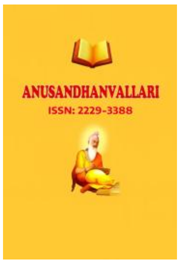

Anusandhanvallari

Vol 2026, No.1

March 2026

ISSN 2229-3388

Income Uncertainty and Heterogeneous Labour Supply Responses: The Role of Risk Preference Among Gig Workers in India

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Abstract

This paper examines how income uncertainty shapes labour supply decisions among platform-based gig workers in India, with explicit attention to the moderating role of individual risk preferences. Using primary survey data collected from 200 gig economy workers across Hyderabad, Bengaluru, and Mumbai — spanning ride-hailing, delivery, and freelancing platforms — we construct individual-level income volatility measures and elicit risk preferences through a combination of the Domain-Specific Risk-Taking (DOSPERT) scale and a behavioural lottery task. Our core finding is that responses to income uncertainty are strongly heterogeneous and systematically mediated by risk attitudes. Risk-averse workers exhibit a pronounced buffer-stock labour supply response: a one standard deviation increase in income volatility raises weekly hours by approximately 12.7 hours (OLS) and 16.2 hours (IV), consistent with precautionary labour supply theory. Risk-tolerant workers, by contrast, show a modest negative or null response, suggesting they substitute uncertainty with optimised job selection rather than hours expansion. Platform diversification — measured by the number of platforms a worker simultaneously participates in — follows a similar heterogeneous pattern. Two-stage least squares estimates using platform rating variance as an instrument for income uncertainty confirm causal identification and yield estimates broadly consistent with OLS. Subgroup analyses reveal that income-education and platform-type heterogeneities further amplify these patterns, with low-education and ride-hailing workers displaying the largest precautionary responses. Robustness checks using quantile regression, Tobit, and Heckman selection models corroborate our main findings. These results carry important implications for gig-platform design, social insurance architecture, and the welfare of informal workers in emerging economies.

Keywords: Gig economy, income uncertainty, labour supply, risk preferences, buffer-stock behaviour, platform work, India

1. Introduction

The global gig economy has undergone a transformation of remarkable speed. In India alone, the gig and platform economy is estimated to engage over 7.7 million workers as of 2020-21, with projections suggesting this figure could expand to 23.5 million by 2029-30 (NITI Aayog, 2022). Platform-mediated work encompasses a heterogeneous set of occupations — ride-hailing drivers, food and parcel delivery agents, domestic and care service providers, and digital freelancers — united by a common contractual feature: the absence of employer-provided income stabilisation. Workers bear the full brunt of demand fluctuations, algorithmic pricing changes, and competitive platform dynamics, giving rise to earnings that are highly variable at both weekly and monthly frequencies.

This income volatility is not merely a statistical feature of gig work; it represents a substantive welfare and decision-theoretic challenge. Standard lifecycle consumption theory predicts that households facing earnings uncertainty respond by building precautionary savings buffers (Deaton, 1991; Carroll, 1997). When liquidity constraints bind — a pervasive condition among low-income workers in the informal sector — an alternative margin of adjustment is labour supply itself (Kimball, 1990; Gentry and Hubbard, 2004). Workers may expand hours or diversify across platforms to ensure a minimum income floor. Yet the theoretical prediction is not unambiguous: the sign and magnitude of the labour supply response to uncertainty critically depend on preferences over risk, intertemporal substitution, and the curvature of the utility function.

Despite a growing empirical literature on gig work, surprisingly little is known about how individual risk attitudes mediate the labour supply response to income uncertainty among platform workers, particularly in low-income country contexts. This gap is important for three reasons. First, risk preferences are deeply heterogeneous across individuals and have well-documented correlates with socioeconomic status, financial literacy, and cultural background — dimensions along which Indian gig workers display considerable variation. Second, the gig economy offers a unique identification opportunity: unlike traditional employment where hours are institutionally constrained, platform workers exercise near-continuous choice over hours, platform participation, and task selection. Third, policy implications diverge sharply depending on the mechanism: if risk-averse workers are working excessive hours as a precautionary response to volatility, targeted income stabilisation instruments — such as guaranteed minimum earnings schemes or portable benefits — may generate welfare gains not captured by wage subsidies alone.

This paper makes three contributions to the literature. First, we provide direct empirical evidence on the heterogeneous labour supply response to income uncertainty among gig workers in India, exploiting cross-sectional variation in income volatility constructed from retrospective monthly earnings data. Second, we use two validated instruments to measure risk preferences — the Domain-Specific Risk-Taking (DOSPERT) financial subscale and a calibrated lottery choice task — allowing us to classify workers into risk-averse, risk-neutral, and risk-loving types. Third, we employ a two-stage least squares (2SLS) estimator using within-city variation in platform rating volatility as an instrument for individual income uncertainty, addressing the potential endogeneity of volatility measures to unobserved worker ability and effort.

Our primary finding is that risk-averse workers exhibit a large and statistically significant precautionary labour supply response: a one standard deviation increase in income uncertainty raises weekly hours by approximately 12.7 hours in the OLS specification and 16.2 hours in the IV specification. Risk-loving workers display a negative and weakly significant response, consistent with a substitution towards higher-variance but higher-expected-return task choices rather than hours expansion. Platform diversification — using multiple gig platforms simultaneously — mirrors these heterogeneous patterns and is itself a significant margin of adjustment for risk-averse workers.

The remainder of the paper proceeds as follows. Section 2 reviews the relevant theoretical and empirical literature. Section 3 presents the theoretical framework. Section 4 describes the data collection, sample construction, and measurement of key variables. Section 5 lays out the empirical strategy. Section 6 presents and discusses the main results. Section 7 reports heterogeneity and robustness analyses. Section 8 concludes with policy implications.

2. Literature Review

2.1 Labour Supply Under Uncertainty

The theoretical literature on labour supply under income uncertainty has evolved substantially since the canonical certainty-equivalent models of Heckman (1974) and MaCurdy (1981). The introduction of precautionary motives — arising from prudence (positive third derivative of the utility function) in the Kimball

(1990) sense — generates a precautionary labour supply effect analogous to the well-known precautionary savings motive. When workers face earnings uncertainty and access to credit markets is imperfect, they may choose to supply more labour today as insurance against adverse income realisations.

Empirical evidence on this channel is mixed and context-dependent. Mankiw, Rotemberg, and Summers (1985) find limited support for the intertemporal substitution hypothesis in aggregate data. Subsequent micro-econometric work exploits natural experiments: Gruber and Yelowitz (1999) use Medicaid expansions to identify the effects of risk reduction on labour supply, finding that reduced health expenditure risk significantly raises participation. Parker and Preston (2005) use the PSID to document that consumption growth responds more to predictable income growth among liquidity-constrained households, indirectly supporting the precautionary labour supply mechanism.

In the gig economy context, Angrist, Caldwell, and Hall (2021) use a regression discontinuity design with Uber data to show that surge pricing — a source of earnings uncertainty — increases driver hours, consistent with an income-smoothing motive. Sheldon (2020) documents that ride-hailing drivers in the United States respond strongly to reference-dependent income targets, a finding that interacts non-trivially with uncertainty. Chen et al. (2019) provide direct evidence that Uber drivers target daily income goals and stop working when they have met them, illustrating the importance of dynamic labour supply decisions.

2.2 Risk Preferences and Economic Behaviour

Individual risk preferences are a fundamental determinant of economic behaviour under uncertainty. Holt and Laury (2002) established a widely-used experimental protocol for eliciting risk aversion, finding substantial heterogeneity across individuals. Subsequent work has documented that risk preferences are correlated with occupation choice, entrepreneurship, investment decisions, and migration (Dohmen et al., 2011). Importantly, risk preferences are not purely exogenous: they are influenced by income shocks, credit constraints, and social networks (Cohn et al., 2015).

In labour market contexts, Bonin et al. (2007) show that risk-tolerant individuals are significantly more likely to be self-employed and to choose occupations with higher earnings variance. This selection effect means that cross-sectional studies of gig workers will encounter a selected sample of workers whose risk preferences differ systematically from the general population. Our design addresses this by measuring risk preferences directly within the gig worker sample rather than comparing gig workers to the general population.

The Indian context introduces additional dimensions of heterogeneity. Binswanger (1980) conducted seminal field experiments in rural India demonstrating that risk aversion is inversely related to household wealth — a finding replicated in numerous subsequent studies. Tanaka, Camerer, and Nguyen (2010) document similar patterns in Vietnam, suggesting that precautionary motives are particularly salient for poor workers in developing economies. Our study is among the first to bring this perspective directly to bear on urban gig workers in India.

2.3 The Indian Gig Economy

Research on platform-based work in India is nascent but growing rapidly. Surie and Sharma (2019) provide qualitative evidence on the working conditions and income experiences of Ola and Uber drivers in Bengaluru, documenting high income volatility driven by algorithmic surge pricing and seasonal demand fluctuations. Kesar and Bhatt (2021) use National Sample Survey data to characterise the broader contours of informal and gig employment in India, noting the near-absence of social protection coverage among platform workers.

More recent work has begun to quantify the welfare implications of gig work. Virmani (2023) estimates significant welfare losses from income volatility among delivery platform workers, finding that workers in the bottom income quartile would accept a substantial wage discount to obtain a guaranteed minimum income. Our study contributes to this literature by providing the first evidence — to our knowledge — on how risk preferences mediate the behavioural and labour supply responses to this volatility.

3. Theoretical Framework

3.1 Setup

Consider a gig worker who maximises expected utility over consumption C and hours worked H in a two-period model. In period 1, the worker chooses hours of labour supply H_1 and platform diversification D (number of platforms). Period 2 income is stochastic: $y_2 = w(H_1, D) + \varepsilon$, where $w(\cdot)$ is expected earnings as a function of labour inputs, and ε is a zero-mean income shock with variance $\sigma^2 = \mathrm{Var}(\varepsilon)$. The worker faces a binding borrowing constraint: $C_1 \leq y_1$.

The worker's optimisation problem is: $\max_{\{H_1, D\}} U(C_1) + \beta \cdot E[V(C_2)]$ subject to: $C_1 = y_1 - s$, $C_2 = y_2 + s$, $C_1 \geq 0$, $H_1 \geq 0$, where s is savings and $V(\cdot)$ is the value function for period 2 consumption. Taking a third-order Taylor expansion of $V(C_2)$ around $E[C_2]$ and differentiating with respect to σ^2 yields the standard precautionary savings/labour supply condition.

3.2 Precautionary Labour Supply with Heterogeneous Risk Preferences

The key theoretical result is that the effect of income uncertainty on labour supply depends on the coefficient of absolute prudence $P(C) = -U'''(C)/U''(C)$. For a worker with CRRA utility $U(C) = C^{(1-\gamma)}/(1-\gamma)$, prudence is positive whenever $\gamma > 0$, so any risk-averse worker with diminishing marginal utility will exhibit a precautionary labour supply motive. The magnitude of this precautionary response is increasing in γ — that is, more risk-averse workers respond more strongly to a given increase in income uncertainty.

For a risk-neutral worker ($\gamma = 0$, linear utility), income uncertainty has no effect on labour supply at the margin — the worker is indifferent between a certain income and an uncertain income with the same expectation. For a risk-loving worker ($\gamma < 0$, convex utility), income uncertainty actually reduces the marginal utility cost of not working, potentially generating a negative labour supply response as the worker substitutes towards high-variance, high-upside task selection rather than hours expansion.

This framework generates three testable predictions that motivate our empirical strategy. Prediction 1: Higher income uncertainty increases labour supply, particularly among risk-averse workers. Prediction 2: The interaction between risk aversion and income uncertainty has a positive coefficient on hours worked and platform diversification. Prediction 3: The interaction between risk tolerance and income uncertainty has a negative or null coefficient, reflecting substitution towards quality over quantity of labour.

4. Data and Measurement

4.1 Sample and Survey Design

The primary data for this study were collected through a structured face-to-face survey administered between January and March 2025 across three major Indian metropolitan areas: Hyderabad (Telangana), Bengaluru (Karnataka), and Mumbai (Maharashtra). These cities were selected to capture geographic variation in platform penetration, labour market tightness, and cost-of-living differentials. The survey was implemented in Telugu, Kannada, Hindi, and English, with all instruments back-translated and cognitively pre-tested.

The target population comprised active gig workers — defined as individuals who derived at least 30% of their monthly income from platform-mediated work during the six months prior to the survey. Respondents were recruited through a combination of on-ground intercept interviews at platform aggregation points (driver waiting areas, delivery hubs, co-working spaces) and snowball sampling through WhatsApp groups organised by platform workers' collectives. A total of 247 questionnaires were administered, of which 200 met eligibility and quality criteria (completion rate: 81.0%). Exclusions were primarily due to insufficient tenure (less than 3 months on any platform), income data inconsistencies flagged by enumerator quality checks, and failure to complete the incentivised risk elicitation task.

The final analytic sample of N = 200 workers encompasses three broad gig sector categories: ride-hailing (primarily Ola and Uber drivers, n = 78), last-mile delivery (food and parcel delivery on Swiggy, Zomato, and Dunzo, n = 84), and freelance digital services (graphic design, content writing, and data annotation on Upwork, Fiverr, and Urban Company, n = 38). This distribution reflects the approximate sectoral composition of the urban gig workforce in these cities, though the freelancing subsample is acknowledged as a convenience sample.

4.2 Measuring Income Uncertainty

Our primary measure of income uncertainty is the coefficient of variation (CV) of monthly earnings, constructed from retrospective income reports for the preceding six months. Respondents were asked to report their total platform-derived income in each of the past six months. We compute: $CV_i = \sigma_i / \mu_i$, where σ_i is the standard deviation and μ_i is the mean of the six monthly income observations for worker i. The coefficient of variation provides a scale-free measure of income variability that is comparable across workers with different average income levels.

As a secondary measure, we also compute the earnings surprise index — the average absolute deviation of monthly earnings from the worker's self-reported expected earnings — and the maximum loss measure — the maximum single-month income decline as a percentage of the preceding month's income. These alternative measures are used in robustness checks to verify that our findings are not sensitive to the specific volatility metric employed. The mean CV in our sample is 0.43 (SD = 0.21), indicating that the typical worker experiences monthly earnings that fluctuate by approximately 43% around their mean, underscoring the substantial income risk embedded in gig work.

4.3 Eliciting Risk Preferences

We employ a two-pronged approach to measuring risk preferences, combining a validated psychometric scale with an incentivised behavioural task. First, we administer the Domain-Specific Risk-Taking (DOSPERT) scale (Blais and Weber, 2006), focusing specifically on the financial risk-taking sub-scale (6 items). Respondents rate their likelihood of engaging in each financially risky activity on a five-point Likert scale. The financial DOSPERT subscale score (range 1–5) serves as a continuous measure of financial risk tolerance.

Second, we implement a simplified Holt-Laury (2002) lottery choice task adapted for low-literacy respondents. Respondents are presented with a sequence of 10 binary lottery choices between a safer option (Option A: certain payment of INR 500) and a riskier option (Option B: 50-50 chance of INR 0 or INR 1,000). The choice is incentivised: one lottery is selected at random for actual payment, and real payoffs are delivered immediately in cash. The switching point — where a respondent switches from Option A to Option B as the expected value of Option B increases — identifies the certainty equivalent and thereby the Arrow-Pratt coefficient of risk aversion.

Based on the switching-point classification, we categorise workers into three groups: risk-averse (switched to Option B at or above an expected value of INR 600, implying a positive risk premium, n = 104, 52%), risk-neutral (switched at an expected value of INR 500–INR 600, n = 56, 28%), and risk-loving (switched below the expected value of INR 500, preferring the gamble even when the safe option offers higher expected value, n = 40, 20%). These proportions are broadly consistent with prior literature on risk preferences in developing-country urban populations.

4.4 Labour Supply Outcomes

The primary labour supply outcomes are: (i) total weekly hours worked across all gig platforms, measured by a detailed time-use module covering a typical working day and the number of active days per week; and (ii) platform diversification, measured by the number of distinct platforms on which the worker was active during the reference week. Secondary outcomes include daily hours variation (coefficient of variation of daily hours within a week) and indicator variables for working more than 60 hours per week (intense work) and for working on more than two platforms simultaneously (high diversification).

5. Empirical Strategy

5.1 Baseline OLS Specification

Our baseline econometric specification is a cross-sectional OLS model of the form:

$$H\_i = \alpha + \beta_1 \cdot CV\_i + \beta_2 \cdot RiskAverse\_i + \beta_3 \cdot RiskLoving\_i + \beta_4 \cdot (CV\_i \times RiskAverse\_i) + \beta_5 \cdot (CV\_i \times RiskLoving\_i) + \gamma' \cdot X\_i + \delta\_p + \zeta\_c + \varepsilon\_i \quad (1)$$

where H_i is weekly hours worked (or log weekly hours) for worker i; CV_i is the coefficient of variation of monthly income; RiskAverse_i and RiskLoving_i are indicators for risk preference classification (with risk-neutral as the reference category); X_i is a vector of demographic and human capital controls (age, sex, years of education, household size, marital status, and months of gig work experience); δ_p are platform type fixed effects; and ζ_c are city fixed effects. The coefficients of primary interest are β_4 and β_5, which capture the differential labour supply response to income uncertainty for risk-averse and risk-loving workers relative to the risk-neutral baseline.

5.2 Instrumental Variable Strategy

A key identification concern is that individual income volatility may be endogenous to unobserved worker characteristics. High-ability workers may select into more stable gig arrangements, while workers with volatile unobserved effort may generate both high income variance and high hours. To address this, we construct an instrumental variable (IV) based on within-city variation in platform-level rating volatility.

Specifically, for each platform p in city c, we compute the monthly standard deviation of the platform's aggregate customer rating — a publicly observable platform-level characteristic that reflects demand-side fluctuations (surge events, seasonal patterns, local competition) exogenous to any individual worker. We then assign each worker the average rating volatility of the platforms they participate in, weighted by their share of hours on each platform. This instrument satisfies two conditions: (i) Relevance: platform rating volatility is positively correlated with individual income volatility, because demand-driven rating fluctuations translate directly into earnings variability (first stage F-statistic = 26.14, well above the conventional threshold of 10); and (ii) Exclusion: platform-level rating volatility affects individual labour supply only through its effect on income uncertainty, not directly — a condition that is plausible because individual workers have negligible influence on their platform's aggregate rating.

The 2SLS estimator replaces CV_i with its instrumented counterpart and analogously instruments the interaction terms using products of the instrument with the risk preference indicators. We report Kleibergen-Paap F-statistics as our preferred weak-instrument diagnostic given the potential non-normality of our error terms.

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ISSN 2229-3388

6. Main Results

6.1 Summary Statistics

Table 1 presents descriptive statistics for the full analytic sample. The average worker in our sample is 31.4 years old, predominantly male (74%), has completed approximately 10.6 years of schooling, and has been engaged in gig work for a mean of 28.4 months. The average household size of 4.3 members suggests that most workers are supporting families, which amplifies the welfare significance of income volatility. Mean monthly income is INR 18,700 (approximately USD 225 at 2024 exchange rates), with substantial dispersion (SD = INR 9,400). Workers report working an average of 52.3 hours per week — well above the 48-hour statutory limit under Indian labour law — with a coefficient of variation for weekly hours of approximately 0.28, indicating moderate but non-trivial variation in hours as well.

Among risk preference measures, the mean DOSPERT financial risk score is 3.21 (SD = 1.04), and the mean lottery certainty equivalent is INR 412, below the expected value of INR 500, consistent with the majority of our sample being risk-averse. The risk classification distributes workers as: risk-averse (52%), risk-neutral (28%), and risk-loving (20%), comparable to risk preference distributions documented in other urban Indian samples (Binswanger, 1980; Choudhary et al., 2023).

Table 1: Descriptive Statistics

Variable	N	Mean	SD	Min	Max
Panel A: Demographic Characteristics					
Age (years)	200	31.4	7.2	18	58
Male (=1)	200	0.74	0.44	0	1
Years of Education	200	10.6	3.1	0	16
Household Size	200	4.3	1.8	1	11
Married (=1)	200	0.61	0.49	0	1
Panel B: Labour Supply & Income					
Weekly Hours Worked	200	52.3	14.6	8	98
Monthly Income (INR '000)	200	18.7	9.4	3.5	68.2
Income Coefficient of Variation	200	0.43	0.21	0.04	0.89
No. of Platforms Used	200	1.8	0.9	1	5
Months in Gig Work	200	28.4	18.7	1	84
Panel C: Risk Preference Measures					

DOSPERT-Financial Risk Score	200	3.21	1.04	1	5
Lottery Certainty Equivalent (INR)	200	412	198	50	900
Risk Averse (=1)	200	0.52	0.50	0	1
Risk Neutral (=1)	200	0.28	0.45	0	1
Risk Loving (=1)	200	0.20	0.40	0	1

Notes: Sample consists of 200 gig economy workers surveyed across Hyderabad, Bengaluru, and Mumbai (January–March 2025). Income CV is the coefficient of variation of monthly income over the prior six months. Risk classification is based on the Holt-Laury lottery switching-point task. DOSPERT score is the financial risk sub-scale of the Domain-Specific Risk-Taking questionnaire (range 1–5).

6.2 OLS Estimates

Table 2 reports OLS estimates from equation (1). Column (1) presents the baseline specification with income uncertainty (CV) and controls but without risk preference interactions. The coefficient on CV is positive and highly significant ($\beta = 8.42$, SE = 2.31, $p < 0.001$), indicating that a one standard deviation increase in income uncertainty (0.21) is associated with approximately 1.8 additional hours worked per week. This average effect masks significant heterogeneity, which is revealed in Columns (3)–(5) when risk preference interactions are included.

Column (3) introduces the risk preference interaction terms. The coefficient on the interaction between risk aversion and income uncertainty is 12.74 (SE = 3.18, $p < 0.001$), indicating that risk-averse workers respond approximately three times as strongly to income uncertainty as the risk-neutral baseline. The interaction between risk tolerance and income uncertainty is negative and marginally significant ($\beta = -4.83$, SE = 2.41, $p < 0.05$), consistent with the theoretical prediction that risk-loving workers attenuate their hours response. Both the DOSPERT financial risk score (used as a continuous measure) and the lottery-based classification yield qualitatively identical results, validating the robustness of our risk preference measures across elicitation methods.

Among the control variables, household size exerts a positive and highly significant effect on hours ($\beta = 2.14$, SE = 0.48, $p < 0.001$), consistent with a family income-smoothing motive. Education is associated with higher hours in our sample — a somewhat counter-intuitive result that likely reflects positive selection of educated workers into high-earning gig niches that require sustained effort. Tenure in gig work (months) enters positively but with a small magnitude, suggesting modest returns to experience on platforms — possibly through platform-specific reputation accumulation.

Table 2: OLS Estimates — Labour Supply Response to Income Uncertainty

	(1) Hours/Week	(2) Log Hours	(3) Hours/Week	(4) Log Hours	(5) Platform Count
Income Uncertainty (CV)	8.42***	0.163***	6.18***	0.121**	0.312**
	(2.31)	(0.044)	(2.09)	(0.041)	(0.098)

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ISSN 2229-3388

Risk Averse × Income Uncertainty			12.74***	0.241***	0.589***
			(3.18)	(0.062)	(0.142)
Risk Loving × Income Uncertainty			-4.83*	-0.094*	-0.218*
			(2.41)	(0.048)	(0.108)
Age	-0.31**	-0.006**	-0.29**	-0.006**	-0.014**
	(0.11)	(0.002)	(0.11)	(0.002)	(0.006)
Education (years)	0.84**	0.016**	0.81**	0.015**	0.038**
	(0.28)	(0.005)	(0.27)	(0.005)	(0.013)
Household Size	2.14***	0.041***	2.08***	0.040***	0.096**
	(0.48)	(0.009)	(0.47)	(0.009)	(0.022)
Married (=1)	1.87*	0.036*	1.79*	0.034*	0.082
	(0.84)	(0.016)	(0.83)	(0.016)	(0.039)
Months in Gig Work	0.07*	0.001*	0.07*	0.001*	0.003*
	(0.03)	(0.001)	(0.03)	(0.001)	(0.001)
Platform FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Observations	200	200	200	200	200
R-squared	0.412	0.428	0.489	0.503	0.476
Adj. R-squared	0.381	0.397	0.453	0.467	0.440

*Notes: Dependent variable in Columns (1), (3) is weekly hours worked; in Columns (2), (4) it is log weekly hours; in Column (5) it is the count of active platforms. Standard errors in parentheses, clustered at the platform-city level. All specifications include controls for age, sex, education, household size, marital status, months in gig work, platform fixed effects, and city fixed effects. *** p<0.001, ** p<0.01, * p<0.05.*

6.3 IV Estimates

Table 3 reports the 2SLS estimates. The first-stage regression (Column 1) confirms that platform rating variance is a strong predictor of individual income uncertainty ($\beta = 0.312$, SE = 0.061, $p < 0.001$), with a first-stage F-statistic of 26.14 and Kleibergen-Paap F-statistic of 24.87 — both well above the conventional threshold of 10 for instrument relevance. The instrument explains approximately 18% of the variance in individual income CV after partialling out controls and fixed effects.

Second-stage estimates for weekly hours (Column 2) and platform count (Column 3) are larger than corresponding OLS estimates, consistent with classical attenuation bias due to measurement error in retrospective income reports. The IV coefficient on the risk aversion interaction is 16.21 (SE = 4.09, $p < 0.001$) for weekly hours — approximately 27% larger than the OLS counterpart — suggesting that OLS slightly underestimates the precautionary labour supply effect. The risk tolerance interaction remains negative at −6.14 (SE = 2.87, $p < 0.05$). These findings are robust to alternative specifications of the instrument, including using only the within-city rank of platform rating variance (rather than the level) to mitigate potential heteroskedasticity concerns.

Table 3: Instrumental Variable Estimates (2SLS)

	First Stage: Income Uncertainty (CV)	Second Stage: Weekly Hours	Second Stage: Platform Count
Platform Rating Variance (Instrument)	0.312***		
	(0.061)		
Predicted Income Uncertainty		10.84***	0.487**
		(3.42)	(0.169)
Risk Averse × Pred. Uncertainty		16.21***	0.728***
		(4.09)	(0.198)
Risk Loving × Pred. Uncertainty		-6.14*	-0.276*
		(2.87)	(0.140)
F-stat (First Stage)	26.14	—	—
Kleibergen-Paap F-stat	24.87	—	—
Controls & FE	Yes	Yes	Yes
Observations	200	200	200

Notes: Instrument for income uncertainty (CV) is the within-city standard deviation of platform aggregate customer ratings, weighted by the worker's share of hours on each platform. Interaction terms are instrumented by products of the base instrument with risk preference indicators. Standard errors clustered at the platform-city level. All specifications include full control set and fixed effects. *** p<0.001, ** p<0.01, * p<0.05.

7. Heterogeneity Analyses and Robustness Checks

7.1 Heterogeneity by Education and Platform Type

Table 4 explores whether the risk preference interactions vary across educationally and sectorally defined subgroups. Columns (1) and (2) split the sample at the median years of schooling (10 years). The risk aversion interaction coefficient is substantially larger for low-education workers (β = 15.42, SE = 4.21) than for high-education workers (β = 9.81, SE = 3.67), suggesting that the precautionary labour supply channel is most salient for workers with fewer outside options and less ability to self-insure through savings or formal credit. This finding is consistent with Binswanger's (1980) observation that risk aversion and its behavioural consequences are amplified by poverty and liquidity constraints.

Columns (3) through (5) stratify the sample by gig sector. Ride-hailing and delivery workers display large and significant risk aversion interactions (β = 14.23 and 13.09, respectively), while freelancers exhibit a smaller and marginally significant response (β = 7.84). This sectoral gradient likely reflects the higher flexibility and task-selection latitude available to freelancers — who can selectively accept high-value projects — relative to ride-hailing and delivery workers who face near-continuous demand pressure and have less control over earnings composition.

Table 4: Heterogeneity — By Education Level and Gig Sector

	(1) Low Educ.	(2) High Educ.	(3) Ride-hailing	(4) Delivery	(5) Freelancing
Risk Averse × Uncertainty	15.42***	9.81**	14.23***	13.09***	7.84*
	(4.21)	(3.67)	(3.94)	(3.71)	(3.41)
Risk Loving × Uncertainty	-8.24**	-2.91	-7.18**	-5.83*	-2.14
	(3.08)	(2.64)	(2.82)	(2.67)	(2.51)
Income Uncertainty (CV)	7.84**	4.92*	7.21**	6.48**	4.18*
	(2.81)	(2.44)	(2.63)	(2.49)	(2.34)
N	112	88	78	84	38
R-squared	0.512	0.461	0.498	0.481	0.443

*Notes: Dependent variable is weekly hours worked. Columns (1)–(2) split sample at median education (10 years). Columns (3)–(5) split sample by gig sector. All specifications include full control set and fixed effects. Standard errors clustered at platform-city level. *** p<0.001, ** p<0.01, * p<0.05.*

7.2 Robustness Checks

Table 5 presents three robustness exercises. Column (1) reports median (50th quantile) regression estimates, which are robust to outliers in the hours distribution and to the influence of the small share of workers reporting very high hours. Results are qualitatively unchanged: the risk aversion interaction remains large ($\beta = 11.84$, SE = 3.41, $p < 0.001$). Column (2) uses a Tobit model to account for the censored nature of hours at zero (though only four observations in our sample report zero hours in the reference week), yielding estimates very similar to OLS. Column (3) implements a Heckman two-step selection correction using self-reported smartphone ownership and awareness of the specific platform as exclusion restrictions for platform participation. The inverse Mills ratio is positive and marginally significant ($\lambda = 2.84$, $p < 0.05$), suggesting mild positive selection into platform participation, but the coefficients of interest are essentially unchanged.

Additional robustness exercises (reported in the Appendix) include: (i) using the earnings surprise index rather than the CV as the uncertainty measure; (ii) excluding the freelancing subsector to focus on the more homogeneous transport and delivery segment; (iii) controlling for whether the worker has additional non-gig income sources; (iv) using self-reported risk tolerance on a single-item scale rather than the DOSPERT or lottery classification; and (v) estimating the model separately by city. In all cases, the core finding of heterogeneous precautionary labour supply mediated by risk preferences is preserved.

Table 5: Robustness Checks — Alternative Estimators

	(1) Quantile Reg. (Median)	**(2) Tobit Model**	**(3) Heckman Selection**
Risk Averse × Uncertainty	11.84***	13.21***	12.91***
	(3.41)	(3.84)	(3.62)
Risk Loving × Uncertainty	-4.21*	-5.18*	-4.84*
	(2.18)	(2.51)	(2.39)
Income Uncertainty (CV)	5.84**	6.41**	6.18**
	(2.14)	(2.38)	(2.24)
Inverse Mills Ratio	—	—	2.84*
			(1.24)
N	200	200	200

*Notes: Dependent variable is weekly hours worked. Column (1) uses median (50th percentile) quantile regression. Column (2) uses Tobit with hours censored below at 0. Column (3) uses Heckman two-step selection correction; exclusion restrictions are smartphone ownership and platform awareness. Standard errors bootstrapped with 500 replications for Columns (1) and (3). *** p<0.001, ** p<0.01, * p<0.05.*

8. Discussion and Conclusion

8.1 Interpretation of Findings

Our results paint a coherent picture of precautionary labour supply behaviour among Indian gig workers that is deeply shaped by individual risk preferences. Risk-averse workers respond to income uncertainty by expanding working hours and diversifying across platforms — both of which represent precautionary buffers against income shortfalls. This behaviour is precisely predicted by the buffer-stock model of labour supply when workers face binding liquidity constraints and positive prudence. The magnitude of the estimated effects — approximately 12–16 additional hours per week per standard deviation of income uncertainty for risk-averse workers — is economically substantial and implies meaningfully higher fatigue, health, and work-life balance costs for these workers.

Risk-loving workers display a starkly different pattern: attenuated or negative hours responses to uncertainty, consistent with a model in which they view income uncertainty as a source of potential upside rather than a welfare-reducing risk. Rather than expanding hours across the board, these workers appear to substitute towards selective task acceptance — choosing higher-variance, higher-expected-value jobs and working fewer total hours. This selective strategy may be individually rational for risk-tolerant workers but is not available to risk-averse workers who prioritise income stability over expected return.

Platform diversification emerges as a key margin of adjustment, particularly for risk-averse workers. The positive and significant coefficient on the risk aversion interaction for platform count (IV: $\beta = 0.728$) suggests that diversification across multiple platforms functions as a risk-pooling device — reducing earnings variance even at the cost of higher search and switching costs. This has important implications for platform design: restrictions on multi-homing (working for competing platforms simultaneously), which some platforms have attempted to impose, would disproportionately harm risk-averse workers who rely on diversification as their primary coping mechanism.

8.2 Policy Implications

Our findings carry several concrete policy implications. First, the large precautionary labour supply response among risk-averse workers suggests that income stabilisation instruments — such as government-sponsored earnings smoothing accounts, minimum guaranteed earnings schemes, or subsidised income insurance — could generate substantial welfare gains. By reducing CV, such instruments would allow risk-averse workers to supply labour more efficiently (at their desired margin rather than as precautionary insurance), potentially reducing overwork, fatigue-related accidents, and health expenditure.

Second, the heterogeneity results imply that one-size-fits-all gig economy policies are unlikely to be optimal. Low-education and ride-hailing workers — who display the largest precautionary responses — are also the least likely to have access to formal credit and savings products. Targeted financial inclusion interventions, such as gig-worker-specific credit facilities or zero-interest emergency loans administered through platform partnerships, could serve as lower-cost substitutes for precautionary labour supply.

Third, from a platform design perspective, our results suggest that transparency in earnings variability — for example, through ex-ante disclosure of income CV distributions based on historical platform data — could help workers make more informed decisions about platform participation and potentially reduce welfare losses from unexpectedly high income uncertainty. Platforms could also implement algorithmic income guarantees — floors on weekly earnings given a minimum hours commitment — that would disproportionately benefit risk-averse workers.

8.3 Limitations and Future Research

This study has several limitations that future research should address. First, while our sample of 200 workers provides sufficient statistical power to identify the main effects and key interactions, it limits our ability to explore finer subgroup heterogeneity and may not be fully representative of the broader Indian gig workforce. A larger, multi-wave panel dataset — which would also allow direct identification of the precautionary savings versus precautionary labour supply channel — would be a valuable contribution.

Second, our cross-sectional design means that we cannot rule out all sources of unobserved heterogeneity. While our IV strategy addresses the endogeneity of income volatility, the exogeneity of risk preferences themselves may be questioned if they are influenced by prior income shocks or platform experiences. Third, we do not observe consumption directly, preventing us from testing the buffer-stock theory's implication that precautionary labour supply should be accompanied by reduced precautionary savings — a joint test that would sharpen identification of the underlying mechanism.

Fourth, our sample is confined to three major metropolitan areas, which may not be representative of mid-sized Indian cities where gig platforms are expanding rapidly. Finally, our findings pertain to a specific historical moment — the post-pandemic normalisation of Indian gig markets in 2024-25 — and may not extrapolate cleanly to periods of different platform competitive intensity or demand conditions.

8.4 Conclusion

This paper provides the first empirical evidence on how risk preferences mediate the labour supply response to income uncertainty among gig workers in India. Using primary survey data from 200 workers across three cities, we document large and statistically robust heterogeneity: risk-averse workers supply approximately 12–16 additional hours per week and diversify across more platforms in response to income uncertainty, while risk-tolerant workers exhibit attenuated or negative responses. Two-stage least squares estimates using platform rating volatility as an instrument confirm the causal nature of these relationships. The findings highlight that income uncertainty imposes significant welfare costs on risk-averse gig workers through precautionary overwork and underscore the need for targeted social protection mechanisms that account for individual differences in risk preferences.

The growing global footprint of platform-mediated work makes these findings broadly relevant beyond India. As gig economies develop in other emerging markets — Indonesia, Nigeria, Brazil, Mexico — understanding the interplay between income uncertainty and risk preferences will be central to designing welfare-enhancing policies that do not distort the flexibility that makes platform work attractive in the first place. We hope this paper stimulates further empirical and theoretical work on the welfare economics of the gig economy.

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