Tenure, Earnings and Productivity of Platform Delivery Workers: Evidence from India

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Abstract

Do platform workers' earnings and productivity increase with tenure? We use a Heckman selection model to estimate the effect of tenure on gross earnings, net earnings and productivity of platform workers using a novel dataset of active and exited workers from a major food delivery platform in India. An additional year of tenure increases monthly gross and net earnings by 3.72% and 4.9%, respectively. Productivity, defined as daily deliveries, increases by 5.66% with an additional year of tenure. Further, part-time workers experience a higher growth in human capital, consistent with platform work providing flexibility. Among different skills, we find that workers self-reported English-speaking and route optimization improves with tenure. Our results show that platform work may yield substantial earnings growth for workers, allaying precarity concerns. These estimates may also inform retention and screening policies for platform firms.

JEL Codes: J24, J28

Keywords: Human Capital, Labour Productivity, Skills

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1 Introduction

The platform-enabled industry has rapidly occupied a sizable share in the labour markets of several countries (Katz and Krueger, 2019, Abraham et al., 2017). In advanced economies, such work arrangements have been beneficial for workers seeking flexible role (Chen et al., 2019). Emerging markets, however, have a large informal sector, a large mass of unskilled workers with poor contract enforcement. While platforms may usher formal labour markets for low-skilled workers, they may also create precarious conditions for unskilled workers. Thus, the impact of platform work in labour markets of developing countries requires an exploration.

To understand if platform work can provide stable employment opportunities, one must analyze the experience of the platform workers. Particularly, do the earnings of platform workers increase as they acquire tenure on the platform? A steeper gradient of earnings will allow workers to cover for the cost of living and and drive stable employment. A low returns-to-tenure, in contrast, will only contribute to higher churn of workers, and may leave workers with lower outside options vulnerable to platform pricing policies. Such measures can also inform platform companies about the relative benefits of retention versus screening policies.

In this paper, we use a novel survey of active and exited platform workers of one of the major food delivery platforms in India. Our survey records daily deliveries and monthly gross and net earnings of active platform workers, apart from other socio-demographic characteristics. We also record the attitude of active and exited workers toward job satisfaction and pre-entry sentiment toward the job.

Tenure-productivity or tenure-earning relationships are likely to be biased due to selection effect—workers with low match quality exit early, leaving behind high productivity workers with high tenure. To address the unobserved match quality, we jointly estimate the exit decision as a function of match quality and earnings equation as a function of tenure[1]. We follow the recent literature on platform worker's motivation to exit and enter (Möhlmann and Zalmanson, 2017, Berger et al., 2019, Chen et al., 2019, Wiener et al., 2023) and job satisfaction (Lévy-Garboua and Montmarquette, 2004, Lévy-Garboua et al., 2007) to find instruments for match quality. To the best of our knowledge, this is the first study to estimate the relationship between tenure, earnings and productivity for platform workers.

Our results show that an additional year of tenure increases gross earnings by 3.72%. Net earnings, obtained by subtracting gross earnings by fuel costs, increase by a bigger margin

[1] See Vella (1998) for a review of methods to address sample selection bias.

of 4.85% due to an additional year of tenure. Firm's workforce policies may also distort earnings-tenure profile (Shaw and Lazear, 2008). To address this concern, we estimate a productivity-tenure relationship, where productivity is measured in the number of daily deliveries. An additional year of tenure improves daily deliveries by 4.72%. In absolute magnitude, these measures translate into an additional INR 610 per month for the worker and 0.75 deliveries per day. The additional earnings for the worker are greater than the minimum wage increase prescribed by the Indian government.

Platforms allow workers with more flexibility and hence, may attract workers who find such arrangements more suitable. We also explore heterogeneity of our tenure-outcome estimates across part and full-time workers.

We conduct more tests to explore the mechanisms behind the results. First, we analyze the acquisition of various skills required by platform workers. These skills could be related to general human capital such as English language and customer service or task-specific human capital such as route optimization and learning GPS. We find that platform workers with higher tenure report having learnt English and route optimization. Thus, platform workers acquire both general and task-specific human capital with tenure.

Platform work, or digitally-enabled on-demand work, has received considerable attention due to its ever growing size (Katz and Krueger, 2019). While some accounts may suggest vulnerability of workers in this market, empirical studies do not support that. Hall and Krueger (2018) and Berger et al. (2019) survey Uber drivers to record high level of job satisfaction in the USA and UK, respectively. They also find that job flexibility drives this satisfaction. Wiener et al. (2023) also find that Uber drivers do not consider algorithmic control of the production process as overbearing. Chen et al. (2019) uses administrative data from Uber to structurally estimate a significantly high value of flexibility for Uber drivers. These studies are based in developed countries, where individuals provide service on these platforms to add to their income through flexible work arrangements. We add to this literature by studying the value of platform work in India, a developing country which has a dominant informal sector, inadequate safety nets and poor contract enforcement. In such economies, digital platforms may allow unskilled workforce to transition into the formal economy but at the same time, poor outside options may also drive down the bargaining power for the workers. Our results suggest that platform workers are able to increase income with tenure in India, even after accounting for the selection bias. This may allay some concerns regarding precarity of this workforce, as has been voiced in popular press.

We also contribute to the literature on tenure-productivity trajectory inside a firm. Baker

(1964) suggested that employees accumulate human capital with tenure through learning-by-doing, and thus improving productivity and earnings. However, selection bias may affect this relationship as argued by Jovanovic (1979). The estimates for the tenure-productivity gradient vary across industries and empirical techniques (Topel, 1991, Williams, 1991). Bronars and Famulari (1997) also documents the evidence on the role of worker characteristics in determining wage-tenure differential. Shaw and Lazear (2008) find strong evidence of tenure effects in a setting which has several advantages such as workers being assigned to individual tasks, thereby ruling out peer effects, well-defined production process, and measuring output. Further, they show that the gradient varies by compensation scheme—differential with respect to tenure is steeper under fixed wage. We study these issues for the platform work labour market. We find a 5% increase in monthly earnings for an additional year of tenure, which suggests precarity concerns are limited. Notably, our setting also has the same advantages as Shaw and Lazear (2008) and we also control for base rate of deliveries in our structural model.

2 Data Collection and Institutional Background

The food delivery platform we study is one of the major food delivery platforms operating in India. The platform company conducts on-ground operations such as hiring, payment, training and grievance management. The recruiting process for delivery workers involves offline and online interviews followed by basic training regarding the functioning of the software application. Once recruited, the worker is provided an ID on the software application which allocates restaurants and delivery locations.

The delivery personnel receives a basic delivery rate along with additional incentives for meeting daily targets which are conveyed at the beginning of the week. A platform worker who accepts the assigned task over the last 180 days is considered *active*. Figure 1 provides the proportion of active workers of the platform across the cities and tenure brackets. Tier 1 workers with less than 1 year of tenure form 30% of the sample. Proportion of workers is smaller in smaller-sized cities and higher tenure brackets. If a worker has not accepted a task in the last 180 days is defined as *exited* in our sample.

2.1 Sample Construction

We access the location and joining date for workers ever engaged on the platform. We draw our sample from the universe by stratifying the workers on location and tenure. Specifically, we stratified worker location into three categories of cities based on their size and three tenure brackets of less than 1 year, between 1-2 years and more than 2 years.[2]

Quality of survey was assured through several checks. First, Focus Group Discussions were held with active workers in three cities (Delhi, Chandigarh and Panipat). These FGDs provided crucial inputs on designing the the questionnaire. The first questionnaire was tested using telephonic pilot surveys conducted in six cities, with two in each tier. Data obtained from pilot surveys were corresponded with administrative data from the firm to check biases and errors in responses. The final questionnaire was updated using the inputs from the pilot. Final surveys were conducted for 924 workers in 28 cities (8 Tier-1, 12 Tier-2 cities and 8 Tier-3 cities).

2.2 Summary Statistics

Columns 1 and 2 of table 1 provides summary statistics for active and exited workers, respectively. The average tenure of active workers is 17.66 months, which is nearly twice the tenure of those who leave early. The two sets of workers appear similar in demographic characteristics. Nearly 70% of active and 75% of the exited platform workers have the highest education status of above 10th standard. Prior to this job, most of the platform workers were engaged as salaried workers, with this ratio slightly lower for exited workers. Interestingly, nearly 5-6% workers were engaged with some other platform prior to this experience, and this proportion nearly the same for both types of workers.

Finally, the bottom panel of Table 1 provides monthly gross and net earnings , daily deliveries and base rate of deliveries (money received per delivery) made by active workers. Gross earnings comprise of money received from deliveries and the incentive bonuses on meeting daily targets, which vary for workers by tenure and city. Net earnings are obtained by subtracting fuel costs from gross earnings. The average gross and net earnings are INR 17364 and INR 11791 per month, respectively. On average, 15.24 deliveries are made by a platform worker per day on this platform.

3 Empirical Model

We consider the following earnings or output function for the platform workers

$$y_i = \beta tenure_i + \gamma_1 \theta_i + \kappa X_i + \epsilon_i \tag{1}$$

[2]Tier 1 cities have a population of more than 5 millions, tier 2 cities have a population between 0.5 millions and 5 millions, and tier 3 cities have a population less than 0.5 millions. In our empirical models, we use tenure in months since we have granular information on the date of joining of each worker.

where, y_i is the earnings of or deliveries made by platform worker i. β informs us about the returns to human capital for one more month of tenure. X includes number of hours worked per day, base rate of deliveries, dummy indicators for education status, dummy indicators for prior work experience, and city fixed effects.

θ_i is the match quality of the worker i. It denotes the stability of the worker-platform match. If match quality is high, workers stay on the job, otherwise they exit.

$$S_i^* = \gamma_2.Z_i + \phi.X_i + \mu_i \tag{2}$$

where, S_i^* is a latent variable which reflects the experience of the worker on the job. Assume that a worker stays in the job if $S_i^* \geq 0$ or if $\mu_i \geq -(\gamma.Z_i + \phi.X_i)$.

We observe equation 1 only if a worker stays in the job; i.e. $\mu_i \geq -(\gamma.Z_i + \phi.X_i)$. Thus, $E(\epsilon_i, \mu_i) \neq 0$ and the two equations are not independent. The expected outcome as per equation 1 can now be written as:

$$E(y_i|X_i, \mu_i \geq -(\gamma.Z_i + \phi.X_i)) = \beta tenure_i + \kappa X_i + E(\epsilon_i|X_i, \mu_i \geq -(\gamma.Z_i + \phi.X_i))$$

Unobserved match quality of a worker with her job induces the sample selection bias, $E(\epsilon_i|X_i, \mu_i \geq -(\gamma.Z_i + \phi.X_i))$. An OLS estimation of 1 would then provide biased estimates of β (and other coefficients as well). To address the selection bias, we jointly estimate the two equations.

3.1 Estimation

For empirical estimation, we assume $\binom{\epsilon_i}{\mu_i} \sim N\begin{pmatrix} \sigma_{11} & \rho.\sigma_{12} \\ \rho.\sigma_{12} & 1 \end{pmatrix}$. Here, ρ is the correlation coefficient between the unobserved components of equations 1 and 2. If $\rho = 0$, then the two equations are independent and unobserved match quality does not create a bias in the OLS regressions. In our analysis, we will conduct a Wald test to show whether the two equations are independent or not.

We follow the Maximum Likelihood Estimation to find $(\beta, \gamma_1, \gamma_2, \kappa, \phi)$ Specifically, given our assumption of bi-normality of We find the Maximum Likelihood Estimators for (ϵ_i, μ_i), we find the estimators of the coefficients which best fit a bi-normal curve for $\binom{\epsilon_i}{\mu_i}$. The variance of μ_i is normalized to 1; i.e.μ_i is assumed to be standard normal.

3.2 Identification

A key requirement in structural models is the exclusion restriction. We require variables, Z_i, to proxy match quality which enter the selection equation 2 but not the production function equation 1. Match quality reflects worker's preference or suitability for the job. To instrument selection equation, we use self-reported indicators of entry and job satisfaction. These indicators serve as proxies of employment quality as shared by the workers. A large body of work, starting from Freeman (1978) and more recently by Lévy-Garboua and Montmarquette (2004), find that such measures are closely associated with actual behaviour such as job quit rates. Bertrand and Mullainathan (2001) and Frey and Stutzer (2002) review the systematic biases that may occur in subjective measures, but conclude that such variables have sufficient explanatory power. For platform work, Berger et al. (2019) uses similar measures to evaluate job satisfaction of Uber drivers in London.

Following this literature, we use four such variables as instruments, described below.

1 *Did you join the job for its flexible work hours?* Chen et al. (2019) shows the value of flexibility to platform work and its appeal in attracting workers who prefer flexibility. A preference for flexibilty implies better match quality, leading to lower exit rates.

2 *Would you recommend the food delivery platform job to your friends/relatives?* A better match quality should imply a preference for a job over others, leading to lower exit rates. Presuming the respondent desires well being of her acquaintances, this question intends to infer if the worker believes the job will be a good match for people in general. We assume that a worker with better (worse) good match quality is more (less) likely to respond positively to this question. Further, by merely claiming to recommend the job, should not increase the earnings of the worker.

Platform work is distinct from other informal labour markets since the control over task assignment and performance evaluation are conducted, to a large extent, by sophisticated computer algorithms. While such control mechanisms exist in every organization, such algorithmic control has been found to drive worker exit on platforms (Möhlmann and Zalmanson, 2017, Wiener et al., 2023). In particular, if workers find the task allocation and performance appraisal process as opaque and transparent, then they will experience a poor match quality due to low job satisfaction. To account for this process, we recorded workers' responses on the degree to which they believe they can control their performance and evaluation.

3 *Do you agree that the number of deliveries you make are in your control?* An unproductive or less matched worker will find it difficult to increase output even with effort. Thus, this question inquires a worker's assessment of control over productivity.

4 *Do you agree that your customer ratings are in your control?* Similar to the above question, the responses for this query reflects a worker's assessment of control over the appraisal process.

For instruments 2, 3 and 4, we collected responses on a Likert scale of 1 to 5. We create dummy variables which takes value of 1 for a worker who responds with a score of 5 to these questions, and 0 otherwise. Table 2 provides the proportion of workers with a positive response to the above questions. 33% of active workers shared that they joined the platform for its flexible hours, while the same proportion was 21% for exited workers. Nearly 46% of active platform workers would recommend jobs to others but the proportion is only 37% for exited workers. Active workers are more likely to believe that they have better control over deliveries and ratings. These statistics suggest that active workers are more likely to have a positive attitude toward job aspects.

4 Results

4.1 Earnings

Table 3 reports the results of one additional month of tenure on log of gross earnings. Column (1) shows the results from an OLS model, which controls for hours worked per day, household size and base rate for delivery. We also include city-, prior experience-, and education category FEs. The coefficient on tenure is 0.00424 in the OLS model. As discussed, this effect is biased upwards due to selection of workers and unobserved match quality.

In columns 2 to 6, we adjust for the selection of workers. We add our instruments one at a time from columns 2 to 6. In column 2, we use the worker's reason for joining the work as the instrument for selection. Specifically, if the worker desired flexibility, then she is more likely to remain with the firm due to her better match. The coefficient on tenure in the main equation (top panel) now falls o 0.00368 but remains statistically significant at 5% level. Importantly, the coefficient on the instrument in the selection equation is also statistically significant. We also conduct the Wald test for the independence of equations 1 and 2. The χ^2 value for the test is 76.78, thereby rejecting the null of independent equations. This test indicates that the correlation coefficient between the unobserved terms is statistically different from zero and that match quality plays an important role in earnings.

In columns (3), (4) and (5), we include instruments *recommending the job to others*, *control on deliveries* and *control on ratings*, respectively. The coefficient on tenure remains statistically significant and positive in each of them. Further, each of these instruments are significant determinants of staying on the job and the Wlad test of indepdence of equation is rejected in all specifications.

Finally, when we include all the four instruments in our selection equation in column (6), the coefficient on tenure is 0.00310. This translates into additional gross earnings of 3.7% for an extra year of tenure.

4.2 Net Earnings

In table 4, we use log of net earnings as the outcome variable, defined as the difference between gross earnings and average fuel costs. By accounting for expenditure on fuel, this variable indicates the amount left for consumption and savings. The effect of tenure on this variable reflects the impact on whether workers can cover the cost of living. In column 1, we show the coefficient on tenure independent of the selection equation. The coefficient is 0.00515 which implies a nearly 6.19% increase in net earnings for one additional year of tenure.

After adjusting for unobserved match quality through instrumenting for reason of joining, the coefficient drops to 0.00494 (column 2). The coefficient ranges from 0.00423 to 0.00487 with different instruments (Column 3-5). Finally, when we include all instruments, the coefficient is 0.00408 (column 6). Twelve additional months of tenure yield nearly 4.9% increase in net earnings for platform workers.

In column 6, the p-value on the Wald test of independence of equation is 126.58. The unobserved terms in the main and selection equation are correlated. This underscores the importance of match quality in earning capacity of platform workers.

4.3 Productivity

Table 5 provides the corresponding results for productivity metric of daily deliveries. OLS coefficient is 0.005009 and is statistically significant at 1% level.

From column 2 onward, we adjust for the selection equation by using one instrument at a time. On using *joined for flexibility*, the coefficient on tenure drops to 0.00497 (column 2). The coefficient on tenure remains within 0.00480 and 0.005003 in columns 3, 4 and 5, where we instrument selection using *recommend job*, *control on deliveries* and *control on ratings*, respectively. In each of the selection adjustment, the instruments remain statistically significant, and the Wald test of independence of equation is rejected.

Finally, in column 6, we use all instruments together. The coefficient on tenure in the outcome equation is 0.00471 (top panel). Thus, deliveries increase by nearly 5.66% in one year ((exp(0.00464)-1)*12). Wald test rejects the null hypothesis of independence of equation. In other words, unobserved components of deliveries and selection are correlated and match quality plays a significant role in productivity of workers.

5 Mechanisms

Platform delivery work requires several soft and hard skills. These include technological skills of using GPS, local information on routes, oral skills of reading speaking English language (which is commonly spoken in India) and inter-personal skills of customer service. Increase in human capital with tenure is likely to occur through improvement in these skills. We test this hypothesis by using a probit model to assess whether the probability of learning these skills, as reported by workers, improves with tenure.

Table 6 provides the marginal effects for tenure. We find significantly positive results for learning routes and English—workers with one more year of tenure reported to have better knowledge of local routes and English language by 3.96% and 3.12%, respectively. Our results indicate that platform work adds general human capital of workers. Improvement in knowledge of local routes may also indicate why the impact of tenure on net earnings is higher than on gross earnings. Better knowledge of routes may allow workers to become more fuel efficient, saving fuel costs and thus increasing net earnings more.

6 Robustness Checks

Identification of the estimates depends on the validity of instruments. Specifically, the instruments should affect the outcome variables; i.e. earnings and productivity, only through match quality. To check for robustness of our results, we use alternative instruments to check for the robustness of our results.

6.1 Likert Scale Ranking for Instruments

We have constructed three of our instruments (control on deliveries, control on ratings and recommending job) as dummy variables from a Likert scale from 1 to 5. Specifically, we code the instrument as 1 if the platform worker responded 5 on these questions. In order to assess the robustness of our results, we modify the instruments by coding their value as 1 if the response was 3, 4 or 5 on the respective Likert scale. Table 7 provides the results for coefficient of tenure on earnings, net earnings and deliveries, respectively. The estimated effect of tenure on gross earnings are similar to our results in table 3. For the other two outcome variables, however, the estimated effects remain similar to the OLS.

6.2 Alternative Reasons for Joining

We consider other reasons for joining the platform as instruments. These are: joining due to a loss of job or a loss in business. A loss in previous job should imply these are less well matched workers and more likely to exit. Table 8 provides the coefficient on tenure from these models for each of the outcome variable. The estimate of tenure coefficient for earnings, net earnings and deliveries are 0.00327, 0.00477 and 0.0044, respectively.

7 Conclusion

Digital economies and digitally-enabled labour markets are increasingly occupying a bigger share of workforce. But do these platforms leave workers vulnerable and precarious by reducing scope for human capital addition, which is common in other labour markets? In this paper, we find that food delivery platform workers in India tend to benefit from a longer duration on these labour markets. Twelve additional months of tenure yield 3.96% higher gross earnings and 5.29% higher net earnings for the worker. Further, platform also benefits from a well-matched employee as the worker with an additional year delivers 5.85% more items. Higher tenure workers improve general human capital, such as conversing in English, and task specific human capital such as knowledge of routes.

Platform companies should try to lengthen job spells given the positive earnings and productivity tenure gradient. This can occur through two means—retention at the time of exit or better screening at the time of recruitment. Retaining exiting workers in tier 1 cities for a spell of one standard deviation higher tenure generates 25% higher gross earnings than retaining all workers in other centers. Incurring the costs of these policies or simulating the effect of better screening is beyond the scope of our paper. However, by providing the expected gains of retention, we throw partial light on this subject. The difference in expected counterfactual values for the two markets can be due to different output demand, distinct demographic characteristics of workers, or lower job destruction rate. We leave exploration of the differential across these factors for future work.

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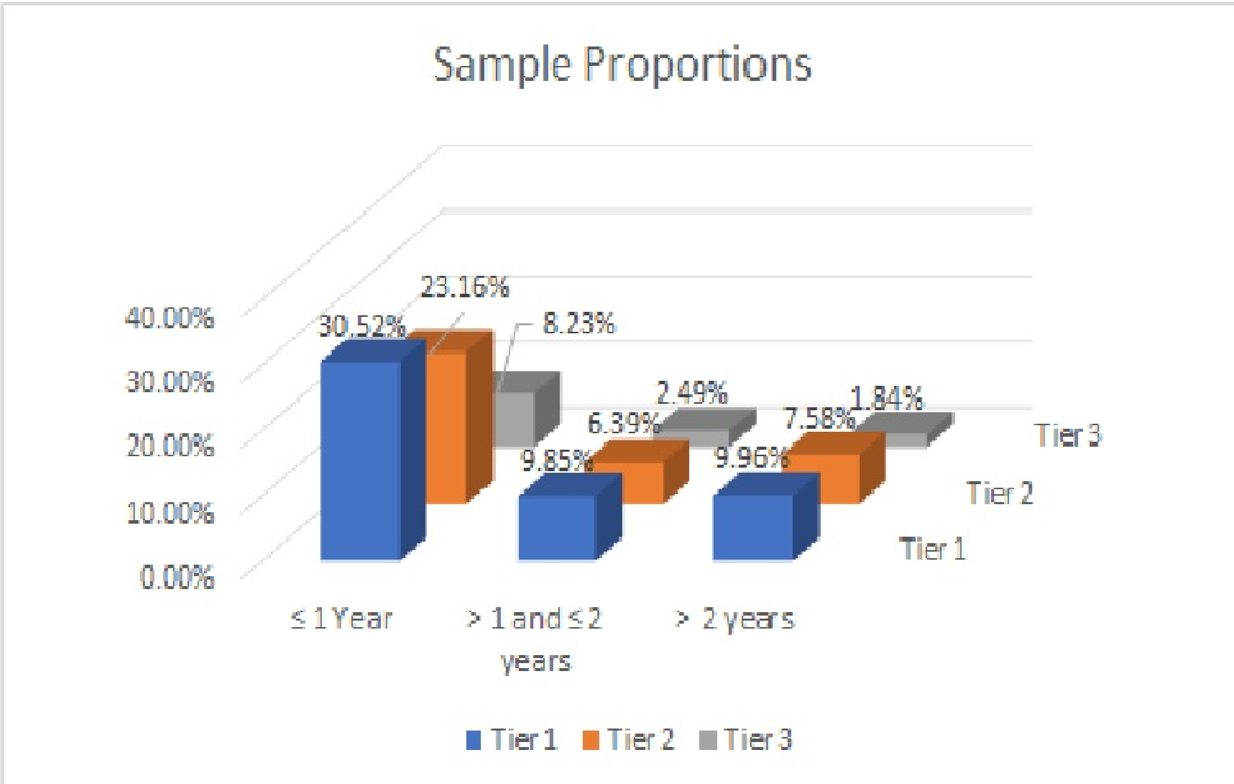
8 Figures

Figure 1: Sample Proportion of Platform Workers across Cities and Tenure Brackets



9 Tables

Table 1: Summary Statistics

	Active	Exited
Tenure	17.66	9.56
	(14.35)	(12.21)
Hours per Day	8.52	8.08
	(3.1)	(3.16)
Household Size	4.87	4.75
	(2.07)	(2.07)
Education		
Below 8th	0.065	0.0538
	(0.25)	(0.23)
8th-10th	0.23	0.19
	(0.42)	(0.39)
10th and Above	0.70	0.75
	(0.46)	(0.43)
Prior Experience		
Not Working	0.19	0.3
	(0.39)	(0.46)
Platform Workers	0.058	0.061
	(0.234)	(0.24)
Salaried	0.64	0.55
	(0.479)	(0.497)
Self-Employed	0.108	0.079
	(0.311)	(0.27)
City		
Tier 1	0.509	0.494
	(0.5)	(0.5)
Tier 2	0.367	0.376
	(0.48)	(0.48)
Tier 3	0.123	0.128
	(0.329)	(0.334)
Earning and Productivity		
Monthly Earnings (Rs.)	16492	.
	(9978.64)	
Monthly Net Earnings (Rs.)	11791	.
	(8514.17)	
Daily Deliveries	15.24	.
	(7.02)	
Base Rates	25.57	.
	(10.303)	
Observations	534	390

Table 2: Summary Statistics on self-reported attitude toward job

	Active	Exited
Joined for Flexibility	0.331	0.217
	(0.471)	(0.413)
Recommend Job	0.468	0.376
	(0.499)	(0.485)
Control Deliveries	0.29	0.18
	(0.45)	(0.39)
Control Ratings	0.323	0.215
	(0.468)	(0.411)
Observations	534	390

Table 3: Tenure-Earning Relationship

	(1) Log(Earnings)	(2) Log(Earnings)	(3) Log(Earnings)	(4) Log(Earnings)	(5) Log(Earnings)	(6) Log(Earnings)
main						
Tenure (Months)	0.00424***	0.00368**	0.00333**	0.00371**	0.00344**	0.00310**
	(0.0016)	(0.0014)	(0.00146)	(0.0014)	(0.0014)	(0.001)
Hours Spent	0.075***	0.061***	0.061***	0.052***	0.056***	0.058***
	(0.020)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)
baserate	-0.002	-0.001	-0.001	-0.001	-0.000	-0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
select						
Joined for Flexible Hours		0.375***				0.373***
		(0.073)				(0.076)
Recommend Job to Others			0.204***			0.247***
			(0.065)			(0.067)
Control on Deliveries				0.328***		0.181**
				(0.076)		(0.089)
Control on Ratings					0.248***	0.104
					(0.075)	(0.085)
Wald Test		76.78	90.09	68.58	75.82	80.50
Observations	528	923	923	923	923	923

Column 1 reports the results from an OLS regression. Column 2 to 6 report the results from a Heckman Selection model. All models include number of hours worked per day, household size, delivery base rates and Fixed Effects for city, prior experience, education and whether worker was involved Full-Time or Part-Time. */**/*** denote significance at 10/5/1 percent level. Standard errors are robust to heteroscedasticity.

Table 4: Tenure-Net Earning Relationship

	(1) Log(Net Earnings)	(2) Log(Net Earnings)	(3) Log(Net Earnings)	(4) Log(Net Earnings)	(5) Log(Net Earnings)	Log(N
main						
Tenure (Months)	0.00515**	0.00494**	0.00423**	0.00487**	0.00444**	0
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Hours Spent	0.052*	0.037	0.036	0.021	0.027	
	(0.029)	(0.024)	(0.025)	(0.026)	(0.026)	
baserate	0.003	0.002	0.003	0.003	0.003	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	
select						
Joined for Flexible Hours		0.342***				
		(0.065)				
Recommend Job to Others			0.195***			
			(0.060)			
Control on Deliveries				0.300***		
				(0.069)		
Control on Ratings					0.215***	
					(0.069)	
Wald Test		123.08	167.06	135.09	136.22	
Observations	479	873	873	873	873	

Column 1 reports the results from an OLS regression. Column 2 to report the results from a Heckman Selection model. All models include number of hours worked per day, household size, delivery base rates and Fixed Effects for city, prior experience, education and whether worker was involved Full-Time or Part-Time. */**/*** denote significance at 10/5/1 percent level. Standard errors are robust to heteroscedasticity.

Table 5: Tenure-Productivity Relationship

	(1) Log(Deliveries)	(2) Log(Deliveries)	(3) Log(Deliveries)	(4) Log(Deliveries)	(5) Log(Deliveries)	(6) Log(Deliveries)
main						
Tenure (Months)	0.005009***	0.00497***	0.00491***	0.005003***	0.00480***	0.00471***
	(0.00136)	(0.00146)	(0.00141)	(0.00144)	(0.0014)	(0.0014)
Hours Spent	0.072***	0.070***	0.071***	0.066***	0.068***	0.067***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)
baserate	-0.004***	-0.005***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
select						
Joined for Flexible Hours		0.409***				0.419***
		(0.088)				(0.091)
Recommend Job to Others			0.187**			0.197**
			(0.091)			(0.083)
Control on Deliveries				0.370***		0.189*
				(0.088)		(0.107)
Control on Ratings					0.327***	0.202*
					(0.091)	(0.107)
Wald Test		15.45	3.94	9.95	8.14	20.46
Observations	523	923	923	923	923	923

Column 1 reports the results from an OLS regression. Column 2 report the results from a Heckman Selection model. Both models include number of hours worked per day, household size, delivery base rates and Fixed Effects for city, prior experience, education and whether worker was involved Full-Time or Part-Time. Proxies for sample selection equation (stage-1 equation) include a dummy for whether the individual will recommend the job, dummy for stress level, dummy for ability to control ratings and deliveries, along with household size and fixed effects for city, prior experience and education. */**/*** denote significance at 10/5/1 percent level. Standard errors are robust to heteroscedasticity.

Table 6: Learning and Tenure of Active Workers

	GPS	Routes	English	Customer Service
Tenure (Months)	0.0012	0.0033*	0.0026**	0.0018
	(0.0016)	(0.0017)	(0.0017)	(0.0016)
Observations	461	461	461	461

The table reports the marginal effects of tenure from a probit regression on a dummy for learning a skill (GPS, Routes, English and Customer Service) on tenure. Each model includes number of hours worked per day, household size, delivery base rates and Fixed Effects for city, prior experience, education and whether worker was involved Full-Time or Part-Time. Sample consists of active workers. */**/*** denote significance at 10/5/1 percent level. Standard errors are robust to heteroscedasticity.

Table 7: Robustness with Alternative Instruments

	Log(Earnings)	Log(Deliveries)	Log(Net Earnings)
main			
Tenure (Months)	0.00371**	0.00507***	0.00510***
	(0.00145)	(0.00187)	(0.00147)
Observations	923	923	873

The table reports the effect of tenure on the outcome variables after adjusting for selection. The instruments of *recommending job*, *control on deliveries* and *control on ratings* take value 1 if the platform worker's rating for the three questions was 3 or above. */**/*** denote significance at 10/5/1 percent level. Standard errors are robust to heteroscedasticity.

Table 8: Robustness with Alternative Reasons for Joining

	Log(Earnings)	Log(Net Earnings)	Log(Net Earnings)
main			
Tenure (Months)	0.00327**	0.00477**	0.0044***
	(0.00147)	(0.00141)	(0.00205)
Observations	923	923	873

The table reports the effect of tenure on the outcome variables after adjusting for selection. Additional instruments include joining due to a loss of a job or a loss in business. Other instruments are same as in the main specification. */**/*** denote significance at 10/5/1 percent level. Standard errors are robust to heteroscedasticity.

Table 9: Distribution of Workers

Region/ Tier	Active				Exited				Final Sample
	<1 year	>1 year & <2 year s	>2 years	Total	<1 year	>1 year & <2 year s	>2 year s	Total	
Overall	259	138	138	535	278	45	66	389	924
Tier 1	129	73	70	272	142	20	31	193	465
Tier 2	96	49	52	197	103	22	21	146	343
Tier 3	34	16	16	66	33	3	14	50	116
East	49	25	25	99	46	13	15	74	173
Tier 1	17	9	8	34	15	3	6	24	58
Tier 2	24	12	13	49	19	10	7	36	85
Tier 3	8	4	4	16	12	0	2	14	30
West	80	41	42	163	88	13	19	120	283
Tier 1	48	25	26	99	53	8	11	72	171
Tier 2	24	12	12	48	29	5	2	36	84
Tier 3	8	4	4	16	6	0	6	12	28
North	48	24	27	99	47	7	20	74	173
Tier 1	16	8	8	32	14	2	8	24	56
Tier 2	24	12	15	51	27	5	6	38	89
Tier 3	8	4	4	16	6	0	6	12	28
South	82	48	44	174	97	12	12	121	295
Tier 1	48	31	28	107	60	7	6	73	180
Tier 2	24	13	12	49	28	2	6	36	85
Tier 3	10	4	4	18	9	3	0	12	30

A Sample Distribution of Workers Across City and Tenure Buckets

Table 9 provides geographic and tenure-wise distribution of active and exited workers in our sample.

B Response Rates for Active and Exited Workers

Table 10 shows the response rates for active and exited workers.

Table 10: Response Rates

City	Active	Exit	Overall
Delhi	26.2	24	25.2
Sirsa	50	22.7	28.6
Jalandhar	18.6	6.9	11.6
Lucknow	40	38.3	39.2
Gorakhpur	37.5	21.2	30.1
Meerut	34	41.9	37.2
Waidhan		31.6	31.6
Jaipur	34	8.7	15.1
Udaipur	42.1	8.8	20.8
Guwahati	15.3	29.2	17.8
Patna	36.2	22.2	30.1
Gaya	100	20	30.4
Bokaro	39.6	34.2	37.1
Agartala	21.3	6.5	11.4
Kolkata	36.5	8.5	22.6
Mumbai	16	7.1	11.4
Pune	35.6	11.5	18.7
Nashik	20.6	60	23.9
Central Goa	22.5	3	6.9
Ahmedabad	13.2	10.2	11.7
Kakinada	22.6	14.3	17.7
Vizianagaram	30	0	28.6
Hyderabad	17.3	10	13.8
Bangalore	32.1	25.3	29
Manipal	37.5	26.7	31.2
Palakkad	34.5	20	33.3
Chennai	29.5	24.2	26.7
Coimbatore	31.6	24.2	27
Tier 1 Cities	22.5	13.2	17.7
Tier 2 Cities	28.6	14.8	21
Tier 3 Cities	28.7	12	18.1
Overall	25.3	13.6	19