treatment is associated with a lower probability of digital platform participation among older workers.

Finally, prospects/career opportunities are positive and precisely estimated in all the three regressions: a one-unit increase in the Prospect/Career Opportunity Index is associated with a 0.5 percentage-point higher probability of digital platform participation in the full sample (0.005, $p < 0.01$), with effects of 0.006 ($p < 0.01$) for the young cohort and 0.003 ($p < 0.01$) for the older cohort. Overall, these results provide partial support for Hypothesis 5, with the most robust relationship arising for perceived prospects and career opportunities.

Associations with demographic controls

Table A6 reports probit estimates for participation in digital platform using the full set of individual controls, and Table A7 reports the corresponding marginal effects of these controls. Several demographics are associated with digital platform participation, with clear heterogeneity by age cohort. Family structure appears to be a critical determinant of labor supply, such that marriage is strongly negatively associated with digital platform participation for both cohorts. The marginal effects indicate that being married is associated with a 17.8 percentage-point lower probability of digital platform participation among young workers (-0.178, $p < 0.05$) and a 38.2 percentage-point lower probability among older workers (-0.382, $p < 0.01$). Household size is positively related to digital platform participation in both cohorts, with marginal effects of 3.8 percentage points for young workers (0.038, $p < 0.01$) and 3.7 percentage points for older workers (0.037, $p < 0.01$). Household employment composition is also an important factor; the number of household members holding a regular job is positively associated with digital platform participation in the full sample (0.149, $p < 0.01$) and especially in the older cohort (0.443, $p < 0.01$). Caste status differs by cohort, such as General Caste is negatively associated with digital platform participation among young workers (-0.142, $p < 0.1$) but positively associated among older workers (0.266, $p < 0.1$).

Finally, the GHQ mental health index enters positively across samples (0.005, $p < 0.01$), implying that higher psychological distress is associated with a higher probability of digital platform participation. This positive correlation warrants careful consideration, as it may suggest that for some individuals, the gig economy functions as a critical, albeit often precarious, survival mechanism. Specifically, platform work can offer a low-barrier entry point for those facing significant challenges or existing vulnerabilities in traditional labor markets, providing a flexible source of income when other options are limited (Woodcock and Graham, 2020). While this flexibility accommodates certain pre-existing vulnerabilities, it is crucial to recognize that it may not alleviate, and in some cases could even exacerbate, the psychological burden experienced by these workers.

Overall, these results suggest that household context and individual constraints shape selection into digital platform differently over the life cycle. For older workers, the positive association with regular household employment is consistent with digital platform serving as a supplementary income margin when a household income floor is already in place. The positive association with psychological distress, in turn, indicates that plat-

form participation is higher among individuals reporting worse mental well-being, underscoring the importance of considering worker vulnerability when evaluating platform-work policies.

Power issue and effect size

Given sample size constraints and the heterogeneity observed across age cohort-specific analyses, we assess statistical sensitivity by computing minimum detectable effects (MDEs) for the key participation specifications in Table 5. We calculate the MDE treating risk tolerance as a continuous regressor under conventional assumptions ($\alpha = 0.05$, power $= 0.80$). For the full sample ($N = 339$), this approach yields an MDE of approximately 0.15 standard deviations. Evaluated at the mean, this corresponds to a change in the predicted probability of digital platform participation of roughly 6 percentage points.[14] Our estimated marginal effects indicate that a single-unit increase in risk tolerance changes participation probability by 3.7 percentage points for the young cohort (0.037^{***}) and 2.0 percentage points for the older cohort (0.020^{**}). Crucially, while the marginal effect of a single unit may fall below this conservative threshold, meaningful variation in risk tolerance typically spans a wider range. A shift of approximately two points less than one standard deviation implies a cumulative probability change that exceeds the detection threshold. This confirms that by exploiting the full continuous variation of the risk-tolerance measure, the study is sufficiently powered to detect the realistic behavioral heterogeneity driving the observed sorting patterns.

We assess economic magnitudes using the marginal effects reported in Table 6. Since Risk Tolerance is measured on a 0–10 scale, the reported marginal effect can be interpreted as the change in the predicted probability of digital platform participation associated with a one-point increase in the risk score, holding other covariates fixed. For the young cohort, a one-point increase in risk tolerance is associated with a 3.7 percentage-point lower probability of working in the digital platform mode (-0.037), and this effect is economically substantial. To illustrate the magnitude, a hypothetical shift is from a relatively low risk-tolerance score of 2 to a relatively high score of 8, which corresponds to an approximate 22.2 percentage-point decrease in the predicted probability of digital platform participation (6×3.7 percentage points), under the local linear approximation implied by marginal effects. This suggests that for young workers, risk tolerance level is a key driver of digital platform labor supply.

For the older cohort, the marginal effect has the opposite sign, and each additional point of risk tolerance is associated with a 2.0 percentage-point higher probability of digital platform participation (0.020). Comparisons with other covariates suggest that this behavioral measure is quantitatively important. In the older cohort, the marginal effect of a one-point increase in risk tolerance (0.020) exceeds the marginal effects associated with

[14] The calculation proceeds in two steps. First, for a continuous regressor in a two-sided test with $\alpha = 0.05$ and $1-\beta = 0.80$, the Minimum Detectable Effect size in standard deviation units is approximated by $MDE_\sigma \approx (t_{\alpha/2} + t_{1-\beta})/\sqrt{N} \approx 2.80/\sqrt{339} \approx 0.152$. Second, to convert this standardized Probit coefficient into a marginal effect (percentage point change), we scale it by the standard normal probability density function (ϕ) evaluated at the sample mean. Given the balanced sample design (participation rate $P \approx 0.5$), the density is maximized at $\phi(0) \approx 0.399$. Thus, the MDE in percentage points is approximately $0.152 \times 0.399 \approx 0.061$, or 6.1 percentage points.

one-point changes in the Working Time Quality Index (-0.005) and the Prospect/Career Opportunity Index (0.003). These magnitudes indicate that, for older workers, variation in risk tolerance is associated with sizable differences in digital platform participation relative to several perceived job-quality dimensions measured on the same 0–100 scale.

All taken together, our analysis leads us to reject Hypothesis 5, which proposed that improvements in working conditions universally attract more informal workers to digital platform platforms. Instead, it appears that enhancements in work-life balance and career development opportunities are the primary motivators for informal workers across all age groups to choose digital platform work. Older informal workers also place a higher value on the level of respect they receive in their workplace.

5 Discussion and conclusion

This paper examines heterogeneity within the urban informal labor market by comparing workers engaged in digital platform and traditional offline in New Delhi. Using incentivized measures of risk tolerance and social preferences, together with validated psychometric measures of soft skills and perceived working conditions, we document differences across work modes and show that these patterns vary by age cohort. Since the workers are observed after selecting into a work mode, the estimates are interpreted as associations consistent with sorting for platform participation.

We have identified three major findings. First, the relationship between risk tolerance and digital platform participation is dependent upon age-cohort. The age-dependent patterns in risk tolerance are consistent with sorting shaped by both job structure and life-cycle heterogeneity (Schildberg-Hörisch, 2018). Among younger workers, higher risk tolerance is associated with a lower likelihood of digital platform participation, whereas among older workers, the relationship is positive. In traditional offline informal markets (e.g., street-hailing taxi services), earnings often depend on search, bargaining, and intense competition, which can amplify day-to-day income risk. By contrast, digital platform typically standardizes dispatching and pricing, which can dampen one margin of uncertainty and make earnings more predictable. This mechanism can rationalize why, among younger workers, platform participation is higher among those with lower risk tolerance, even though risk-averse individuals are often found to prefer more stable work arrangements in other settings (Anderson and Mellor, 2008; Dong, 2017). For older workers, entry into digital platform may require adapting to new technologies and platform protocols; as a result, selection into platform work may be concentrated among relatively more risk-tolerant individuals. These patterns challenge the view of a homogeneous "gig worker" type (Keith, Harms and Tay, 2019) and suggest that the relevant divide is not only technological but also behavioral. This heterogeneity is consistent with the conceptual framework, which states that platform work can reduce some sources of uncertainty (e.g., bargaining frictions through standardized terms), but it can also introduce

platform-specific risks (e.g., monitoring and enforcement through ratings and deactivation) and involve entry and compliance costs. As a result, the mapping between risk tolerance and platform participation need not be uniform over the life cycle (Schildberg-Hörisch, 2018). In addition, the age-dependent reversal in the association between risk tolerance and platform participation highlights the value of allowing preferences and constraints to interact with age, rather than treating age solely as a control.

Second, we find that soft skills are associated with platform participation in economically meaningful and non-monotonic ways, suggesting that participation is not simply a function of having better soft skills. Openness is positively associated with digital platform participation across cohorts, with the largest marginal effect observed among younger workers. In contrast, grit and conscientiousness are negatively associated with platform participation, a relationship that is particularly pronounced among older workers. While self-control is higher among digital platform workers in simple mean comparisons, the relationship is not precisely estimated once additional covariates are included. Overall, the evidence suggests that platform participation is related to a specific profile of soft skills rather than a single unidimensional or monotone notion of “better" soft skills (Heckman and Kautz, 2012).

Third, perceived job attributes are closely linked to platform participation. Prospects/career opportunities are positively associated with digital platform participation in all samples, whereas worse working-time quality (higher index values) is associated with lower platform participation. Effective voice is negatively associated with participation in the full sample and among older workers. Respect-related conditions matter primarily for older workers. These patterns indicate that workers place weight on perceived advancement opportunities and day-to-day work organization when selecting work mode, while other dimensions play a more limited role in the participation margin.

The results have implications for both platforms and policymakers. For platforms, the robust association between perceived prospects and participation suggests that recruitment and retention may be strengthened by credible investments in skill development and progression pathways. The negative association between poor working-time quality and participation highlights the potential value of predictable scheduling, transparent rules, and policies that reduce time-related burdens. For policymakers, the evidence is consistent with segmentation within informal service work. Platform work may expand opportunities for some workers, but entry frictions and platform-specific risks can limit access or reduce the attractiveness of participation, particularly for younger workers facing liquidity constraints. Policies that lower up-front barriers (e.g., digital access and training) and strengthen portable protections across work arrangements may improve welfare. In addition, the negative associations for voice- and respect-related dimensions among older workers point to the importance of accessible grievance mechanisms and procedural protections in platform work.

This study advances the literature through a “same work, different work modes" approach, where we directly compare workers performing similar low- to mid-skill tasks under digital platform and traditional arrangements.

This design allows for the precise identification of the behavioral and preference-based drivers of occupational sorting. These insights are particularly relevant to policymakers and platform designers seeking to promote worker engagement, retention, and job satisfaction in a rapidly evolving labor market. However, several limitations qualify interpretation. First, the sample is almost entirely male; therefore, conclusions are best interpreted as applying to the male segment of the urban informal service workforce. Second, the cross-sectional design limits causal inference and does not allow us to separate sorting from within-worker preference change. Third, the study is conducted in a single urban labor market and focuses on selected occupations, which may limit external validity. Future research could combine panel data with incentivized measures to distinguish selection from learning and adaptation, and extend the analysis to female-dominated platform segments and other cities to assess the generality of the age-dependent patterns documented here.

In sum, the paper provides evidence of behavioral heterogeneity within the informal sector and shows that the association between risk tolerance and platform participation depends on age. These findings contribute to a more nuanced understanding of labor market segmentation in developing economies and highlight the role of workers' soft skills and perceived job attributes in shaping participation in digital platform work.

Appendix

Table A1: Variable explanation

Variable	Definition
Age	It is a continuous variable that indicates the age of the subject.
Education	It is a continuous variable that indicates Years of education.
Married	Marital status of the subject. It takes the value of 1 if the subject is married and 0 otherwise. Other marital statuses include: single, divorced, widowed, and separated.
Household size	It is a continuous variable that indicates the number of family members.
General caste	It is a dummy variable that indicates the caste type of the subject. It takes the value of 1 if the subject reports "general caste" and 0 otherwise. Other caste types include: other backward class (BC), scheduled caste (SC), scheduled tribe (ST).
Taxi driver	It is a dummy variable that indicates the type of informal work of the subject has. It takes the value of 1 if the subject is a taxi driver and 0 otherwise. The other type of informal work is street delivery.
Earning family members	It is a continuous variable that indicates the number of family members who can earn a living.
Family members with a regular job	The number of family members who have a regular job.
GHQ mental health index	The mental health condition of subjects is measured through the 12-item General Health Questionnaire (GHQ-12). GHQ-12 consists of 12 items such as loss of sleep, concentration and confidence, ability to overcome difficulties. The answer to each question is frequency, from "Not at all" to "Extremely". We rescaled the total score to make it range from 0 to 100, so the lower values indicate better mental health.
GHQ physical health index	The physical health condition of subjects is measured through the other 12 General Health Questions associated with physical distress. We rescaled the total score to make it range from 0 to 100 and the lower the value, the better the health condition.

Note: This table explains the major demographics of the subjects, which are used as individual controls in this study.

Table A2: Dimensions and components of Job-Quality Indices

Index	**Dimensions**
Worker Rights and Social Protection	Contract
	Income security and volatility
	Social security
Working Time Quality	Duration
	Non-atypical working time
	Work-life balance
Effective Voice	Contact
	Representation
Respect Index	Relationship
	Change in workplace activity
	Workplace social support
Professional Prospect/Career Opportunities	Training, job insecurity

Source: Authors

Table A3: Difference in risk preference and soft skills by worker type: 32 years old as age cutoff

Panel A: Below 32 years old			
Variable	Mean Traditional	Mean Digital	Diff.
Risk tolerance	4.735	5.146	0.412
	(2.439)	(2.816)	(0.397)
No tolerance of risk	0.102	0.061	-0.041
	(0.304)	(0.241)	(0.041)
Risk neutral/seeking	0.051	0.171	0.120**
	(0.221)	(0.379)	(0.047)
Self-control	22.402	25.493	3.091***
	(6.974)	(6.496)	(1.031)
Grit	31.695	26.864	-4.831***
	(4.715)	(5.137)	(0.748)
Openness	30.031	33.927	3.896***
	(6.683)	(5.363)	(0.898)
Conscience	38.480	34.878	-3.602***
	(4.486)	(4.930)	(0.708)
Agreeableness	36.485	36.148	-0.336
	(4.433)	(4.307)	(0.657)
Pro-social	0.673	0.622	-0.052
	(0.471)	(0.488)	(0.072)
Observations	98	82	180
Panel B: Above 32 years old			
Variable	Mean Traditional	Mean Digital	Diff.
Risk tolerance	5.608	4.778	-0.830**
	(2.418)	(2.607)	(0.340)
No tolerance of risk	0.049	0.094	0.045
	(0.217)	(0.293)	(0.035)
Risk neutral/seeking	0.088	0.060	-0.028
	(0.285)	(0.238)	(0.036)
Self-control	23.120	26.893	3.773***
	(7.067)	(5.715)	(0.904)
Grit	31.083	26.953	-4.130***
	(4.488)	(5.312)	(0.688)
Openness	32.162	33.621	1.459**
	(4.075)	(5.403)	(0.648)
Conscience	37.287	34.077	-3.210***
	(4.316)	(5.748)	(0.683)
Agreeableness	35.637	34.474	-1.163**
	(3.848)	(4.785)	(0.585)
Pro-social	0.539	0.581	0.042
	(0.501)	(0.495)	(0.068)
Observations	102	117	219

Note: Columns (1) and (2) present the mean token investments of non-digital workers and digital workers, respectively. Column (3) displays the difference in means between the two groups using a two-tailed t-test, conditional on individual features (age, gender, education attainment, marital status, household size, caste type, whether works as a taxi driver, number of earning family members, number of family members with a regular job, mental health, and physical health score). Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Difference in risk preference and soft skills by worker type: 40 years old as age cutoff

Panel A: Below 40 years old			
Variable	Mean Traditional	Mean Digital	Diff.
Risk tolerance	5.529	4.840	-0.689**
	(2.464)	(2.711)	(0.297)
No tolerance of risk	0.051	0.089	0.037
	(0.222)	(0.285)	(0.029)
Risk neutral/seeking	0.096	0.095	-0.001
	(0.295)	(0.294)	(0.034)
Self-control	22.769	26.371	3.602***
	(6.967)	(5.988)	(0.774)
Grit	31.318	26.987	-4.330***
	(4.642)	(5.259)	(0.585)
Openness	31.880	33.881	2.001***
	(4.797)	(5.402)	(0.589)
Conscience	37.430	34.160	-3.270***
	(4.322)	(5.493)	(0.563)
Agreeableness	35.838	34.988	-0.850*
	(3.941)	(4.755)	(0.499)
Pro-social	0.544	0.592	0.048
	(0.500)	(0.493)	(0.057)
Observations	136	169	305
Panel B: Above 40 years old			
Variable	Mean Traditional	Mean Digital	Diff.
Risk tolerance	4.438	5.433	0.996*
	(2.302)	(2.582)	(0.550)
No tolerance of risk	0.125	0.033	-0.092*
	(0.333)	(0.183)	(0.053)
Risk neutral/seeking	0.016	0.167	0.151**
	(0.125)	(0.379)	(0.071)
Self-control	22.762	25.926	3.164**
	(7.166)	(6.668)	(1.563)
Grit	31.532	26.533	-4.999***
	(4.547)	(5.104)	(1.092)
Openness	29.484	33.000	3.516***
	(6.782)	(5.246)	(1.276)
Conscience	38.812	35.800	-3.013***
	(4.542)	(4.895)	(1.055)
Agreeableness	36.508	36.172	-0.336
	(4.582)	(3.965)	(0.933)
Pro-social	0.734	0.633	-0.101
	(0.445)	(0.490)	(0.105)
Observations	64	30	94

Note: Columns (1) and (2) present the mean token investments of non-digital workers and digital workers, respectively. Column (3) displays the difference in means between the two groups using a two-tailed t-test, conditional on individual features (age, gender, education attainment, marital status, household size, caste type, whether works as a taxi driver, number of earning family members, number of family members with a regular job, mental health, and physical health score). Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: Sub-sample probit regression based on different age cutoffs

	32 years old (50pc)		40 years old	
DV: $Digital_i$	Young	Older	Young	Older
Risk Tolerance	-0.327***	0.202***	-0.140***	0.385***
	(0.073)	(0.074)	(0.046)	(0.028)
Self-Control	0.025	-0.025	-0.010	0.544***
	(0.042)	(0.036)	(0.025)	(0.024)
Grit	-0.067	-0.195***	-0.082***	-1.522***
	(0.043)	(0.060)	(0.027)	(0.072)
Openness	0.174***	0.032	0.056***	0.140***
	(0.032)	(0.026)	(0.021)	(0.046)
Conscientiousness	-0.019	-0.063	-0.036	0.250***
	(0.043)	(0.046)	(0.028)	(0.025)
Agreeableness	-0.021	0.092*	0.005	1.054
	(0.048)	(0.054)	(0.028)	(0.000)
Pro-Social Behavior	0.026	0.693	0.144	0.049
	(0.322)	(0.511)	(0.213)	(0.000)
Workers' Rights and Social Protection Index	-0.020	0.033**	-0.000	0.437***
	(0.018)	(0.016)	(0.012)	(0.031)
Working Time Quality Index	-0.065***	-0.045***	-0.032***	-0.287***
	(0.010)	(0.012)	(0.005)	(0.013)
Effective Voice Index	-0.015	-0.077***	-0.015**	-0.273***
	(0.010)	(0.020)	(0.007)	(0.011)
Respect Index	0.009	-0.020**	0.005	-0.063***
	(0.007)	(0.009)	(0.005)	(0.004)
Prospect/Career Opportunity Index	0.053***	0.038***	0.027***	0.328***
	(0.008)	(0.008)	(0.005)	(0.014)
Observations	178	161	258	81
Individual Controls	YES	YES	YES	YES

Note: $Digital_i$ is an indicator for digital platform work (= 1) and traditional offline informal work (= 0). The column title indicates the corresponding subgroup defined by different age cutoffs. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Individual controls include age, gender, education level, marital status, household size, caste, job, number of earning members in the family, number of family members with a regular job, years of work, mental health, and physical health status. The detailed variable explanation could be found in Table A1.

Table A6: Probit regression: Individual controls

DV: $Digital_i$	All			Young			Old		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Personality Traits									
Risk tolerance	-0.054*	-0.051	-0.081**	-0.106***	-0.130***	-0.252***	0.013	0.040	0.312***
	(0.030)	(0.035)	(0.040)	(0.041)	(0.049)	(0.067)	(0.047)	(0.055)	(0.115)
Self-control		0.001	-0.010		0.034	0.027		0.000	0.049
		(0.017)	(0.020)		(0.025)	(0.034)		(0.028)	(0.046)
Grit		-0.079***	-0.087***		-0.045	-0.053		-0.145***	-0.417***
		(0.021)	(0.025)		(0.028)	(0.032)		(0.048)	(0.085)
Openness		0.044***	0.056***		0.056**	0.127***		0.038	0.089**
		(0.016)	(0.019)		(0.024)	(0.032)		(0.025)	(0.044)
Conscience		-0.069***	-0.047*		-0.045*	-0.014		-0.137***	-0.143**
		(0.020)	(0.025)		(0.026)	(0.036)		(0.040)	(0.070)
Agreeableness		0.046**	0.034		0.014	-0.008		0.141***	0.185**
		(0.021)	(0.026)		(0.029)	(0.037)		(0.043)	(0.086)
Pro-social		0.137	0.125		0.052	0.098		0.889**	2.918***
		(0.170)	(0.200)		(0.211)	(0.249)		(0.362)	(0.676)
Job Quality Indices									
Workers' rights and social protection			0.015			-0.011			0.035*
			(0.010)			(0.014)			(0.021)
Working time quality index			-0.027***			-0.046***			-0.081***
			(0.004)			(0.009)			(0.016)
Effective voice index			-0.021***			-0.007			-0.180***
			(0.006)			(0.010)			(0.039)
Respect Index			0.002			0.010			-0.049***
			(0.004)			(0.007)			(0.013)
Prospect/Career opportunity Index			0.028***			0.042***			0.054***
			(0.004)			(0.008)			(0.015)
Demographics and Controls									
Age	-0.022*	-0.018	-0.002	0.064**	0.062	0.183***	-0.035**	-0.023	0.119**
	(0.011)	(0.013)	(0.014)	(0.032)	(0.038)	(0.055)	(0.016)	(0.022)	(0.058)
Education	0.108***	0.111***	0.109**	0.068	0.062	0.093	0.145***	0.239***	0.252**
	(0.028)	(0.038)	(0.046)	(0.044)	(0.058)	(0.082)	(0.040)	(0.063)	(0.119)
Married	0.333	0.323	-0.064	-0.083	-0.100	-1.205***	-0.683	-1.788***	-6.070***
	(0.210)	(0.254)	(0.262)	(0.269)	(0.308)	(0.434)	(0.533)	(0.557)	(1.271)
Household size	0.049	0.099**	0.097*	0.057	0.156***	0.258***	0.059	0.074	0.583***
	(0.033)	(0.048)	(0.055)	(0.041)	(0.056)	(0.078)	(0.051)	(0.067)	(0.129)
General caste	0.136	0.089	-0.294	-0.468	-0.341	-0.959**	1.204***	1.178	4.235**
	(0.221)	(0.274)	(0.316)	(0.337)	(0.369)	(0.452)	(0.411)	(0.810)	(1.789)
Taxi driver	0.099	0.202	0.543*	0.186	0.440	0.293	-0.099	-0.584	-0.193
	(0.189)	(0.224)	(0.297)	(0.268)	(0.299)	(0.514)	(0.323)	(0.396)	(0.710)
# earning family members	-0.054	-0.074	-0.032	-0.129	-0.190	-0.229	0.230	0.647**	0.837**
	(0.099)	(0.114)	(0.113)	(0.132)	(0.159)	(0.169)	(0.197)	(0.268)	(0.399)
# family members with regular job	0.562***	0.516**	0.825***	0.279	0.229	0.715	1.322***	1.803***	7.046***
	(0.174)	(0.206)	(0.258)	(0.224)	(0.278)	(0.438)	(0.336)	(0.418)	(1.533)
GHQ Mental health index	0.031***	0.024***	0.026***	0.037***	0.031***	0.035***	0.028***	0.024**	0.072***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.007)	(0.009)	(0.023)
GHQ physical health index	-0.000	0.002	0.003	0.005	0.004	0.002	-0.008	0.002	0.025
	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)	(0.009)	(0.007)	(0.010)	(0.015)
Observations	391	344	339	225	191	189	166	153	150

Notes: Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. $Digital_i$ is an indicator for digital platform work (= 1) and traditional offline informal work (= 0).

Table A7: Marginal effects of individual controls

	(1)	(2)	(3)
DV: $Digital_i$	All	Young	Old
Age	-0.000	0.027***	0.008
	(0.002)	(0.007)	(0.004)
Education	0.020*	0.014	0.016*
	(0.008)	(0.012)	(0.007)
Married	-0.012	-0.178**	-0.382***
	(0.048)	(0.062)	(0.083)
Household size	0.017	0.038***	0.037***
	(0.010)	(0.011)	(0.008)
General caste	-0.053	-0.142*	0.266*
	(0.057)	(0.063)	(0.109)
Taxi driver	0.098	0.043	-0.012
	(0.053)	(0.074)	(0.045)
# earning family members	-0.006	-0.034	0.053*
	(0.021)	(0.026)	(0.024)
# family members with a regular job	0.149***	0.106	0.443***
	(0.043)	(0.059)	(0.093)
GHQ Mental health index	0.005***	0.005***	0.005**
	(0.001)	(0.001)	(0.001)
GHQ physical health index	0.001	0.000	0.002
	(0.001)	(0.001)	(0.001)
Observations	339	189	150

Notes: Marginal effects from probit regression. Dependent variable, $Digital_i$, is an indicator for digital platform work (= 1) and traditional offline informal work (= 0).

Standard errors in parentheses (derived from t-statistics). $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

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References

Aguilar, Adrian Guillermo, and Flor M. López Guerrero. 2020. "Informal Sector." In *International Encyclopedia of Human Geography*. , ed. Audrey Kobayashi, 279–288. Oxford:Elsevier.

Alan, Sule, Nazli Baydar, Teodora Boneva, Thomas F Crossley, and Seda Ertac. 2017. "Transmission of risk preferences from mothers to daughters." *Journal of Economic Behavior & Organization*, 134: 60–77.

Anderson, Lisa R, and Jennifer M Mellor. 2008. "Predicting health behaviors with an experimental measure of risk preference." *Journal of health economics*, 27: 1260–1274.

Andreoni, James, Amalia Di Girolamo, John A List, Claire Mackevicius, and Anya Samek. 2020. "Risk preferences of children and adolescents in relation to gender, cognitive skills, soft skills, and executive functions." *Journal of economic behavior & organization*, 179: 729–742.

Bester, Helmut. 1994. "Price commitment in search markets." *Journal of Economic Behavior Organization*, 25: 109–120.

Bonan, Jacopo, Sergiu Burlacu, and Arianna Galliera. 2023. "Prosociality in variants of the dictator game: Evidence from children in El Salvador." *Journal of Behavioral and Experimental Economics*, 107: 102084.

Campos-Vazquez, Raymundo M., and Emilio Cuilty. 2014. "The role of emotions on risk aversion: A Prospect Theory experiment." *Journal of Behavioral and Experimental Economics*, 50: 1–9.

Canale, Natale, Alessio Vieno, Michela Lenzi, Mark D Griffiths, Douglas D Perkins, and Massimo Santinello. 2018. "Cross-national differences in risk preference and individual deprivation: a large-scale empirical study." *Personality and Individual Differences*, 126: 52–60.

Charlesworth, Sara, Jennifer Welsh, Lyndall Strazdins, Marian Baird, and Iain Campbell and. 2014. "Measuring poor job quality amongst employees: the VicWAL job quality index." *Labour and Industry*, 24: 103–123.

Desai, Preyas S., and Devavrat Purohit. 2004. "Let Me Talk to My Manager: Haggling in a Competitive Environment." *Marketing Science*, 23: 219–233.

Dong, Hsiang-Kai Dennis. 2017. "Individual risk preference and sector choice: are risk-averse individuals more likely to choose careers in the public sector?" *Administration & Society*, 49: 1121–1142.

Duckworth, Angela L, Christopher Peterson, Michael D Matthews, and Dennis R Kelly. 2007. "Grit: perseverance and passion for long-term goals." *Journal of personality and social psychology*, 92: 1087.

Fairwork. 2023. "Gender and Platform Work: Beyond Techno-Solutionism." Fairwork Gender Report 2023.

Falco, Paolo. 2014. "Does risk matter for occupational choices? Experimental evidence from an African labour market." *Labour Economics*, 28: 96–109.

Falk, Armin, and Andrea Ichino. 2006. "Clean Evidence on Peer Pressure." *Journal of Labor Economics*, 24(1): 39–57.

Farrell, Diana, and Fiona Greig. 2016. "Paychecks, Paydays, and the Online Platform Economy: Big Data on Income Volatility." JPMorgan Chase & Co. Institute. Report.

Ghosh, Anweshaa, Risha Ramachandran, and Mubashira Zaidi. 2022. "Women Workers in the Gig Economy in India: An Exploratory Study." Institute of Social Studies Trust Working Paper.

Gneezy, Uri, and Jan Potters. 1997. "An experiment on risk taking and evaluation periods." *The quarterly journal of economics*, 112: 631–645.

Gneezy, Uri, and John A. List. 2006. "Putting Behavioral Economics to Work: Testing for Gift Exchange in Labor Markets Using Field Experiments." *Econometrica*, 74: 1365–1384.

Gneezy, Uri, Andreas Leibbrandt, and John A List. 2016. "Ode to the sea: workplace organizations and norms of cooperation." *The Economic Journal*, 126: 1856–1883.

Goldberg, D., R. Gater, N. Sartorius, T. B. Üstün, M. Piccinelli, O. Gureje, and C. M. Rutter. 1997. "The validity of two versions of the GHQ in the WHO study of mental illness in general health care." *Psychological Medicine*, 27: 191–197.

Hafeez, Sadia, Charlotte Gupta, and Madeline Sprajcer. 2022. "Stress and the gig economy: it's not all shifts and giggles." *Industrial health*, 61: 140–150.

Hall, Jonathan V., and Alan B. Krueger. 2018. "An Analysis of the Labor Market for Uber's Driver-Partners in the United States." *ILR Review*, 71: 705–732.

Heckman, James J, and Tim Kautz. 2012. "Hard evidence on soft skills." *Labour economics*, 19: 451–464.

Hernuryadin, Yayan, Koji Kotani, and Tatsuyoshi Saijo. 2020. "Time preferences of food producers: Does cultivate and grow matter?" *Land economics*, 96: 132–148.

Holden, Stein T, and Mesfin Tilahun. 2022. "Are risk preferences explaining gender differences in investment behavior?" *Journal of Behavioral and Experimental Economics*, 101: 101949.

ILO. 2002. "Women and men in the informal economy–A statistical picture, International."

International Labour Office. 2000. "Resolution concerning statistics of employment in the informal sector, adopted by the Fifteenth International Conference of Labour Statisticians (January 1993)."

John, Oliver P, Laura P Naumann, and Christopher J Soto. 2008. "Paradigm shift to the integrative big five trait taxonomy." *Handbook of personality: Theory and research*, 3: 114–158.

Keith, Melissa G, Peter Harms, and Louis Tay. 2019. "Mechanical Turk and the gig economy: Exploring differences between gig workers." *Journal of Managerial Psychology*, 34: 286–306.

Kelishomi, Ali Moghaddasi, and Roberto Nisticò. 2024. "Economic sanctions and informal employment." *Labour Economics*, 89: 102581.

Leibbrandt, Andreas. 2012. "Are social preferences related to market performance?" *Experimental Economics*, 15: 589–603.

Leibbrandt, Andreas, Uri Gneezy, and John A. List. 2013. "Rise and fall of competitiveness in individualistic and collectivistic societies." *Proceedings of the National Academy of Sciences*, 110: 9305–9308.

Leschke, Janine, and Andrew Watt. 2014. "Challenges in Constructing a Multi-dimensional European Job Quality Index." *Social Indicators Research*, 118: 1–31.

Maloney, Patrick W, Matthew J Grawitch, and Larissa K Barber. 2012. "The multi-factor structure of the Brief Self-Control Scale: Discriminant validity of restraint and impulsivity." *Journal of Research in Personality*, 46: 111–115.

Maloney, William F. 2004. "Informality Revisited." *World Development*, 32: 1159–1178.

Murphy, R., K. Ackermann, and M. Handgraaf. 2011. "Measuring social value orientation." *jdm*, 6: 771–781.

Myhill, Katie, James Richards, and Kate Sang. 2023. "Job quality, fair work and gig work: the lived experience of gig workers." In *Technologically Mediated Human Resource Management*. 116–141. Routledge.

Obermeier, Vanessa, and Thorsten Schneider. 2015. "Educational choice and risk preferences: How important is relative vs. individual risk preference?" *Journal for educational research online*, 7: 99–128.

OECD. 2024. "Breaking the Vicious Circles of Informal Employment and Low-Paying Work."

Pickard, Harry, Thomas Dohmen, and Bert Van Landeghem. 2024. "Inequality and risk preference." *Journal of Risk and Uncertainty*, 69: 191–217.

Ramachandran, Sreelakshmi, and Aishwarya Raman. 2021. "Unlocking Jobs in the Platform Economy: Propelling India's Post-Covid Recovery." Ola Mobility Institute. Suggested citation: Ramachandran, S. Raman, A., 2021. Unlocking Jobs in the Platform Economy: Propelling India's Post-Covid Recovery. Ola Mobility Institute. [cite: 30, 31].

Schildberg-Hörisch, Hannah. 2018. "Are risk preferences stable?" *Journal of Economic Perspectives*, 32: 135–154.

Suryavanshi, Pushpa. 2022. "India's booming gig economy." *Juni Khyat*, 12.

Woodcock, Jamie, and Mark Graham. 2020. *The Gig Economy: A Critical Introduction.* Cambridge:Polity Press.

Wooldridge, Jeffrey M. 2025. *Introductory Econometrics: A Modern Approach.* . 8 ed., Mason, OH:Cengage Learning.

World Bank Group. 2023. "Digital Pathfinders: The Role of Youth in the Online Gig Economy." *https://blogs.worldbank.org/en/jobs/digital-pathfinders-role-youth-online-gig-economy*, Accessed: 2025-11-01.

Xie, Lusi, Wiktor Adamowicz, Maik Kecinski, and Jacob R. Fooks. 2022. "Using Economic Experiments to Assess the Validity of Stated Preference Contingent Behavior Responses." *Journal of Environmental Economics and Management*, 114: 102659.

Yu, Shu, and Franziska Ohnsorge. 2019. "The challenges of informality." *https://blogs.worldbank.org/en/developmenttalk/challenges-informality*, Accessed: 2025-06-19.