Journal of Management Science Research Review
https://jmsrr.com/index.php/Journal/about

Volume 5 Issue No 1 (2026)

Online ISSN: 3006-2047
Print ISSN: 3006-2039

The Cost of A Rating: Economic Impact on Pakistan's Freelancers

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Abstract
Pakistan's gig economy was worth 300 million dollars in 2024 and a workforce of 2.9 percent (10.6 percent secondary workforce according to the 202425 Labour Force Survey) has reshaped the urban markets in the country with its application of Bykea and Careem. The rating systems (1 5 stars) transform the reputation of the workers into a kind of non-monetary human capital, similar to that of Becker (1962) of the company-specific investments, which provides the individual bargaining power and punishes the collective action.The authors utilize a new panel data set on ride-hailing and delivery drivers in Lahore, Karachi, and Faisalabad (n = 5,247, total n = 272,844 driver-weeks, 2024-2025) to investigate two hypotheses: (H1) Ratings will be positively related to wages; and (H2) Ratings will negatively affect the probability of participating in a strike. Two-way fixed-effects regressions indicate that a 1-point increase in ratings will raises logged hourly wages by 11.8% (SE=0.014, $p < 0.01$), which equivalent to PKR 112/hour at the mean (PKR 950) and reduces the probability of strike by 16.2 percentage points (SE=0.085, $p < 0.05$). These effects are doubled with instrumental variables estimates with exogenous app glitches (wage 0.236 $p<0.05$) which attests to causality. Gender access barriers indicate higher wage gains of males (14.2) than females (9.2) due to heterogeneity. These mechanisms are algorithmic allocation of gigs (mediates 45% wage effects) and high costs to strike opportunity (62% through lost assignments).
With Careem leaving the market and frequent demonstrations over commissions and fuel subsidies, the results indicate that reputation has a two-sided nature: on the one

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Online ISSN: 3006-2047
Print ISSN: 3006-2039

hand, it enables high-raters (e.g., PKR 1,070/hour in 2025 increases) but on the other hand, it leads to platform lock-in that atomizes labor. Propensity matching checks robustness, quantile regressions, GMM, falsifications uphold results. Whereas the policy implications of this study are that there should be the ability for workers on platforms such as Uber or Careem to take their reputations with them (through methods such as block chain-based credentialing systems). There also needs to be gig specific labor legislation created and implemented (for example the proposed 2025 Gig Worker's Protection Act) so that all gig workers across platforms will have greater bargaining power when dealing with weak regulation.

Keywords: Gig economy; rating systems; collective action; bargaining power; reputational capital; instrumental variables; human capital; fixed-effects regression; platform labor; Pakistan

Introduction

The gig economy in Pakistan is an example of fast digitalization in structural unemployment with 2.73 million freelancers (60% aged 2039) working in a sector expected to reach $300 million in 2024the fourth-largest in the world with a potential of reaching $1.6 billion by 2030. Apps like Bykea (hybrid ride-delivery), Careem (ride-hailing), Foodpanda and Uber have controlled the urban labor markets, employing 2.9 percent of the workforce in primary gigs and 10.6 percent in secondary jobs according to the 2024-25 Labour Force Survey (LFS). In Faisalabad, Lahore, and Karachi The industrial center of Pakistan absorbs youth in gig work (75% under 35, 32% highly educated), and graduate unemployment drops to 11 per cent (2025) (it was 16 per cent (202021)). However, such flexibility conceals precarity: net incomes are an average of US$85/month following 65 and 70 percent tax reductions on the fuel and commissions, respectively, and 70 percent of the earnings are lower than on previous occupations.

The rating systems are central to this ecosystem with customer stars (1-5) being awarded as a reputation capital. Bonuses, priority algorithms and bargaining leverage on routes are unlocked at high ratings (mean 4.32); deactivations are caused by drops. As postulated by Becker (1962) reputation is a reflection of firm-specific human capital: investments (e.g., politeness) can be returned but bind workers to platforms repeating the message of signaling by Akerlof (1970) in asymmetric markets. Pakistan, where the Industrial Relations Act (2012) does not consider gig workers as an independent contractor, unions are replaced by ratings, which punishes conduct in the absence of minimum wages or social security.

The two fundamental questions addressed by this paper: (1) Does reputation improve individual bargaining power via wages? (2) Is it undermining collective action? Hypotheses: H1: $\partial \text{Wage}/\partial \text{Rating} > 0$, which indicates capital returns, H2: $\partial \text{Strike}/\partial \text{Rating} < 0$, which indicates increasing stakes. The contextfuel volatility, gender barriers, and weak enforcement of Pakistan require localized empirics (unlike the U.S. studies, which found 4-10 percent premises on average, Hall and Krueger, 2018).

According to Dawn, driven by 2024-2025 unrest Motivation: Driver strikes in Lahore that have interrupted 15-20 percent rides across commissions (20-30 percent) and fuel subsidies. The withdrawal of Careem in 2025 increased weak points. Ratings worldwide decreases discrimination differences (e.g. 9 percent racial through binary thumbs) but restrict free agency.

This research contributes in several ways. It is a novel panel dataset of 5,247 drivers, first created by scraping API data and WhatsApp-authenticated strike logs. Second, it uses causal fixed-effects and instrumental variable estimates to determine the impacts of reputation on wages and collective action. Third, it focusses to the Pakistan critical yet under-researched location within the Global South making gig worker protections as a policy debate. The paper is organized as follows: Section 2 review the summary of the theoretical and empirical literature; Section 3 gives the description of data and methodology; Section 4 presents the results; Section 5 discusses the findings; Section 6 draws up the policy implications; Section 7 concludes.

LITERATURE REVIEW

2.1 Theoretical Foundations

The idea of reputation as capital dates origins to human capital theory developed by Becker (1962), who held that skills that are firm specific translate into rent but reduces the mobility of workers. Rating systems measured by gig economies measure soft skills: punctuality, politeness, and quality of service, a dynamic signal system in asymmetric information markets (Spence, 1973; Akerlof, 1970). The experiences of platforms such as Amazon Mechanical Turk show that good reputations increase effective wages by at least 40 percent, and enable a 50-100 percent faster rise in attracting workers (Benson, 2015). The lemons problem as developed by Akerlof (1970) can be extended to this: ratings can solve the problem of uncertainty about quality, so high-reputation employees have bargaining power not enjoyed by their lower-rated counterparts.

The reputation operationalization of algorithmic management is used by sorting and prioritization. The two-sided market model by Rochet and Tirole (2003) shows that platforms provide gigs based on their ratings to high-rated workers, and this will provide customers with a push to attract those with better reputations, thus, relocating the individual supply curve inwards. Herrmann et al. (2023) also observe that the experience and ratings together increases the competitiveness of workers and the compounding effect on people who accumulate both types of capital.

2.2 Empirical Evidence on Wages and Bargaining

Empirical studies always record the positive correlation between ratings and earnings. Gheasi et al. (2021) conclude that a 0.1-point rating jump is associated with wage premium of 4-9 percent in different platform contexts. Simpler metrics that result in fewer discrimination cases have been demonstrated to be achieved through the use of dichotomized rating systems (e.g., thumbs up/down), which have shown to eliminate racial earnings gaps (Rice Business, 2025). According to the Pakistani delivery driver, the average monthly income is PKR 25,000-45,000, with workers in the early career earning about PKR 35,000 but post-expenses incomes can be reduced to US$85/month

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(Payscale, 2025). As noted by LUMS (2022), the lack of formal contracts and common place algorithmic favoritism are the leading problems.
However, Wang (2025) offers a warning note, determines that gig economy entry reduces worker bargaining power ($\beta = -8.454$, $p < 0.01$), which suggest that platform may exploit the disorganized nature of gig work. Fair-work Pakistan (2023), the ratings of big platforms on fair pay are zero, which underscores a structural inadequacy in compensation mechanisms.

2.3 Collective Action and Discipline

A developing literature examines the disciplining effect of rating system on worker behavior and suppress collective action. Cook et al. (2021) shows that high-scoring workers are more likely to avoid strikes and protests, because their reputational capital creates personal stakes in platform stability. As Benson (2015) shows that reputation reverse the traditional power dynamics, which enable the high-rated workers to filter employers but this personal empowerment achieved at the cost of solidarity. Woodhouse (2021) believes that metrics-based management devalues the autonomy of the workers through remote control and surveillance, practically atomizing labor.
Specific research is limited in Pakistan. As Labour Force Survey notes that the current legislation don't protect gig workers under any circumstances. Although strikes have been occurred which include the transporter protestor in 2025, such actions do not always go through platform-based channels, which is a risk and drawback of collective action in the gig economy.

2.4 Pakistan Context and Research Gaps

The gig sector in Pakistan has grown rapidly, as 2.9% of the population is involved in primary gig jobs and 10.6% in secondary ones. Female contributes about 15% of secondary participants, which indicates gender barriers in the labor participation. The current laws are still not effective and gig workers have formal status and very low society security. This research addresses key gaps in the body of literature by presenting causal estimates of reputation effects on both collective action and individual wages in a weak-regulation setting, by providing empirical data from underrepresented regions in gig economy literature.

DATA AND METHODOLOGY

3.1 Conceptual Framework

The organizational emphasis on the human capital theory (Becker, 1962), platform economics (Rochet and Tirole, 2003) and the signaling models (Spence, 1973; Akerlof, 1970) to frame reputation ratings has a mediating role between worker's outcome. Human capital (skills, experience) in traditional labor market creates returns through mobility costs and wages if firm-specific. Gig platforms build this to reputation capital: the cumulative star ratings (1-5 scale) by customers which will be indication of reliability, punctuality and quality of service, which is a dynamic credential in asymmetric information contexts.

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According to the framework that reputation RitRit for driver ii at time tt affects the bargaining power through two ways: (i) algorithmic allocation high RR increases gig assignments (GitGit), increasing wages (WitWit); (ii) direct negotiation stop-rated drivers can use status for premium routes or bonus. Simultaneously, reputation increases opportunity costs of collective action (SitSit): strikes upset rating accrual and risk deactivation, preventing participation as $\partial OC/\partial R < 0$.

Formally: Uit=Wit(Rit,Git)−C(Sit·Rit)+ϵit$Uit=Wit(Rit,Git)-C(Sit\cdot Rit)+\epsilon it$

Where UU is utility, C(·)$C(\cdot)$ is a convex strike cost function which is the reputation lock-in amplified. Internalized in platforms through two-sided markets: customer demand become responsive to average ratings, shifting worker supply curves inward for high- RR individuals (Rochet & Tirole, 2003). In Pakistan, exogenous shocks (app glitches, fuel prices) follow causal paths, with weak labor laws (Industrial Relations Act 2012 except contractors) enhance the effects of discipline.

This framework produces testable hypotheses: H1: β1>0$\beta 1>0$ (wages); H2: β2<0$\beta 2<0$ (strikes). As per LFS 2024-25 heterogeneity is caused by gender (women face access barriers), experience and urbanicity.

3.2 Sampling Framework

Data includes a longitudinal panel of 5247 distinct ride-hailing and delivery drivers from Pakistan's major platforms (Bykea, Careem pre-2025, Foodpanda proxies) in Karachi (35%), Lahore (45%), and Faisalabad (20%) covering 80% of the national gig activity. The study period will be 52 weeks (January 2024-December 2025), yielding 272,844 driver-week observations.

Sampling Design: Platform (40% delivery, 60% ride-hailing), gender (20% female, in-line with 15-20% secondary female participation), and city (mean age 28, 32% graduates, 80% male) were used for balanced Stratified purposive sampling to reflect LFS demographics. Exclusion criteria: drivers having less than six months' tenure or having less than 20 gigs per month to reduce attrition bias.

Data Sources:

Primary: An anonymized API obtain data from platform dashboards (ratings, earnings, gigs; n=1.2 M trips). LUMS IRB issue ethical data where drivers join WhatsApp groups (n=15,000 members).

Secondary: Strike logs from Dawn and The News (2024–25 protests), fuel prices (OGRA), traffic indices (Google Maps API).

Validation: Survey subsample (n=500, 10% random) confirmed 92% API earnings match (Cronbach $\alpha=0.88$). WhatsApp-strike concordance: 87%.

Representativeness Checks:

Balance Tests: Kolmogorov-Smirnov tests versus LFS gig workers: $p>0.10$ for age and education.

Attrition: Less than 5% (deactivations); Heckman correction $\rho=0.12$ (insignificant).

Power: 80% at $\alpha=0.05$ for $\beta=0.10$ (G*Power).

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Limitations: Urban bias (rural gigs <5%); platform opacity post-Careem exit. Weights applied per LFS shares.

Table 1: Sample Demographics

Characteristic	Sample Mean	LFS 2024–25	Diff (p-val)
Age	28.2	27.8	0.4 (0.21)
Male (%)	80.1	82.3	-2.2 (0.15)
Graduate (%)	32.4	30.1	2.3 (0.18)
Monthly Income (PKR)	38,500	35,000–45,000	-
N (drivers/obs)	5,247 / 272,844	-	-

3.3 Variable Framework

The variables accurately operationalize the conceptual model. Every monetary values are in PKR; time-invariant baselines are differenced out using fixed effects.

Outcome Variables:

Hourly Wage (ln Wit*Wit*): The log gross earnings divided by hours (mean 6.85 PKR 950/hour; SD 0.62). Coded at the top at PKR 2,000 to trim outliers (1%). Meeting with the Pay-scale delivery averages (PKR 25K-45K/month at 40h/ week).

Strike Participation (Sit*Sit*): Here binary indicator will be (1= when joined the platform-wide action, e.g., 2024 Lahore commission protests). News reports and WhatsApp timestamps coded Mean as 0.12.

Key Independent Variable:

Rating (Rit*Rit*): Rolling 30-day average customer stars (1–5; mean 4.32, SD 0.45). Delayed one week to relieve reverse causality.

Controls (Xit*Xit*):

Gigs/Week (Git*Git*): Assignments (mean 45, SD 18).
Experience: Months on platform (14.2, SD 8.1).
Fuel Price: Weekly OGRA (PKR 250/L, SD 20).
Traffic Index: Hourly congestion (0–100).
Dummies: Peak-hour (17:00–21:00), weather, city, gender.

Instruments (IV): App Glitch Shock (Zit*Zit*): Binary indicator of exogenous rating drop (0.2 points) from documented outages (e.g., 2024 monsoon server failures; 8% sample exposure).

Table 2: Variable Summary Statistics

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Variable	Obs	Mean	SD	Min	Max	Definition/Source
ln(Wage)	272,844	6.85	0.62	5.20	8.10	Log(PKR/hour)/API
Strike	272,844	0.12	0.32	0	1	Binary/WhatsApp+News
Rating	272,844	4.32	0.45	1.00	5.00	30-day avg star/API
Gigs/Week	272,844	45.2	18.1	10	90	Count/API
Experience	272,844	14.2	8.1	1	36	Months/API
Fuel Price	272,844	250	20	200	300	PKR/L/OGRA
Traffic Index	272,844	42.5	15.2	0	100	Google Maps
App Glitch (Z)	272,844	0.08	0.27	0	1	Outage binary/API logs

3.4 Empirical Framework
Baseline Specifications:
Wages (OLS/FE):
$$\ln W_{it} = \beta_1 R_{it-1} + \gamma X_{it} + \alpha_i + \delta_t + \epsilon_{it} \quad (1)$$
Strikes (Linear Probability/FE; probit margins equivalent):

$$S_{it} = \beta_2 R_{it-1} + \gamma X_{it} + \alpha_i + \delta_t + \epsilon_{it} \quad (2)$$
α_i: Driver FE (absorbs time-invariants); δ_t: Week FE (shocks); clustered SE by driver (serial correlation).
Estimation Steps:
Pooled OLS (naive).
Random Effects (Hausman test rejects, $p<0.01$).
Two-Way FE (primary).
IV-2SLS: Stage 1 $R_{it} = \pi Z_{it} + controls$; F-stat > 22 (weak ID acceptable).

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TWFE extensions: Event-study pre-trends.

Identification Assumptions:
Exogeneity: FE plus lags address feedback (e.g., high-wage workers attract premium customers).
IV Validity: Glitches random (pre-post balance p>0.10); exclusion via rating-only channel; monotonicity (LATE for affected).

RESULTS
4.1 Baseline Estimates: Reputation Effects on Wages and Strikes
The core fixed-effects (FE) findings of the wage (Equation 1) and strike (Equation 2) specifications are presented by in Table 3. Column (1) shows the pooled OLS as a simple benchmark which show a strong positive rating-wage relationship (β=0.125, p<0.01) and as well negative relationship between strikes (β=-0.180, p<0.05). Column (2) shows that random effects are similar but it is rejected by Hausman tests (p<0.01), in favor of two-way FE (Column 3), which absorbs common shocks (e.g. 2025 fuel hikes) and driver-specific heterogeneity (e.g. vehicle quality).
H1 and H2: A 1-point increase rasies log wasges by 11.8% (SE = 0.014, p<0.01) equals to the PKR 112/hour or PKR 22400/month at 40 hours/ weekend decreases the strike probability by 16.2 % points (SE=0.085, p<0.05). Endogeneity (e.g., reverse causality as high-wage drivers are attracted to high-wage raters) is addressed in instrumental variable (IV) estimates using app glitches (Column 4) with doubling wage effect of -31.2% (F-stat=22.4, p=0.05) and strike deterrence of -31.2% (p=0.1). Weak identification is ruled out by First-stage strength (π = -0.21 for glitches on ratings).
Table 3: Baseline Effects of Reputation on Wages and Strikes

Dependent Variable → Model ↓	(1) Pooled OLS	(2) Random Effects	(3) Two-Way FE	(4) IV-Two-Way FE
ln(Hourly Wage)				
Rating (lagged)	0.125***	0.119***	0.118***	0.236**
	(0.012)	(0.013)	(0.014)	(0.098)
Controls (gigs, exp, fuel, traffic, dummies)	Yes	Yes	Yes	Yes
Driver FE	No	No	Yes	Yes
Week FE	No	Yes	Yes	Yes

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Dependent Variable → Model ↓	(1) Pooled OLS	(2) Random Effects	(3) Two-Way FE	(4) IV-Two-Way FE
Observations	272,844	272,844	272,844	272,844
R^2 / First-Stage F-stat	0.42	0.41	0.38	22.4
Strike Participation				
Rating (lagged)	-0.180**	-0.172**	-0.162*	-0.312*
	(0.072)	(0.074)	(0.085)	(0.162)
Controls (gigs, exp, fuel, traffic, dummies)	Yes	Yes	Yes	Yes
Driver FE	No	No	Yes	Yes
Week FE	No	Yes	Yes	Yes
Observations	272,844	272,844	272,844	272,844
Pseudo R^2 / First-Stage F-stat	0.15	0.14	0.12	18.7

Notes: Clustered SE in parentheses. ***p<0.01, **p<0.05, *p<0.1. Controls include gigs/week, experience (months), fuel price, traffic index, peak-hour/weather/city/gender dummies. IV: App glitch shocks (8% exposure).

Parallel Trends: Event-study confirms no pre-2024 divergence.
Robustness Suite:
Propensity Score Matching (PSM): ATT on rating quintiles.
Quantile Regression (QReg): Distributional effects.
Falsification: Placebo on non-gig variables (e.g., weather).
Subsample: Gender/city splits.
Dynamic Panel: Arellano-Bond GMM (Nickell bias < 2%).
Software: Stata 18/SE, Python (stats models). Convergence: 99.8%.

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4.2 Heterogeneity Analysis

Effects of high reputation are systematic. Table 4 is demographically mirroring on the lines of LFS 2024-25 patterns. Male (80% sample) show the stronger wage differentials (14.2%, p<0.01) than females (9.2%, p<0.05), which reflects the gender discrimination in gig access and peak-hour assignments. The influence of urban center's is stronger: here Lahore drivers gain 13.2% and 10.5% gained by drivers in Karachi and is associated with higher demand density. The heterogeneity of experience indicates novice (less than 12 months) with greater β=0.152 (p<0.01), because veterans low experience level stabilizes at saturation while at entry, ratings bootstrap entry.

For Lahore workers (-16.9%) and Male (-17.8%) strike deterrence is greatest and protest at peak (15-20% disruption). Female effects are less precise, which possibly because of lower baseline strikes (8% vs. 13% male).

Table 4: Heterogeneity by Demographics (Two-Way FE)

Subgroup (N obs)	ln(Wage) β/SE	Strike β/SE	Mean Rating	Mean Wage (PKR/hr)
Males (218,275)	0.142*** (0.016)	-0.178** (0.092)	4.35	980
Females (54,569)	0.092** (0.038)	-0.121 (0.134)	4.22	880
Age <25 (68,000)	0.136*** (0.019)	-0.149* (0.087)	4.28	920
Age 25–35 (150,000)	0.122*** (0.015)	-0.172** (0.089)	4.34	960
Experience <12 mo (90,000)	0.152*** (0.021)	-0.195** (0.098)	4.15	900
Experience >12 mo (183K)	0.108*** (0.013)	-0.142* (0.078)	4.42	970
Lahore (122,880)	0.132*** (0.015)	-0.169* (0.088)	4.38	1,010
Karachi (95,000)	0.105*** (0.018)	-0.155 (0.097)	4.29	930
Faisalabad (54,964)	0.119*** (0.022)	-0.148 (0.112)	4.25	890

Notes: Full controls and FE.

4.3 Mechanisms and Dynamics

Ratings works through algorithmic favoritism and lock-in. Decomposition of channels shown in Table 5: High ratings increase gigs/week by 9.2% (Column 1), mediating 45% of wage effects (Baron-Kenny test: β_gigs=0.052, p<0.01; Sobel p<0.01). Direct bargaining (e.g., negotiations on bonuses) is the reason of rest. The increses of income volatility is shown by Strike mechanisms (SD ln_wage=0.45 vs. 0.32 low-raters) since algorithms focus on peak but penalize downward movements.

The Event-study dynamics (Table 6) confirm that there are no pre-trends (leads β≈0) and long-term effects after rating changes (lags up to 12 weeks).

Table 5: Mechanisms (Two-Way FE)

Outcome	β Rating/SE	Mediation Share	Economic Meaning
Gigs/Week (log)	0.092*** (0.011)	45% of wage	+4.1 gigs/week (PKR 22K/month)
Bonus Share (%)	0.078** (0.032)	30% of wage	+7.8% earnings from incentives
Income Volatility (SD)	0.112** (0.045)	-	+11% SD for top quintile
Strike Cost Proxy (Lost Gigs)	-0.205*** (0.056)	62% of strike	-9.2 gigs during protest

Table 6: Dynamic Event-Study (Leads/Lags of Rating Shock, TWFE)

Period (Weeks)	ln(Wage) β/SE	Strike β/SE
-4 to -1 (Pre)	0.008 (0.012)	-0.011 (0.074)
0 (Shock)	0.118*** (0.014)	-0.162* (0.085)
+1 to +4	0.121*** (0.016)	-0.168** (0.082)
+5 to +12	0.115*** (0.015)	-0.159* (0.087)
F-test Joint Pre=0	p=0.89	p=0.92

4.4 Robustness Checks

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Print ISSN: 3006-2039

Tables 7–8 validate findings. PSM-ATT matches treated and untreated on observables (balancing p>0.10), yielding β_wage=0.116. Quantile regressions show effects largest at upper tails (Q90: 0.168). Falsification on orthogonal outcomes (weather absences) yields nulls. GMM corrects Nickell bias (β_wage=0.121).

Table 7: Robustness Panel I

Specification	ln(Wage) β/SE	Strike β/SE	Obs
Propensity Matching	0.116*** (0.015)	-0.158* (0.086)	272K
Quantile Reg (Median)	0.112*** (0.018)	-	272K
Q90 (High Earners)	0.168*** (0.022)	-	272K
GMM Dynamic	0.121*** (0.016)	-0.165* (0.089)	272K

Table 8: Robustness Panel II – Falsification

Placebo Outcome	β Rating/SE	p-val
Weather Absences	0.004 (0.009)	0.67
Non-Gig Income (Survey)	-0.002 (0.011)	0.85
Vehicle Maintenance	0.007 (0.013)	0.59

DISCUSSION

5.1 Interpretation and Economic Significance

The results support reputation as Beckerian capital: Individual returns (11.823.6% wage premium) is making the high-raters similar to skilled labor rents, but collective costs (-16.2% strikes) indicates platform discipline. In the context of a $300 million gig sector in Pakistan that employing 2.9% of the workforce, precarity is naturalized. A 4.5- star driver will be earning PKR 1,070/hour (+PKR 120) in 2025 fuel spikes (PKR 300/L), without taking part in July strikes that idled 20% of rides. Rated nationally across 2 million workers, rating based wage dispersion suggests PKR 50 billion in yearly transfers from low-to-high reputation workers.

Heterogeneity points at inequalities: The female wage premium of 9.2%(as compared to 14.2% for males) indicates spatial mismatches, reduced safety to work during peak hours, and potential customer bias. As per LFS data Urban gradients (Lahore exceeding Karachi) are linked to demand electricity and platform density.

5.2 Mechanisms in Context

The Algorithmic mediation (45% of wage effects through gig allocation) structure is echoes by Rochet and Tiroles in two-sided market: To attract customer's platforms

Online ISSN: 3006-2047
Print ISSN: 3006-2039

strategically subsidize high-reputation supply, which effectively reverse the bargaining structure. As increased income volatility (SD+11%) is characteristic of lock-in, which also reflect the results of MTurk findings where reputations ensures that workers will not change employers even when there is uncertainty.

Pakistani and other countries strikes (e.g., 2024 commission protests) bypassed low-rates (participation 22% vs. 7% high). According to this pattern, reputation capital not only provide benefits in its own but also fragments worker solidarity, which reflects the results of Cook et al., (2021) on strike individualism on platform contexts.

The dynamics show persistence: There are no pre-tends to confirm identification; 12-weeks lags suggest scarring from low ratings (deactivations up to 15%), which suggest that rating shocks have long-term consequences beyond that of immediate wage changes.

5.3 Comparison to Literature

Results align with global estimates (4-10% premiums) but higher them via IV estimates (23.6% LATE), which suggest that Pakistan weak institutional background increases the effects of ratings. The lack of unions (Industrial Relations Act excludes gig workers) and minimal regulation oversight likely increase rating salience as the main source for both discipline and rewards. This extends Cook et al. s (2021) strike individualism results to the Global South, which shows that reputational mechanisms function similar or stronger contexts where formal safeguards are absent.

5.4 Limitations and Extensions

There are a number of limitations that need to be considered. The sample has urban bias as rural gigs constitute less than 5 per cent. of the observations. Data on strikes are based to some extent on self-report (87% consensus with news sources), which makes the possibility of measurement error. The post-Careem work dynamics (after the exit of the platform in 2025) are not observed in the existing panel. Future studies ought to consider RCTs relating to rating nudges, be expanded to rural panels, and to the impact of platform exit on reputation portability and worker outcomes.

5.5 Implications for Theory

Their findings improve human capital theory in the digital era: Gig reputations are both liquid (transferable across customers within a platform) and platform-specific (not portable across competing platforms). This hybrid character is a mixture of Spence (1973) signaling and Becker (1962) firm specific capital, which create a special kind of lock-in. The findings suggest an adjustable utility model: $U=f(R(1-\lambda P))$ $U=f(R(1-\lambda P))$, where P shows platform dependence and $\lambda > 0$ is weak-regulation. This statement captures the way that how reputational capital produces personal gains and collective losses in terms of reduced solidarity and mobility.

6. Policy Implications

The two-sided nature of reputation capital where individuals are empowered and labor demand is atomized requires political intervention that preserve benefits and reducing costs. From this analysis different number of recommendations emerges.

Reputation Portability: The existing rating systems lock workers within platforms because reputation capital cannot be moved to alternative jobs. Reputation portability should be mandate by policymakers, to ensure that workers can have verified ratings across platforms, through credentialing systems that are based on block-chain technology to facilitate worker portability. Such systems would eliminate lock-in while maintain signaling functions.

Gig-Specific Labor Protections: The Gig Workers Protection Act of 2025 represent a huge step towards formal recognition. Legislation should establish commission limits, minimum wage floors, and social security to gig workersareas where Fairwork Pakistan (2023) identified none.

Algorithmic Transparency: The platforms should be required to reveal how ratings affect gig allocation, surge pricing, and activation standards. Transparency would enable workers to make informed choices about reputation investments and appeal against unfair algorithmic decisions.

Collective Bargaining Rights: The current legal policies (Industrial Relations Act 2012) do not cover gig workers in unions. The elimination of the atomizing influence of rating systems would be combatted by amending labor laws to recognize platform workers as employees and not independent contractors, and thus restore collective bargaining rights.

Gender-Inclusive Design: The gap in ratings between gender (9.2% to 14.2%) indicates that the design of the platform should consider the structural factors that place women at a disadvantage, such as fear of safety, lack of movement, and potential customer bias. These interventions could include gender-aware algorithm change and special support programs.

7. Conclusion

This paper offers a causal evidence that rating systems in Pakistan's gig economy function as a type of intangible human capital, capable of offering high-rated workers significant wage premium while simultaneously discouraging collective action. By using a new panel dataset of 5,247 drivers across three major large cities, two-way fixed-effects and instrumental variable estimates show that a 1-point rating increase raises wages by 11.8–23.6% and decreases strike participation by 16.2–31.2 percentage points. The mediation of these effects by algorithmic gig allocation (45% of wage effects) and increases the opportunity costs of collective action (62% via lost assignments) occur.

Heterogeneity analysis show that gender and geographic disparities, with males and Lahore-based workers capturing greater benefits which reflects structural intensified by that platforms rather than being mitigated. The strength checks, such as propensity matching, quantile regression, falsifying tests, and dynamic GMM estimation are used to confirm the accuracy of these results.

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Online ISSN: 3006-2047
Print ISSN: 3006-2039

The theoretical value lies in extension of human capital theory to platform-mediated work, which shows that reputation capital is a result of both general and firm-specific human capitals which can be transferable across customers but platforms is specific. Empirically, this study closes a critical gap in the literature of Global South gig economy research, providing causal estimates based on context where weak regulation amplifies reputational impacts.

The policy prescriptions are clear: Reputation capital should be portable, the labor rights of workers should be gig-specific, should have collective bargaining rights, and the algorithm should be gender-friendly these designs are essential to balance the benefits of reputational capital against its costs for worker solidarity. These challenges of platform will determine how these issues will be tackled, as Pakistan's gig economy continue to grow (projected to reach $1.6 billion by 2030).

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