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PLATFORM WORK: EVIDENCE FROM DRIVERS IN INDIA, INDONESIA, AND KENYA

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Platform Work: Evidence from Drivers in India, Indonesia, and Kenya
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ABSTRACT

Using surveys and administrative data from representative samples of drivers working on three leading gig platforms in India, Indonesia, and Kenya, we document the composition, economic experiences, and labor market trajectories of platform workers. Combining platform-based earnings with operating cost data, we estimate earnings net of costs (in PPP-adjusted terms) in each context. We find that the flexible nature of platform work enables drivers to work substantially more than the full-time equivalent, generating higher monthly net earnings than low-skill or casual employment, despite comparable or lower hourly net earnings relative to these outside options. Drivers who exit platform work in India and Indonesia do so to take up better-paying full-time positions. In contrast, Kenyan drivers often exit involuntarily, returning to offline driving with adverse financial consequences. One-third of drivers across countries rely on platform work to supplement earnings during emergencies or slow work periods, suggesting that platform work may play an important role as a financial safety net.

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1 Introduction

The rapid expansion of digital labor platforms and technology-driven intermediaries connecting independent service providers with customers has reshaped employment landscapes globally. Particularly in low- and middle-income countries (LMICs), platform-based gig work is often viewed as a potential driver of economic inclusion, providing flexible earning opportunities in contexts where employment opportunities remain limited (World Bank, 2022b). The growth of digitally mediated earning opportunities has also been driven by smartphone penetration and internet connectivity.

Despite the rapid expansion of platform-based gig work globally, most of the research to date has focused on High-Income Countries (HICs), where this sector originated and has rapidly grown. In the United States, it is estimated that the share of work that is online or location-based gig work has increased from 1% in 2017 to 4–5% in 2021 (Katz and Krueger, 2019; Garin et al., 2023). Studies from HICs reveal that while platform work offers flexibility, it often fails to provide adequate earnings. For example, Berg et al. (2018) find that ride-hailing drivers in the UK earn an average of \$580 per week, significantly lower than the London median gross weekly pay of \$750. In the U.S., Hyman et al. (2020) report that only 15% of ride-hailing drivers work full-time, and although median hourly earnings are \$17.40, around 34% of full-time drivers earn less than the minimum wage. For Uber drivers across all US cities, Cook et al. (2020) report hourly gross earnings of \$21.07 and net earnings of \$10.80 after Uber service charges and expenses. Parrott and Reich (2018) similarly find that 40% of drivers qualify for government assistance due to low earnings. Compared to LMICs, gig work in HICs is characterized by a greater gender diversity and lower entry barriers, largely due to the widespread availability of "idle assets" such as personal vehicles.

Research on gig work in LMICs is still relatively nascent and often limited in scope and/or representativeness. Studies such as Hunt and Samman (2020) in South Africa (focusing on domestic workers), Azuara et al. (2019) in Latin America (ride-hailing), Octavia (2022) in Indonesia (motorbike taxis and domestic work), Zollman (2023) in Kenya (car drivers), and National Council of Applied Economic Research (2023) in India (motorbike drivers) provide important context-specific insights. These studies show considerable variation in pay and experiences of workers. Hunt and Samman (2020) report that earnings are low and most workers rely on a mix of informal and platform-based work to make ends meet. Azuara et al. (2019), however, find more positive outcomes, with platform drivers earning roughly three times their country's minimum wage and valuing flexibility; however, they do not consider operating expenses in their calculation. Zollman (2023) study of car drivers presents a more sobering picture in Nairobi, where only 16% of drivers earn above the city's hourly minimum wage after adjusting for operating expenses, and 47%

of full-time drivers exceed the monthly minimum wage. Zollman (2023) highlights that low net earnings are partially driven by rental vehicle costs. The National Council of Applied Economic Research (2023) study on two-wheeler delivery drivers in India finds lower estimates for gross earnings (possibly due to a different surveying time period). They also find the sector serves as a stepping stone for young urban males, equipping them with skills relevant to future employment opportunities. Among the few cross-country studies available, the International Labour Organization (2021) analyzed data from application-based taxi and delivery workers across 20 countries. This report finds that, in many LMICs, earnings from platform work tend to exceed those in corresponding offline sectors.

Despite these valuable contributions, significant research gaps persist in LMIC contexts. Existing studies often rely on small or unrepresentative samples, many recruited through convenience methods such as street recruitment (e.g., Zollman 2023; International Labour Organization 2021), and rarely have access to administrative data to enable random sampling or post-stratification. Moreover, few studies allow for direct cross-country comparisons of platform worker demographics, earnings, and labor market transitions in LMICs. This limits our understanding of how platform work fits into broader economic trajectories in these settings, and how policy responses should be tailored accordingly. Our work aims to fill these gaps.

India, Indonesia, and Kenya provide compelling case studies for examining the gig economy's role in emerging labor markets, especially in the transport sector. India, home to one of the largest and fastest-growing digital labor markets, is projected to see its gig workforce expand from 6.8 million in 2019–20 to 23.5 million by 2029–30 (NITI Aayog, 2022). This growth is primarily driven by the widespread adoption of two-wheelers in the e-commerce, delivery, and ride-hailing sectors, which account for most platform-based gig work (KPMG India, 2024). Similarly, in Indonesia, motorcycles are the backbone of platform work, with gig platforms offering employment opportunities amid a labor market that balances formal and informal work (Kementerian Perencanaan Pembangunan Nasional, 2023a). Kenya, where over 80% of workers engage in informal employment (Kenya National Bureau of Statistics, 2024), has also witnessed a surge in platform-based work, particularly in the *bodaboda* (motorcycle) sector, which now constitutes a primary earning source for urban and peri-urban workers (Pollio et al., 2023).

We partner with three different location-based gig work platforms in India, Indonesia, and Kenya (referred to as [platform] to preserve anonymity) that mediate driving and delivery services for two-wheeler drivers (motorcycles, scooters, and electric motorbikes). The services these platforms provide differ in the three countries, and hence, worker experiences vary. In India, the platform is exclusively focused on deliveries. In Indonesia and Kenya, in addition to deliveries, workers drive passengers, as well.

We add to the aforementioned body of work in several ways. First, to the best of our knowledge, our paper is the first to provide representative estimates of drivers' earnings net of operating costs using data from major platforms in the developing world. Second, by administering very similar surveys to drivers in all three countries, we provide more comparable estimates of platform drivers' demographic and economic characteristics, which highlight variations in worker profiles across diverse labor markets. Third, using these survey data, we study the role of platforms in fostering financial inclusion, social protection, and financial security. We also survey drivers who no longer work for the platform to characterize exit from platform work and post-platform economic trajectories.

We obtained driver listing data from each of the platforms and drew a random sample from two populations of drivers: "active" (those who logged in on the platform at least once in the past 2–3 months[1]) and "inactive" (drivers who have not made a delivery in 9 months but were active within the last 1–2 years).[2] The sampled drivers were reached and surveyed by an independent team of enumerators over the phone, with phone numbers provided by the platforms. The response rate to the phone survey was 18%, 45%, and 14% for active drivers and 11%, 16%, and 6% for inactive drivers for India, Indonesia, and Kenya, respectively. The response rates are comparable to other studies using similar surveying methods (e.g., 25% in National Council of Applied Economic Research 2023 report in India, 9% in Azuara et al. 2019 in LATAM). The final sample consists of 2,547 active and 114 inactive drivers in India, 3,006 active and 196 inactive drivers in Indonesia, and 989 active and 193 inactive drivers in Kenya.

Analysis of the administrative data reveals that part-time driving (defined as less than 8 hours per day) is highly prevalent across all three countries, with 80% of drivers in India and Kenya and 50% in Indonesia working part-time on the [platform]. The overwhelming majority of drivers are male: female representation is 0.8% in India, 1.5% in Indonesia, and 0.77% in Kenya, likely reflecting cultural norms and safety concerns that restrict women's participation in platform-based transport work (World Bank, 2021a; Consultative Group to Assist the Poor, 2023). In line with previous studies in LMICs (e.g., Zollman 2023; National Council of Applied Economic Research 2023; Azuara et al. 2019), the population of drivers is relatively young: the average driver is 31 years old.

The survey data reveal striking demographic differences between gig workers in the three countries. In India, drivers are younger and more educated than the average urban Indian, consistent with both a high unemployment rate for urban youth and a preference in this population for flexible work arrangements (Ministry of Statistics and Programme

[1]Varies based on country context.

[2]To preserve anonymity of the platforms, we are unable to share the exact population numbers. The population of active drivers was >500,000 and >100,000 for active drivers and >50,000 and >200,000 for inactive drivers for India and Indonesia, respectively. The total population for both driver types was ∼10,000 in Kenya, with the vast majority being active.

Implementation, 2024). In contrast, Kenyan drivers tend to be slightly older, with the average age of active drivers exceeding the national median of 19.9 years (Statista, 2024b). Indonesian drivers are older than their Indian and Kenyan counterparts but are broadly similar in age to other gig workers in the transportation sector in that country (Permana et al., 2023).

Work patterns differ across countries, as well. A higher proportion of Kenyan drivers (27%) engaged in driving-related work before joining the platforms, whereas Indonesian drivers were the most likely to have been involved in full-time formal work before joining the [platform] (58%, significantly higher than in India (45%) and Kenya (30%)). Indonesian drivers report working the most hours across all earnings sources at 76.81 hours/week, followed by Kenyan drivers at 66.16 and Indian drivers at 57.9. Indonesian drivers allocate a significantly larger share of their total working hours to platform activities (91%) compared to Kenyan (71%) and Indian drivers (60%), reflecting their heavy reliance on gig work amid challenges in transitioning to formal employment or preferences for flexible work arrangements (Pratomo and Manning, 2022). In all three countries, drivers have diverse work portfolios relying on multiple earning sources with an average of 1.74 in India, 1.62 in Indonesia, and 2.01 in Kenya. Drivers in Kenya are the most likely to work on multiple driving platforms simultaneously, with 41% "multi-homing" (working on multiple platforms) compared to 10% and 12% in India and Indonesia. Kenyan drivers are the most likely to strategically select hours to maximize profits, aligning with the theoretical expectations of gig work, where workers can capitalize on surge pricing and peak demand periods (Chen et al., 2017). In contrast, drivers in Indonesia are the most likely to work the same fixed hours every day, whereas Indian drivers work whenever they have free time.

Earnings analysis reveals substantial variation in both gross and net earnings across countries. PPP-adjusted gross earnings per hour are $5.02 for India, $2.96 for Indonesia, $5.39 (during peak price survey period), and $3.38 (wider time period) for Kenya. After subtracting operating costs (e.g., fuel, parking, repairs, loan and rent payments), PPP-adjusted hourly *net earnings* are $3.50 in India, $1.84 in Indonesia, and for Kenya, $2.32 (during surveying period) and $1.45 (wider time period). Operating expenses in Kenya are the highest, constituting about 57% of gross earnings, compared to 30% in India and 38% in Indonesia. PPP adjusted net earnings per month are $1,039.80 in India, $589.90 in Indonesia, and $465.60 (during survey period) and $328.07 (wider time period) in Kenya.

We then benchmark [platform] earnings against other opportunities available to the drivers. In India and Indonesia, full-time platform drivers' monthly net earnings exceed those in casual labor. In India's major cities, monthly net earnings in platform work exceed income from minimum wage low-skill employment, though hourly rates are similar. Drivers in Jakarta in contrast earn below the minimum wage in both hourly and monthly terms. In Kenya, both per-hour and per-month compensation are generally lower than for other low-skill salaried work; however, they can exceed earnings per month in other formal work during price peak seasons.

Financial security is a pressing issue for many gig workers: 35% of Indian drivers, 16% of Indonesian drivers, and 22% of Kenyan drivers report struggling to meet basic expenses, highlighting persistent vulnerabilities despite diverse earning streams. Low earnings are also reported as a major challenge in platform work among Indonesian and Kenyan workers (cited by 29% of Indonesian drivers and 18% of Kenyan drivers), but only 6% of Indian drivers, which is consistent with our independently derived estimates of net earnings (which are highest in India).

Next, we address the links between platform work and financial inclusion. Platforms may be pathways for previously unbanked individuals to acquire bank accounts; further, payments and transactions are done with digital currencies, which may improve familiarity and comfort with digital financial tools. We find the most substantial evidence of this in Indonesia, where 26% and 79% of drivers reported gaining access to banking accounts and mobile money, respectively, due to platform work. This may be driven by platforms' efforts to assist potential drivers with bank account acquisition in the early days of the platform economy (GSMA, 2019). These fractions are much lower in India and Kenya, likely reflecting the presence of well-developed financial inclusion initiatives like PMJDY in India, which brought over 450 million people into the formal banking system through zero-balance accounts, and the widespread adoption of M-Pesa in Kenya (World Bank, 2022a). Digital loan adoption among drivers varies widely, with uptake highest in Kenya (86%) and lowest in India (19%), reflecting national trends in those countries' digital credit access and usage. Platform influence on digital loan-taking was most pronounced in Indonesia (13%), followed by Kenya (10%) and India (6%).

Examination of individuals who left platform gig work (which we term inactive drivers) yields several interesting findings. Given the high churn rate, young age of drivers, and prevalence of students, we surmise that drivers in India view gig work as a temporary occupation, using it as a stepping stone while aspiring to move into more stable or better-paying employment. In contrast, Indonesian drivers view these occupations as longer-term professions, potentially due to limited alternatives—particularly among those with lower education levels—though those with better qualifications tend to exit into improved work opportunities. Kenyan drivers treat platform work more as a long-term profession (given the highest prevalence of offline drivers before platform work) than a transitional gig, with many moving into the offline driving sector after exiting. Post-exit, over 50% of drivers in India and Indonesia report transitioning to formal employment, frequently citing better earnings prospects, whereas in Kenya, exits are more often involuntary, with a significant share of drivers terminated from the platform. Consequently, 50% of inactive drivers in India and Indonesia report earning more post-exit, compared to just 30% in Kenya. Across all three countries, around 30% of those who exited eventually rejoined the platform, often during periods of financial distress, reinforcing gig work's role as a flexible fallback during economic turmoil (Michuda, 2023; Rosenblat and Stark, 2016).

2 Methodology

2.1 Sampling and Response rates

In all countries, we partnered with location-based driving and/or delivery platforms to obtain a random sample of drivers[3]; the population range of active drivers was over 500,000, 100,000, and 10,000 for India, Indonesia, and Kenya, respectively. Before sampling, we excluded approximately 24% of the population in India, due to budgetary considerations of surveying in more than three local languages[45]. In India, our sample is representative of 17 states/regions and excludes about 25% of all drivers, according to the administrative platform data. In Indonesia, we omitted individuals under the age of 18 (excluding <1%). We then drew a stratified random sample using variables from the administrative data, oversampling underrepresented groups such as female drivers to allow for heterogeneity analysis. In Kenya, given the smaller population size, we attempted to survey all drivers in the population.

The process for surveying varied across countries. In India and Kenya, the platforms were required to first request explicit permissions from their drivers to share personally identifiable information (PII) with external partners. In Indonesia, the platform sent notifications to sampled drivers about being contacted to take part in the survey, but was able to share PII information with us without individual permissions. The differences in processes affected the survey response rates. In India, we were able to complete interviews with 2,547 active drivers (including 404 female drivers), resulting in a response rate of approximately 18% and 989 active drivers in Kenya with a response rate of 10.4%, This aligns with rates typically reported in previous literature such 9.5% in Azuara et al. (2019)

[3]The dataset included demographic and operational variables such as age, gender, average daily/weekly driving hours, total deliveries completed, tenure on the [platform], and average driver ratings at the time of data extraction.

[4]Hindi is one of the widely spoken languages in North India, and 58% of the active driver population works in Hindi-speaking states. For South India, Telugu and Kannada were selected based on operational ease and the number of drivers in these states (11% and 12% of the active driver population, respectively). This exclusion meant the removal of states in the East, North-east, and South of India where these 3 languages are not spoken majorly.

[5]Other exclusions for India include: drivers with zero tenure days (0.01% excluded), drivers included in our pilot (0.01% excluded), and drivers with a status not equal to active as defined by the [platform] (4% excluded).

that used random sampling through platform data for ride-hailing drivers in LATAM and 25% of active food delivery drivers in India, sampled using platform database for National Council of Applied Economic Research (2023). In Indonesia, we successfully reached 3,006, achieving a response rate of 45.1%, which is higher than other studies in this sector. Inactive drivers were harder to reach with reach rates of 11% in India, 17% in Indonesia, and 6% in Kenya, potentially due to frequent changes in phone numbers and lack of time, since they were engaged in other types of work, such as formal work, post-leaving the [platform]. Response rates for all drivers are listed in Table 1 [6]. All estimates are weighted with sampling and post-stratification weights as described in Section 2.2.

In all three countries, we note that non-response is not random, and some active drivers were more likely to respond and complete the survey than others. For instance, in India, male full-time drivers with higher platform ratings and longer tenure are easier to reach; in Indonesia, we were able to reach younger drivers who are more likely to have in-application financial tools and more likely to be engaged in delivery work (compared to passenger driving). In Kenya, part-time drivers with higher tenure on the platform, with more total deliveries, and higher ratings are more likely to participate in the survey.

2.2 Weights

The weighting strategy differed slightly in each country, though the core principle was the same—namely, to adjust the sample with post-stratification weights to increase comparability between the sample reached and the population based on observable characteristics provided in the platform administrative data. In Indonesia and India, the estimates were adjusted with inverse probability weights (IPW) applied within the strata that were used for sampling. Differential sampling probabilities were also incorporated into weight construction. In Kenya, we applied inverse probability weighting in weight construction. In all countries, IPW weights were generated using logistic regression, with "survey completed" as the dependent variable and independent variables including age, tenure, number of hours worked, number of completed deliveries (if available), and geographic location (if available). This weighting approach produced a sample that reflects the population regarding observable characteristics. Tables A1 - A3 in the Appendix present the differences in means before and after applying weights for all three countries.

2.3 Adjustment of p-values

To reduce the risk of type I errors, we adjust all p-values from subgroup comparisons using the false discovery rate (FDR) method proposed by Benjamini et al. (2006). This

[6] We also surveyed offline drivers in Indonesia, but the results are not included in this report.

adjustment is applied within each country and encompasses all p-values used for various comparisons (e.g., gender, driver type comparisons, and location). The adjustment is applied to a comprehensive set of variables analyzed as part of the larger report within each country.

3 Sources of Data

For our analysis, we use two types of data: survey data collected via phone surveys conducted in each of the countries, and platform administrative data for India and Kenya.

3.1 Survey data

Our objective was to comprehensively describe the driver population and cover a wide range of topics. This resulted in a survey questionnaire of around 200 questions. To ensure a manageable survey duration, the sample was randomly divided into four equal groups in India and Indonesia, and some sections were only administered to a subsample. All groups were administered core questions (such as demographics, earnings, and labor supply), with each subsample participating in different sections of the full questionnaire. This approach resulted in different numbers of observations for each module. In Kenya, all drivers answered all questions, but the survey was divided into two parts and administered in random order on two different occasions.

For all three countries, all sections were covered, with most questions in each module being the same across countries. However, some questions were adjusted based on feedback from the enumeration teams to ensure relevance to each country's context. A detailed breakdown of all modules and their respective sample sizes is provided for each country in Table A4 in the appendix.

3.2 Administrative data

3.2.1 Data used for Sampling

For all three countries, we received [platform] administrative data on the entire population of drivers. This was de-identified data that contained key variables used in the sampling stratification process, such as age, gender, location of the driver, driving patterns (average number of hours logged in per day/month), number of total deliveries made on the platform, the tenure on the platform, and the platform rating of the driver. For clarity, we refer to this dataset as 'Admin data 1'.

3.2.2 Detailed data for additional analysis

For India, we received additional, more detailed driving records of 9,162 drivers (out of the 13,914 sampled) who drove at least once between January and May 2024. This administrative data, covering 20 weeks (Table 2), was aggregated by time of the day, week, and driver. Each observation represents the total number of hours driven and compensation received by a single driver in a particular week and time of the day[7]. Drivers who participated in the survey but did not grant permission for IDinsight to access their data were excluded from this dataset. In Kenya, we received administrative data from the platform from July to December 2024 on key variables, including average earnings (not including bonuses) and hours driven.

3.3 Supplementary data sources

Where possible, we provide comparisons between drivers and the urban or general population in each country using the best possible data available. We used the national datasets such as National Health and Family Statistics (NFHS) 2021, Periodic Labour Force Statistics (PLFS) 2023, Comprehensive Annual Modular Survey (CAMS) 2023 in India, Badan Pusat Statistik (BPS) 2022, 2023, and 2024 in Indonesia, and Kenya Bureau of National Statistics (KBNS) 2023, Kenya Demographic and Health Survey (KDHS) 2022 in Kenya, and international datasets from the World Bank, OECD, and International Labour Organisation. Where reliable data sources were unavailable, we used the next best source, such as official reports.

4 Administrative Data: Description of the population

In all three countries, the population of drivers using the platform's administrative data was used for sampling purposes. The population numbers differ by country: >500,000 in India, >200,000 in Indonesia for active drivers, >50,000 in India and >200,000 in Indonesia for inactive drivers, and a combined population of ∼10,000 for both driver types in Kenya. For the description of the population (in Table 3), we use the sampling frame, which has been described in detail in Section 2.1.

We start by looking at the driving patterns, from the detailed [platform] administrative data coverage (referred to as 'Admin data 1' in Table 2). Panel A reveals variation in the

[7]The data we received was structured to show the hours driven by Driver A during Week 1 (starting 1/01/24), categorized into morning, afternoon, evening, night, and late-night hours.

average number of hours logged in per week[8][9] – This differs slightly between countries; in India, we had access to average hours driven per day. Indonesian drivers work the most hours weekly, averaging 41.9, compared to 33.6 in India and 23.7 in Kenya. Contrary to what is reported in previous studies (such as International Labour Organization 2021; Zollman 2023; National Council of Applied Economic Research 2023) for this population, we find that part-time driving (defined as less than 8 hours/day) is more prevalent among drivers, and that 80% of drivers in India and Kenya, and 50% in Indonesia, drive part-time. The distribution of hours for all drivers is shown in Figure 1.

The drivers on the platforms provide different types of services (Panel B). Indonesian drivers engage in passenger and food services equally (90%), while parcel delivery is slightly less standard (70%). In Kenya, passenger services dominate (97%). In India, all drivers are involved in delivery work, but to preserve the anonymity of the [platform], we are unable to disclose the type of delivery services they are engaged in.

Most Indian drivers were driving in northern and central states, followed by other regions, and southern states (Panel C). For Indonesia, the top geography to drive was Greater Jakarta, followed by the Java region. In Kenya, 98.2% of drivers operate out of Nairobi.

In Panel D, all three countries exhibit an overwhelming male majority among drivers, with only 0.8%, 1.5%, and 0.77% of female drivers in India, Indonesia, and Kenya, respectively. It is important to note that we were only able to interview two female drivers in Kenya, and hence, the experiences of women are excluded from this analysis. This is a common trend in platform-based transport work (World Bank, 2021a; International Finance Corporation, 2018), reflecting cultural norms restricting women's participation in sectors traditionally occupied by men (Indian School of Business, 2022; Badan Pusat Statistik, 2022) as well as safety concerns surrounding this type of work (Consultative Group to Assist the Poor, 2023). The average age of drivers varies, with Indian drivers being the youngest at 27.9 years, Kenyan drivers at 32.3 years, and Indonesian drivers at 38.4 years. This difference suggests platform driving attracts significantly younger workers in India, potentially due to high youth unemployment and the gig economy's role as a transitional labor market for young individuals, such as students (World Bank, 2021b). In contrast, Indonesia's relatively older driver population aligns with previous findings on the country's informal transport sector, where gig work serves as a stable earning source

[8] There are differences in how driving hours are derived in the sampling frame data we received from the platforms. In India, driving hours were defined as the average number of hours driven per day on the [platform] from October to December 2023. In Indonesia, it was defined as total active online hours per week, which covers a combination of hours drivers spent waiting and delivering via the platform, for a period from March to April 2024. In Kenya, the dataset included the average weekly hours each driver worked in each time slot over the past nine months, from October 2023 to June 2024.

[9] To make comparisons, we have created hours worked per week in India by multiplying hours worked per day by 6 days. We consider 6 days instead of 7 for the week, as the weekly hours from the former are a closer match to the detailed administrative data we received for all sampled drivers.

for middle-aged workers (International Labour Organization, 2020). Tenure on the platform is longest in Indonesia, with drivers averaging 2,000 days or 5 years, significantly higher than in India (383.4 days) and Kenya (744.0 days), suggesting that attrition rates are highest for Indian drivers, and they are likely to exit the platform sooner.

5 Survey Data

5.1 Demographics

Table 4 presents the demographic characteristics of drivers across India, Indonesia, and Kenya. All estimates are adjusted for weights. Self-reported age is highly correlated with what's reported in the administrative data, with India having the youngest cohort (28.1 years), followed by Kenya (32.2 years) and Indonesia (37.9 years) (Panel A). The proportion of married drivers is significantly lower in India (49%) compared to Indonesia (80%) and Kenya (81%), likely due to the younger average age of Indian drivers.

Indian drivers are the most educated among the three countries, with the percentage of drivers holding tertiary education being 31% compared to 12% in Indonesia and 20% in Kenya (Panel C). While the driver population seems to be similar to an average urban male in Indonesia and Kenya, where tertiary completion rates are 12.7% and 21%, respectively (Badan Pusat Statistik, 2024; Kenya National Bureau of Statistics, 2022), in India, the [platform] drivers are more educated than the population, where about 21% of youth hold a tertiary degree (Organisation for Economic Co-operation and Development, 2023). Highly educated Indian youths are attracted to this work perhaps either due to limited employment opportunities for tertiary educated individuals, as seen by the high unemployment rates for this group (Ministry of Statistics and Programme Implementation, 2024), or are using this work as an intermediate while looking for other work, or higher pay in this work compared to other opportunities available. Additionally, the gig workforce attracts significantly more current students in India, with the prevalence of students being at 23% in India, 13% in Kenya, and only 2% in Indonesia, suggesting higher use of gig work as supplementary earnings for students (World Economic Forum, 2023; Wheebox et al., 2023).

In Kenya, 81% of drivers are migrants to their current work location, compared to 49% in India and only 22% in Indonesia, as seen in Panel D, where the lower rates for the latter might be because of the comparatively lower internal migration rates. Among migrants, a considerable share moved specifically for platform work in India (16%). In contrast, this proportion is much lower in Kenya (1%)[10] and most Kenyan drivers migrated for

[10]This question was not asked during the survey in Indonesia and has been excluded from the com-

non-platform work, suggesting that platform work may serve as a fallback employment option in Kenya rather than being a primary reason for migration decisions.

5.2 Entry into platform work

There are four essential requirements to enter platform work: a national ID, a smartphone, a vehicle, and a bank account. We collected information on being able to satisfy these requirements before entering the platform to evaluate the accessibility of this work to the general population.

The vast majority of drivers across the three countries had a national ID before joining the platform. This is similar for the general population in India, where 93% possessed an Aadhar card (Unique Identification Authority of India, 2025) and 98% of 17-year-olds and above Indonesians owned Kartu Tanda Penduduk (KTP), which is also mandated by law, but slightly lower for the national average for Kenya at 91% (Financial Sector Deepening Kenya, 2021). Bank account ownership before entry is nearly universal in India (99%) but significantly lower in Indonesia (83%) and Kenya (82%). This could be because, in India, bank account ownership is high among urban adults (at 94.4%) due to multiple government-driven financial inclusion initiatives (Ministry of Statistics and Programme Implementation, 2023). In contrast, Indonesia and Kenya (52.5%) have much lower rates, even amongst the general population (DBS Bank Indonesia, 2024; Central Bank of Kenya et al., 2024).

Smartphone ownership was lower in Kenya (at 89%) compared to near-universal in India (98%) and Indonesia (96%). This is again very similar to the general population in India, where 97.1% of urban households reported owning a landline or smartphone (Ministry of Statistics and Programme Implementation, 2023), and 73.5% in Indonesia (Badan Pusat Statistik, 2022). However, the lower percentage for Kenya could possibly reflect lower smartphone penetration rates in Kenya's general population, which was only at 49% among men aged 15-49 (Kenya National Bureau of Statistics et al., 2023).

Ownership of a two-wheeler before joining the platform was highest in Indonesia (99%), followed by India (94%) and Kenya (89%). This difference may be attributed to Indonesia's strong reliance on motorcycles for personal transport, a trend reinforced by government policies promoting two-wheeler ownership (Kementerian Perencanaan Pembangunan Nasional, 2023b). In contrast, the relatively lower rate in Kenya may reflect that platform work is more accessible to those who can afford vehicle financing or secure informal rental arrangements (Njuguna et al., 2022). In India, the slightly lower two-wheeler ownership rate compared to Indonesia could be driven by the growing avail-

parison.

ability of metro systems and improved public transportation infrastructure, which has contributed to a gradual decline in two-wheeler ownership in recent years (Vasudevan et al., 2021).

Possession of a driver's license was notably higher in Indonesia (97%), followed by Kenya (90%) and India (82%). This variation likely reflects differences in enforcement and regulatory practices between countries. In Indonesia, strict enforcement and clear regulations by local police contribute to the high licensing rate (Badan Pusat Statistik, 2024). In contrast, in India, nearly half of the vehicles are operated by individuals without valid licenses, stemming from lax enforcement, a cumbersome licensing process, and social norms around informal driving practices (Khandelwal, 2024; Gadepalli et al., 2018).

For prior employment (Panel B), we find a significantly higher proportion of Kenyan drivers (27%) engaging in driving-related work before joining the platforms compared to India (8%) and Indonesia (5%). This difference could be explained by the history of motorcycle taxis in these countries. Even before digital platforms, motorcycle taxis were deeply integrated into the transportation systems of Kenya, serving as essential modes of mobility (Martin, 2023). On the other hand, these were fairly uncommon in India before the expansion of digital platforms in the mid-2010s. Indonesian drivers were the most likely to have been involved in full-time formal work before joining the [platform] (58%), significantly higher than in India (45%) and Kenya (30%). This is consistent with Indonesia's labor market conditions, where a larger percentage of people (41%) are employed in the formal sector (International Labour Organization, 2023), relative to India (15%)(Citi Research, 2024) and Kenya (10%) (Statista, 2024a; World Bank, 2024). Conversely, Kenya had the highest proportion of drivers previously working as full-time informal workers (21%), reinforcing the country's limited formal work prospects. We also find unemployment before platform work was relatively low across all three countries, with the highest rate in Indonesia (4%) and the lowest in Kenya (2%).

5.3 Labour Supply

5.3.1 Comparing hours online over time using platform administrative data

In India and Kenya, we can observe working patterns of sampled drivers across time using administrative data provided by the platform (Figure 2 and 3) to understand how the survey window (indicated in grey) generalizes to working patterns outside of the survey window. We split the sample into two types of drivers: (1) full-time consistent—those who consistently worked over 40 hours per week throughout the study period[11]and did

[11]The definition of "consistent" is derived using the platform data in India and Kenya. In both cases, we focused on full-time drivers (those who work 40 hours/week on average), excluded those who skipped at least one week of work during the data coverage period, which was before the individual survey date

not engage in multi-homing (according to self-reported data), and (2) all others. This differentiation is useful in calculating net earnings in Section 5.4.1 and gives a sense of work patterns between drivers who rely more or less on the platform for work. We present labor supply unconditional on logging in (Figure 2) to give a sense of attrition and conditional on logging in (Figure 3) to understand how working patterns change for drivers who do log in. We see a high decline in hours in India over the observation period, suggesting high attrition and decline in working hours for drivers who log in. The latter might be a consequence of a heat wave that started at the end of March 2024, during which working conditions were more challenging. In Kenya, the hours are fairly constant, suggesting a lower attrition rate and more consistent schedules of drivers.

5.3.2 Labor Supply (using survey results)

We examine labor supply choices of the drivers in Table 6. In all three countries, platform work is one of the few earning activities, suggesting earning portfolio diversification. The number of earning sources is highest among the Kenyan drivers, averaging at 2.01 (compared to 1.74 in India and 1.62 in Indonesia). This reflects a strategy of earning diversification among Kenyan drivers, who tend to work fewer hours on the [platform], with over 80% driving part-time (Table 3), and instead pursue a broader portfolio of earning opportunities. This trend is likely partly driven by the higher prevalence of multi-homing (driving on multiple platforms) seen in 41% of Kenyan drivers, compared to just 10% and 12% in India and Indonesia, respectively[12].

Full-time work outside platform driving is also more common in Kenya (35%) and India (30%) compared to Indonesia (8%), suggesting that formal employment earnings for the drivers may be insufficient in Kenya and India, prompting individuals to use platform work as a supplementary source of earnings. In India, persistent underemployment in the formal sector may drive workers to combine various work opportunities to secure adequate earnings (Centre for Monitoring Indian Economy, 2023a). In contrast, the relatively low incidence of full-time non-platform work in Indonesia could indicate a lack of formal employment opportunities for this demographic (World Bank, 2023).

Indonesian drivers report the highest average weekly working hours across all earnings sources at 76.81, Kenyan drivers at 66.16, and Indian drivers at 57.9. Indonesian drivers allocate 91% of their total working hours to platform activities, compared to 71% for Kenyan drivers and 60% for Indian drivers. This indicates a greater dependence on plat-

in India, and before the end of December in Kenya. Since we do not have administrative data from Indonesia, we use the initial definition of full-time workers from the sampling frame.

[12]In Kenya, there are regulations on maximum number of hours worked per day (15 hours/day), however, it is unlikely that these limits are binding, since the platform data suggests that drivers work far fewer hours.

form earnings among Indonesian drivers, likely driven by a combination of demographic and economic factors. Previous research indicates that in Indonesia, the transition from informal to formal employment is challenging, often favoring younger and more educated workers (Pratomo and Manning, 2022; World Bank, 2023). Additionally, Indonesia has experienced premature deindustrialization, leading to limited growth in formal manufacturing work and ongoing layoffs in labor-intensive industries (Kurmala, 2025).

In Indonesia, 61% of drivers work the same hours every day full-time, compared to 36% in Kenya and only 29% in India (Panel C), suggesting that platform workers in Indonesia operate with greater routine and structure, unlike in Kenya and India. The working choices of Kenyan drivers align most closely with theoretical expectations of gig work in which workers seek to maximize their earning potential by taking advantage of surge prices (Hall and Krueger, 2016)—45% adjust their working hours based on work volume and prices, compared to 26% in Indonesia and 21% in India. This flexibility is a core advantage of platform work. It allows drivers to strategically optimize their earnings by capitalizing on surge pricing and peak demand periods (Chen et al., 2017); however, it is a smaller consideration among Indonesian and Indian drivers. The primary benefit of working on the [platform] reported was extra earnings, which were significantly higher in Kenya (72%) compared to Indonesia (58%) and India (50%) (Table 9). On the other hand, Indonesian drivers were significantly more likely to report freedom as a key benefit (72%) compared to Kenya (44%) and India (26%), suggesting that it may be the key reason to remain on the platform long term for Indonesian drivers. The result is surprising since out of all drivers, the Indonesian drivers have the least flexible schedules.

The adoption of electric bikes among platform drivers varies across countries (Panel D): 11% of Kenyan drivers report using electric vehicles compared to 7% in India[13]. These differences likely stem from variations in market availability, infrastructure, and policy support for electric vehicles (Mishra, 2024; ESI Africa, 2025).

Platform churn rates, defined as the proportion of drivers who exit within a given period (in our case, January to May 2024), are at 16% for India (Panel E). This suggests that digital platforms witness significant worker movement in India (International Labour Organization, 2021). We do not have estimates of churn in Indonesia and Kenya. Utilization rates, defined as the percentage of hours spent on productive delivery work out of total logged-in time, are highest in India (72%), followed by Indonesia (60%) and Kenya (40%) for all drivers[14]. In India, the relatively high utilization rate may be driven by either more optimal algorithmic assignment, lower saturation of drivers (and/or higher demand for deliveries), or the ability of Indian workers to switch out of platform work during

[13] We did not ask drivers on what type of vehicle they used in Indonesia, and hence, have excluded this metric.

[14] In India and Kenya, this is calculated using the platform data, and in Indonesia using survey data.

less busy times and engage in other productive activities. The low utilization rates in Kenya might be a function of the oversupply of drivers, but also a high prevalence of multi-homers on the platform who simultaneously work on several platforms, reducing the utilization rate on a single platform. Anecdotal, drivers report that the market is oversaturated and it's challenging to stay productive.

5.4 Examination of longitudinal platform data

Platform earnings are subject to frequent fluctuations, which reflect supply/demand forces, economic, and environmental shocks. Those factors might change how drivers respond to the market conditions, and ultimately, take-home pay. To understand the generalizability of our survey findings, we examine longitudinal administrative data provided by the platforms in India and Kenya.

We plot longitudinal data on utilization rates per hour defined as hours delivering orders and/or driving passengers divided by hours online (Figure 4), PPP-adjusted gross earnings per hour online and per productive hour (Figure 5), PPP-adjusted gross earnings per order (Figure 6) and number of orders per hour (Figure 9).

It is important to note that in India, we have access to both driving and bonus earnings, whereas the Kenyan platform does not track bonus earnings in the administrative data. We visually differentiate between driving earnings and total earnings (driving and bonus earnings) in India to allow better comparisons to the Kenyan datasets, which exclude bonus payments. However, we believe that the driving earnings in Kenya are an accurate approximation of the total earnings. According to informal conversations with drivers in Kenya, there are daily and weekly bonuses based on the number of trips completed within a particular time slot (e.g., evening) and a requirement of high trip acceptance rate, which drivers report to be rarely attainable[15]. The platform has also informed us that bonuses are only paid to drivers who drive branded bikes. From this information, we conclude that bonuses do not factor into their earnings in any meaningful way.

In all the graphs, we differentiate between *full-time consistent* drivers and all others. This differentiation allows for examination of a subset of drivers whose work patterns resemble full-time work from all others who drive on the platform more asynchronously.

In India, the data spans January to May 2024, with survey collection between the last week of January and the first week of May in two phases, excluding a two-week pause in March. The Kenyan dataset covers the months of July-December 2024, with the survey taking place between the last weeks of November and the end of December. Both

[15] We don't have enough detail in the data to precisely calculate the bonuses based on these conditions, however, we estimated that less than 5% of driving slots were eligible for bonuses based on number of trips.

datasets cover periods that may be unrepresentative of the remainder of the year. In India, major cities experienced a heat wave starting around the end of March, making working conditions more challenging. In Kenya, the data collection period overlaps with the preparation for the end-of-year holiday season, which is driving up utilization rates. Based on the administrative data, we conclude that the survey period is possibly representative of the average typical earning potential throughout the year in India, but not in Kenya.

During our study period in India, we observed several key trends. Firstly, the utilization rate remained relatively stable at about 70% throughout our observations (Figure 4). Interestingly, gross earnings per hour online saw a significant 17% increase during the heat wave at the end of March, as illustrated in Figure 5. This spike in earnings was largely attributed to higher prices per order, as shown in Figure 6. Meanwhile, operating costs per hour, based on our survey data, stayed fairly constant (see Figure 7). While it is not entirely clear if the heat wave affected the driver attrition rate, we generally noted a consistent attrition among full-time drivers over the course of the study (Figure 8). This pattern indicates that while the heat wave did not alter the amount of work undertaken by drivers, it did elevate their earnings for the effort put in.

In our examination of Kenya, several notable trends emerged. Before December 2024, the utilization rate stood at approximately 40%, which subsequently rose to about 50% in December, as depicted in Figure 4. This pattern is similarly reflected in the number of orders per hour (Figure 9). The increased utilization rate corresponded with elevated earnings per hour online, as shown in Figure 5. However, earnings per order remained relatively unchanged (Figure 6). These findings suggest a period of heightened productivity per hour worked during the survey period, possibly indicative of increased demand for driving services and/or a diminished supply of drivers on the platform.

Comparing the two countries, we find the following. The utilization rates differ significantly between countries, with Indian drivers being productive about 75% of the hours, compared to about 40% in Kenya. While our conjectures are speculative, this finding may be due to contextual factors (such as density of the urban populations), algorithmic assignment differences between platforms, driver saturation, and/or any supply control measures that the platform in India may implement. Furthermore, we observe that the utilization rates and earnings are different between full-time consistent drivers and all others in Kenya, while being similar in India. The platform's algorithm possibly explains these differences between drivers in Kenya to reward loyal drivers or the high prevalence of multi-homing among drivers in Kenya, which may result in higher rejection rates of [platform] orders while working for competitor platforms. Average driving earnings per hour online (excluding bonuses) are about \$6 in India (indicated by the red dashed line in Figure 5(A)) compared to about \$2.7 in Kenya; however, earnings per productive hour online (Figure 5(B)) is more similar between the two countries, with a difference of about

\$2 per productive hour. This suggests that the higher earnings per hour online in India (in Figure 5) are attributable to a higher utilization rate rather than higher earnings per order/delivery. Secondly, full-time-consistent drivers in India make less per hour, compared to all other drivers, suggesting that other drivers selectively drive during surge price periods. The opposite pattern is visible in Kenya, and full-time consistent drivers earn more per hour online and per productive hour. This likely indicates that the Kenyan platform rewards loyal drivers with more orders per hour and more productive orders, or that full-time, consistent drivers can take advantage of surge price periods more often.

5.5 Gross and net earnings

To assess net earnings (gross earnings adjusted for operating expenses), we focus on a sub-sample of *full-time consistent* drivers—those who worked over 40 hours per week throughout the study period and did not engage in multi-homing. The rationale for this choice is that part-time drivers may selectively choose to drive on more profitable hours, which might overestimate *average* earnings potential. The choice to exclude multi-homers is driven by challenges in attributing operating expenses to a single platform, especially if the drivers use multiple platforms simultaneously, a common practice in Kenya. This sub-sample also more closely resembles full-time work patterns and allows for more accurate benchmarking against other work opportunities.

The calculation of *per-hour* equivalent gross and net earnings varied by country and data availability, and we constructed per-hour net earnings using two methods. Method 1 relies on survey data for a time period, and Method 2 utilizes full coverage of administrative data in Kenya. We do not have administrative data in Indonesia to perform this calculation. The conclusions between methods 1 and 2 are very similar in India, given the wide coverage of survey dates, and we abstain from presenting them for brevity. In Kenya, we do not expect these methods to yield the exact estimates since there is high temporal variation in gross earnings across time. We compare survey results to the administrative data for a subsample of drivers who are expected to have a high correlation between survey and administrative data due to the timing of the survey and the level of data aggregation (Appendix Section X). Generally, we find high comparability of earnings reporting in India (in Kenya, we don't have comparable metrics) but lower comparability of hours worked reporting in India and Kenya. Hours in the administrative data are 9–15% lower. The latter is likely due to drivers' inability to accurately estimate actual hours online and the likely inclusion of breaks.

To ensure comparability across countries, we adjust gross and net earnings by Purchasing Power Parity (PPP) using World Bank data to convert country estimates to a US-equivalent dollar[16]. The estimates in nominal dollars are reported in Appendix Table A7 for reference.

5.5.1 Estimation of net income during the surveying period (Method 1)

The results are presented in Table 7. The estimates of net income varied by country. In Kenya and Indonesia, we asked drivers to report *all* gross earnings on the platform and hours worked for the last working day. Fuel and parking expenses were also collected for the same day. For less frequent expenses such as rent/loan payments, we collected the values for the last month and converted them to an hourly equivalent. Total daily-equivalent expenses were calculated and subtracted from the reported gross income on the last working day. (Panel A in Table 7). The monthly inference assumes that the last working day represents a typical day for that driver, which may or may not be the case. To ensure higher generalizability of the last survey day to the general working patterns of full-time drivers, we excluded individuals who worked less than 7 hours on the last working day, since that would inflate their daily-equivalent fixed costs relative to their daily earnings.

In India, we used platform administrative data to derive typical monthly gross earnings covering January 2024 through the week the individual driver took the survey. This ensured a closer match between the administrative data on earnings and the self-reported expenditures, which were collected for a typical month. Net earnings (gross earnings adjusted by expenses) were calculated by subtracting monthly expenses from typical monthly earnings. To estimate monthly hours, we use self-reported data[17] for hours worked last week and multiply them by 4.33 to estimate monthly hours worked. Hourly equivalents for gross and net earnings are derived by dividing monthly earnings by monthly hours worked.

PPP-adjusted gross earnings *during the surveying period* are the highest in Kenya at \$5.39/hour, followed by India at \$5.02/hour, and then Indonesia at \$2.96/hour. This suggests that this work effectively pays differently across countries, and the differences are likely driven by a myriad of economic factors such as the nascent nature of the platform, the presence of direct competitors, and the timing of the survey. Hourly expenses are significantly higher in Kenya, primarily due to fuel and electric vehicle charging costs—fuel/electricity expenses amount to \$1.97 per hour in Kenya, compared to only \$0.59 in Indonesia and \$1.06 in India. Higher vehicle and charging costs per hour may reflect

[16]These figures are obtained by converting from local currency to international dollars, using the conversion factor for each country (World Bank, 2021c).

[17]We are using self-reported hours to create higher comparability between definitions of work between countries, as we have found that drivers report higher hours than what is recorded by the platform in both India and Kenya. As we discussed in Section 5.4, we believe it is due to including break times into definitions of work.

differences in driving radius between Indian and Kenyan drivers and/or differences in population density. We do not have visibility into the average mileage that is covered by the drivers, and are unable to conclude this with certainty. Additional costs, such as vehicle repairs and rental costs of 2-wheelers, are also the highest in Kenya. This result is partially driven by the high prevalence of renters in the Kenyan context, but also by higher labor costs in Africa. Consequently, total expenses account for 57% of gross hourly earnings in Kenya, 38% in Indonesia, and 30% in India.

Accounting for expenses, net hourly earnings in PPP terms are the highest in India, $3.50, $1.84 in Indonesia, and $2.32 in Kenya. The lowest per-hour earnings in Indonesia might be the primary reason for higher working hours among Indonesian drivers compared to other countries.

Monthly-equivalent gross and net earnings are calculated using average working patterns reported in the survey (for Indonesia/Kenya) and platform monthly gross earnings adjusted for expenses in India. Drivers in India take home about $1,039 USD equivalent, Indonesian drivers $589, and Kenyan drivers $465. The higher monthly earnings in Indonesia result from higher working weekly hours for full-time drivers, 77.27 in Indonesia and 58.88 in Kenya.

5.5.2 Estimation of net income using full coverage of administrative data (Method 2)

Given that the surveying period is highly unrepresentative in Kenya, we provide an estimation of net earnings using all administrative data, and reducing the gross earnings by expected amounts is taken by expenses (found in Panel A of Table 7). We assume that fuel/parking expenses proportionally decrease with gross earnings since the utilization rate is lower outside of the surveying period, suggesting that they are driving less. Fixed expenses, such as vehicle rent, are kept at the same level as reported in the survey month since they do not fluctuate with driving. Using the full data coverage, we find that per-hour and per-month PPP-adjusted net earnings are $1.45 and $328.07, respectively, which are significantly lower compared to the surveying period. Overall, we conclude that the method 2 estimate of earnings is more representative in the Kenyan context compared to the method 1 estimation.

5.6 Benchmarking of earnings against other sources of earnings for full-time drivers

To benchmark these earnings to other opportunities in local economies, we make comparisons of per-hour and per-month earnings of full-time drivers to 1) earnings by platform drivers who hold other non-platform full-time work, 2) minimum wage in local economies, 3) alternative employment options that are likely available to this demographic based on education levels and previous work reported in survey data, and 4) casual labor due to its lack of fixed-term contracts, flexible hours, and ease of entry and exit resembling platform work. In Panel A of Table 8, we present estimates of net earnings from driving in row 1 for a relevant subsample, e.g., DKI Jakarta in Indonesia and the five largest cities in India (New Delhi, Bangalore, Hyderabad, Mumbai, and Pune). For Indonesia, we also include a comparison from a sample of offline full-time drivers interviewed as part of this data collection in Jakarta. In Panel B, we present comparisons derived from secondary data sources such as labor surveys (PLFS) in India and (BPS) Indonesia, and the economic surveys (KNBS) in Kenya. All estimates are expressed in USD and PPP-adjusted.

(1) Comparison against offline drivers in Indonesia Identical earnings and expenditure questionnaires were administered to a sample of offline (drivers not working on platforms) drivers in Jakarta. Compared to online drivers, offline drivers make significantly less per hour ($1.21 PPP-adjusted USD compared to $2.15 USD among online drivers). This difference is largely attributed to the utilization rate (proportion of time spent driving or delivering orders), which is about 62% and 26% for online and offline drivers, respectively. The higher utilization rates of platform motorbike drivers can be explained by the platform's capacity to link drivers with a larger number of potential customers at any moment (International Labour Organization, 2021), whereas offline drivers spend more time waiting. Besides ride-hailing, the platform enables drivers to offer additional services, like food delivery and courier services, which present more earning opportunities during periods of low demand—options not accessible to offline drivers.

(2) Comparisons against full-time work currently occupied by platform drivers For drivers engaged in non-platform full-time work, the reported hourly-equivalent salaried earnings were $4.08 in India, $4.07 in Indonesia, and $4.95 in Kenya (all PPP-adjusted), which are higher than the platform earnings of $3.72, $2.15, and $2.45 in those countries reported in Table 8. However, the disparity is the lowest in India, compared to Indonesia and Kenya. This suggests that in India, hourly earnings from non-platform full-time work are more comparable to work that other drivers engage in. In contrast, the larger gap in Indonesia and Kenya, and drivers who are employed full-time effectively make more per hour. It is important to note that in all three countries, the availability of full-time work is limited.

(3) Comparison to casual labor While platform work in India pays much higher than casual labor for per-month earnings ($513), in hourly terms, we estimate that casual labor compensation is about 83% of platform earnings in India based on PLFS 2023 data, and this is because platform workers work a lot more hours. We see similar patterns in Indonesia. While the drivers' monthly compensation is higher than that of a casual worker, the per-hour equivalent (adjusted by standard working 40 hours among casual labor) is lower. The ability to work long hours in the driving gig sector helps drivers surpass the earning potential of casual work. In Indonesia, platform drivers in Jakarta earn less compared to all self-employed workers (Badan Pusat Statistik, 2023)[18].

(4) Comparisons to other full-time employment available to this demographic Formal employment offers structured hours, job security, and benefits like health insurance and paid leave; platform work trades these protections for flexibility and the potential for higher earnings through longer hours. Some workers value this autonomy and the more direct link between effort and earnings, though earnings can be volatile and protections limited.

Comparable work options in India include occupations in job divisions 4-8 as per NCO 2004 job divisions from India's Periodic Labour Force Survey (PLFS) for 2023. Full-time drivers earn more monthly than comparable options, but their hourly compensation is equivalent to service/sales workers and crafts/trade workers ($3.76 and $3.75 PPP-adjusted). In Kenya, the average monthly net earnings for full-time platform drivers during peak earning periods (method 1) are higher than semi-skilled machine operators and service workers, as per the KNBS Economic Survey 2024; however, the earning potential is lower when incorporating a wider time period (method 2). Per hour equivalent on the platform is lower than any low-skilled full-time work.

(5) Comparison to minimum wage Before making comparisons, we caveat that compliance with minimum wage requirements in the broader economy in all three countries is limited. However, these comparisons give a sense of what the earning standard provides, a minimum standard of living, and how platform compensation compares to that. In India, we benchmark platform earnings to full-time drivers working in the top 5 cities[19]. The per-hour minimum wage[20]. is higher than the platform work earnings ($4.09 compared to $3.72 PPP-adjusted), however, due to higher working hours the monthly equivalent is

[18] We have not included Kenya here due to lack of comparable national level data.

[19] Minimum wages in India vary by state and location, and since the survey was conducted across 17 states, it is challenging to make conclusions about how the [platform] pays compared to minimum wage across the whole country. Therefore, we focus on the top 5 cities of Bangalore, Delhi, Hyderabad, Mumbai, and Pune, which cover ∼40% of drivers in our sample for more accurate analysis.

[20] Since the minimum wage does not provide information on the number of hours worked, we use weekly hours based on the Factories Act of 1948, which limits factory workers to 48 hours per week. It is important to note that compliance with minimum wage laws in India is inconsistent, with non-compliance rates reaching as high as 90% in some states and sectors (Mansoor and O'Neill, 2021)

$709 is much lower than the net monthly earnings of $1109 earned by the drivers working in these five cities. In Indonesia, the minimum wage far exceeds platform pay.

5.6.1 Overall perception of work

The overall perception of platform work is most positive in India—drivers in India were most likely to report no downsides of platform work (40%) compared to Indonesia (12%) and Kenya (11%) (Table 9). The cross-country differences are likely a reflection of take-home pay, which is the highest in India, and road driving conditions, which are the worst in Kenya (Section 5.5). Interestingly, this work is also viewed as the least accepted by family members in India, with 45% of drivers in India reporting that their family considers platform work to be good work and approves of their choice. This share rises to 51% in Indonesia and 63% in Kenya (Appendix Table A5). These cross-country differences are likely explained by the fact that Indian drivers are the most educated among the three countries and view this work as a stepping stone to something else, compared to Kenya and Indonesia, where they are drivers by profession or intend to stay in driving in the long term.

5.7 Safety Concerns

As reported in Table 9, Kenyan drivers were more likely to report safety risks and traffic problems (33%) compared to Indian drivers (21%) as a downside of working for the platform, reflecting the challenges of navigating dense urban areas and security issues in Kenya (Nairobi Transport Report 2024). Indonesian drivers reported encountering fake deliveries (52%), reflecting a possible systemic issue with platform operations in the country (Kompas TV, 2024) which was not documented in India or Kenya.

Safety is a prominent concern, particularly in Indonesia, where 64% of drivers reported experiencing unsafe situations, compared to 56% in Kenya and 45% in India. The main safety concern reported was road accidents, both in India (24%) and Indonesia (26%), while significantly lower in Kenya (14%). Unsafe delivery areas were more commonly reported by Kenyan drivers (27%), likely reflecting localized risks related to some urban regions (Overseas Security Advisory Council, 2024). Confrontations with customers, merchant staff, or police were most frequent in Kenya (31%), compared to Indonesia (26%) and India (11%).

5.8 Financial security

Gig workers often experience volatility in their earnings and may lack access to employer-provided benefits like pension and insurance, which are common in more traditional work structures (World Bank, 2021a; International Labour Organization, 2023). We find that a significant percentage of drivers struggle to meet basic expenses: 35% in India, 16% in Indonesia, and 22% in Kenya (Table 10). This suggests that, despite diversified earning opportunities, current earnings may be insufficient for financial security. This is further highlighted as low earnings are reported as one of the challenges working for the platform, by 29% and 18% of Indonesian and Kenyan drivers, respectively, but only 6% of Indian drivers. This discrepancy may reflect broader economic perceptions, as 32% of Indians report struggling with expenses and 46% view the country's economic outlook as negative, suggesting that drivers may attribute financial insecurity to broader economic conditions rather than platform earnings (Kantar, 2023). In Kenya, KDHS reports that 29% of the urban population lacks food or money to purchase food (Kenya National Bureau of Statistics, 2022).

Panel B examines saving behaviors—39% of Indian drivers report saving monthly, compared to 47% in Indonesia and 63% in Kenya. Savings are most commonly kept in banks across all countries, with the highest prevalence in India, though not significantly different from figures in Indonesia and Kenya. Keeping savings as cash is more common in Indonesia (31%), significantly higher compared to India (13%) and Kenya (5%). This aligns with findings from Indonesia's financial landscape, where reliance on cash-based transactions remains prevalent, particularly among informal workers (World Bank, 2022a).

Digital saving tools are least used in India (1%), with significantly higher usage in Indonesia (10%) and Kenya (27%), with the high prevalence of mobile money in Kenya likely driving these estimates (S&P Global, 2024a). Across all three countries, adoption of higher-return savings instruments (e.g., stocks, bonds, or investment accounts) remains extremely low, indicating a limited shift towards formal wealth-building strategies among platform workers. Platforms have the potential to bridge these financial gaps by providing financial literacy sessions and helping overcome the lack of awareness of formal savings instruments or mistrust in financial institutions that gig workers might have (Consultative Group to Assist the Poor, 2015).

5.9 Financial Inclusion

In many LMICs, limited access to financial services such as banking, credit, and insurance hampers economic resilience and restricts opportunities for social mobility. Without formal financial tools, families often struggle to manage financial fluctuations, invest in education, or access emergency funds, perpetuating cycles of poverty (Cicchiello et al., 2023). This gap highlights the urgent need for innovative financial solutions and regulatory reforms to foster inclusive growth and economic stability. Digital platforms can promote financial inclusion via multiple channels, such as requiring bank accounts for participation, directly offering financial products like automatic savings, generating digital credit scores for better loan terms, and fostering familiarity with digital transactions (Consultative Group to Assist the Poor, 2022; Bansal et al., 2019; Inter-American Development Bank, 2023). To evaluate drivers' access to financial tools and the role of platforms in facilitating their use, we asked whether they had access to or used these tools, whether they obtained them before joining the platform, and whether platform work directly influenced adoption[21]. Results are presented in Table 11.

All drivers in India reported currently having a bank account, with prevalence being lower in Indonesia and Kenya, at 92% and 93%, respectively. While this is similar to the national averages seen in India, where almost 95% of adults have an individually or jointly operated account (Ministry of Statistics and Programme Implementation, 2023), we find a much higher proportion for drivers than average in other countries, 35% in Indonesia (Moorena et al., 2020) and 35.9% in Kenya[22] (Central Bank of Kenya et al., 2024). This is unsurprising as having a bank account is one of the prerequisites for joining digital platform work. Furthermore, 62% in Indonesia and 82% of drivers in Kenya had one before joining the [platform], compared to a much higher 98% in India. Notably, 26% of drivers in Indonesia attributed this ownership to the work they did on the platform, but it was minimal in India (1%) and Kenya (7%). The stronger platform effect in Indonesia reflects a higher share of previously unbanked workers entering gig work, whereas government schemes such as the Pradhan Mantri Jan Dhan Yojana (PMJDY) in India have already led to high account ownership before drivers joined platforms.

Access to formal credit varies substantially across countries. A much higher proportion of Kenyan drivers (40%) reported having taken out a bank loan, compared to 27% in India and 16% in Indonesia, with most drivers in India and Kenya doing so before joining the [platform]. The role of platforms in getting a loan was minimal across all three

[21] Respondents were asked "I am going to ask you a series of questions related to usage of various financial products. For each, I am going to ask if you've ever (had it or) used it and whether you got it or the usage happened before or after joining the [platform]." If the respondent reported having access to the product after joining the [platform], a follow-up question was asked whether it was because of their work on the platform "Do you think you have X because of your work with the [platform]?"

[22] This figure is only for males in Kenya.

countries, suggesting limited use of platform earnings as proof of earnings, a key area where platforms could better support financial inclusion. However, there is often a lack of financial infrastructure that recognizes gig work as verifiable employment, making it difficult for drivers to demonstrate creditworthiness. Addressing these challenges would require platforms to collaborate with financial institutions to develop systems that better integrate gig earnings into formal credit assessments (Brailovskaya, 2023). Credit card ownership was reported by 10% and 4% of Indian and Indonesian drivers, respectively, with no drivers reporting that they got a credit card because of their work on the platform[23]. Nationally, credit card penetration remains low in both countries—around 3% in India and 1.6% in Indonesia in the general population (PricewaterhouseCoopers, 2022; World Bank, 2021c), but slightly higher among drivers, suggesting that they may have better access to credit than the general population.

Mobile money/wallet[24] usage was nearly universal, with 99% of drivers in India and all drivers in Indonesia and Kenya reporting usage. However, usage before platform work varied significantly: 65% in India and 98% in Kenya, compared to just 17% in Indonesia. Consequently, 79% of Indonesian drivers attributed their digital money usage to platform work, indicating a stronger impact on financial behavior in a cash-reliant context (World Bank, 2022a). This difference could be explained by the rapid expansion of digital payments in India, driven by platforms like PayTM and GPay and accelerated by the 2016 demonetization (Fouillet, 2021), and the widespread adoption of mobile money in Kenya, particularly M-Pesa, which is used by 80% of adults (S&P Global, 2024b).

About 19%, 27%, and 86% of drivers reported taking out at least one digital loan in India, Indonesia, and Kenya, respectively. Kenya's high adoption of mobile-based credit aligns with broader national trends, where over 40% of the adult population has taken out a digital loan through services like M-Shwari and Tala (Central Bank of Kenya et al., 2024). On the other hand, informal sources such as local money lenders, family, and friends play a pivotal role in India's borrowing culture, particularly for consumption and emergency expenses, which may help explain the low percentage reported (Centre for Monitoring Indian Economy, 2023b). The [platform]'s influence on digital loan-taking was more significant in Indonesia (13%), followed by Kenya (10%) and India (6%), with these differences being statistically significant at the 10% level.

Finally, self-purchased life insurance was acquired by 23% of drivers in India, but only 1% and 6% by drivers in Indonesia and Kenya, respectively. This difference could be because of India's relatively well-developed and widely promoted life insurance market, with government-backed campaigns (e.g., PMJJBY—Pradhan Mantri Jeevan Jyoti Bima Yojana). However, only 1% of Indian drivers made this purchase due to their work on

[23] Data on credit card ownership was not collected in Kenya.
[24] This includes popular apps such as GPay, PayTM (India), GoPay (Indonesia), and M-Pesa (Kenya).

the [platform]. For health insurance, over 50% of Kenyan drivers had taken one, and this figure was much lower in India (16%) and Indonesia (3%). Again, very few drivers attributed obtaining this to the [platform]. It is important to note that the [platform] in India already provides its active drivers[25] with different types of insurance, such as accidental death insurance, disability insurance, and health insurance, similar to those provided by other platforms, and hence, may have reduced the perceived need to purchase these on their own.

While these estimates are not causal, there is an indication that platform work can enhance financial inclusion, particularly for tools with low penetration rates, such as digital money and credit services in Indonesia. However, further studies are necessary to establish causal relationships and to understand whether and through which platforms facilitate financial access and for whom.

5.10 Economic trajectories after exiting the [platform]

To understand the possible post-platform economic circumstances of drivers, we interviewed a sample of inactive drivers[26] in all three countries. First, we examine differences between current and past drivers in demographics to understand the types of drivers who are more likely to leave platform work, as well as reasons for leaving. Next, we present their current working portfolio and assessment of how their financial security compares to the time when they worked for the platforms (Table 12). The sample sizes for these drivers are small and may not have enough power to reach definitive conclusions for smaller differences between the groups. We rely on the magnitude of the estimates to make suggestive conclusions.

Inactive drivers in India and Kenya are similar to active drivers in terms of age and gender, while inactive drivers in Indonesia tend to be younger and less likely to be male, suggesting higher attrition rates among women drivers. This aligns with insights from Brailovskaya et al. 2025 cross-gender comparison paper, where we find women drivers frequently reported facing gender-based discrimination. We also see significantly higher education levels for Indonesian inactive drivers, a trend also found in the other two countries, but not statistically significant, implying that better-educated drivers might find it easier to transition out of platform gig work to other formal or higher-paying work (Herrmann et al., 2023). Additionally, active drivers in India and Kenya are more likely to be migrants compared to inactive drivers, potentially because non-migrants have better access to resources like housing and food, making it easier to exit the [platform] and

[25] As defined by the [platform] and not as per the definition we have used throughout the report.

[26] Inactive drivers are defined as drivers with at least one delivery between 9 to 18 months before data extraction in India, between 12 and 24 months prior in Indonesia, and between 3 to 9 months prior in Kenya. This is different from how the [platform] in each country identifies inactive drivers.

seek other work (Wills et al., 2009; Deshingkar and Grimm, 2005). In contrast, migrant workers often face greater barriers to leaving gig work due to limited support networks and a stronger dependence on urban earnings, which are typically higher than what they would earn back home (Czaika and de Haas, 2014).

Low earnings were a key reason for exiting the platform work for 38% of Indian and 40% of Indonesian drivers, but only 15% of Kenyan drivers (Panel B). Indonesian drivers cited personal or health reasons more frequently (35%) than Indian (22%) or Kenyan (8%) drivers, possibly due to their older age profile and also the higher number of hours worked, as seen in Table 7. The majority of inactive drivers in Kenya left because they were terminated by the platform, compared to only 7% and 2% in India and Indonesia, respectively, showing that drivers in Kenya left unwillingly. Across countries, around 30% of those who left eventually rejoined; most rejoined during an emergency period when they needed money (28%, 34%, and 24% in India, Indonesia, and Kenya, respectively), or during lean work periods, particularly in India (25%) and Kenya (24%). This pattern underscores the transient nature of gig work and the relative ease of re-entering platforms, highlighting gig work's role as a crucial fallback option during economic shocks (Michuda, 2023; Rosenblat and Stark, 2016). In Kenya, some drivers also returned after realizing that platform earnings were higher than their current earnings (26%) or when the [platform] reactivated their accounts (24%), suggesting that gig work remains a more financially favorable option for these individuals.

In India and Indonesia, most inactive drivers are currently in full-time employment (57% and 59%, respectively), significantly higher than the proportion of active drivers (Panel C). This suggests that platform work may serve as a transitional or stopgap occupation while workers search for more stable opportunities (Heeks, 2017). A lower percentage of inactive drivers (11%) are working full-time in Kenya compared to active drivers (35%), possibly reflecting a scarcity of formal employment opportunities and the involuntary exit. A significantly higher proportion of inactive drivers in India and Indonesia are currently running their own businesses than active drivers, indicating a shift toward self-employment after leaving the platform. However, this pattern does not hold in Kenya, where most inactive drivers continue to work in offline driving, likely because they didn't want to leave the platform in the first place.

Approximately 50% of inactive drivers in India and Indonesia report that their current earnings are higher than when they worked on the platform, and they are now able to meet expenses and save money compared to when they were working on the platform. This indicates that drivers transition to higher-paying work after quitting. However, the narrative is the opposite in Kenya, where only 30% of inactive drivers report earning more after leaving the platform, suggesting that many are financially worse off and report being less likely to meet basic expenses and save now compared to before.

6 Limitations and further research

This study has several limitations that should be considered when interpreting the findings. First, the administrative data used to estimate driving earnings were collected during a specific time period that may not reflect typical seasonal or economic conditions. As a result, earnings may be over- or underestimated relative to long-term trends. Second, our survey data rely on self-reported responses, which may be subject to recall bias or social desirability bias. This is particularly relevant for questions related to sensitive topics such as safety incidents or family perceptions of gig work.

The study is also limited to a single platform operating in each country. Platform-specific algorithmic features, incentive structures, and support mechanisms may vary widely, making it difficult to generalize our findings across the broader gig economy. Drivers on other platforms, or in different regions, may experience different working conditions, constraints, and earnings dynamics.

Future research could explore the effects of formal support mechanisms, such as access to health or accident insurance, savings and credit programs, and vehicle rental schemes, on the well-being and earnings stability of gig workers. Experimental or quasi-experimental evaluations could help identify which interventions are most effective at improving drivers' resilience and financial security. Additionally, studying driver behavior and earnings during atypical or adverse conditions, such as extreme weather events, economic shocks, or public health crises, could provide valuable insights into the vulnerabilities of platform workers and the coping mechanisms they employ. Finally, cross-platform comparative studies using harmonized data would enhance understanding of how platform design, local regulations, and labor market structures shape worker outcomes in the gig economy.

7 Direction of Future Research

While this paper provides a comprehensive descriptive narrative of the lives of digital workers, it does not shed light on causal relationships between access to platform work and welfare outcomes. Future research should broadly focus on the following theme. First, little is currently known about whether platform work is actually welfare improving compared to a valid counterfactual. Studying this topic is challenging given the proliferation of platforms and prominence of platform work, and requires either unique natural experiment settings or finding populations that would respond to recruitment efforts. An example of such a study could be the impact of offering rural migrants the opportunity to join a digital gig workforce in urban environments. Given the limited female participation in driving gig work, recruitment efforts of women by the platforms (which are currently underway in many major driving gig platforms) could be combined with research activities.

Second, it remains an open question whether access to digital gig platforms actually improves financial inclusion, and the answer likely depends on the degree to which digital gig platforms are embedding financial services. A promising integration is the use of earnings platform records to create alternative credit scores and extend new lending opportunities to those who are otherwise excluded from the lending market. Embedding financial tools, such as savings, could also improve the cash flow of workers.

Third, platforms have a lot of influence on the experiences of workers through algorithmic management, and systematic study on the impacts of algorithmic tweaks on working experiences would shed light on the systems that could be both sustainable to the platform and also favorable to the workers.

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8 Tables and Figures

Table 1: Number of completed interviews and response rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Active				Inactive			
	No. of completed interviews				No. of completed interviews			
	Male	Female	Total	Response rate	Male	Female	Total	Response rate
India	2,143	404	2,547	18.3%	114	0	114	10.9%
Indonesia	2,114	892	3,006	45.1%	110	86	196	16.7%
Kenya	987	2	989	14.4%	193	0	193	6.0%

Table 2: Timeline of descriptive studies

Activities	2023	2024											
	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Administrative data and sampling													
[Platform] supplied administrative data for sampling ("Admin data 1")													
Detailed administrative data coverage ("Admin data 2")													
Quantitative survey													
Training of enumerators													
Data collection period													
Qualitative survey													
Data collection period													

India Indonesia Kenya

Table 3: Active driver population characteristics according to the platform administrative data

	(1)	(2)	(3)
	India	**Indonesia**	**Kenya**
		Mean	
A. Driving Patterns (at the time of sampling)			
Number of working hours/week at the time of data extract	33.61	41.92	23.73
Full time	0.22	0.51	0.15
Part time (all)	0.78	0.49	0.81
Part time flex	0.39	–	0.60
Part time fixed	0.39	–	0.21
B. Driver Service Types			
Passenger	–	0.90	0.97
Delivery:	1.00		
Food	–	0.86	0.12
Parcel	–	0.68	–
C. Geography			
India:		–	–
North and central	0.41	–	–
South	0.29	–	–
Other	0.31	–	–
Indonesia:			
Greater Jakarta	–	0.54	–
Java Non Greater Jakarta	–	0.26	–
Non Java	–	0.20	–
D. Demographics			
Male	0.99	0.98	0.99
Age	27.92	38.39	32.30
Tenure on the [platform] (in days)	383.39	1999.20	744.05
Sampling frame	76% of population	98.5% of the population	Full population

Notes: Population values are derived from the [platform] company administrative data extract from December 2023 in India, May 2024 in Indonesia, and July 2024 for Kenya.

There exist differences in the unit of administrative data by countries, and hence, driving patterns are not defined in the same way. In India, Full-time drivers are defined as drivers whose average working hours were more than or equal to 8 hours per day over a period of 3 months, and Part-time as less than 8 hours per day. In Indonesia and Kenya, Full-time drivers are defined as those driving 40 hours or more per week, and Part-time as less than 40 hours a week.

In our survey, active drivers completed at least one delivery within a three-month period between October to December 2023 in India and April and June 2024 in Kenya. In Indonesia, active drivers completed at least one order on the platform within the past two months (population at the time of the data extract in May 2024).

Figure 1: Distribution of average weekly hours online using sampling platform administrative data: all drivers

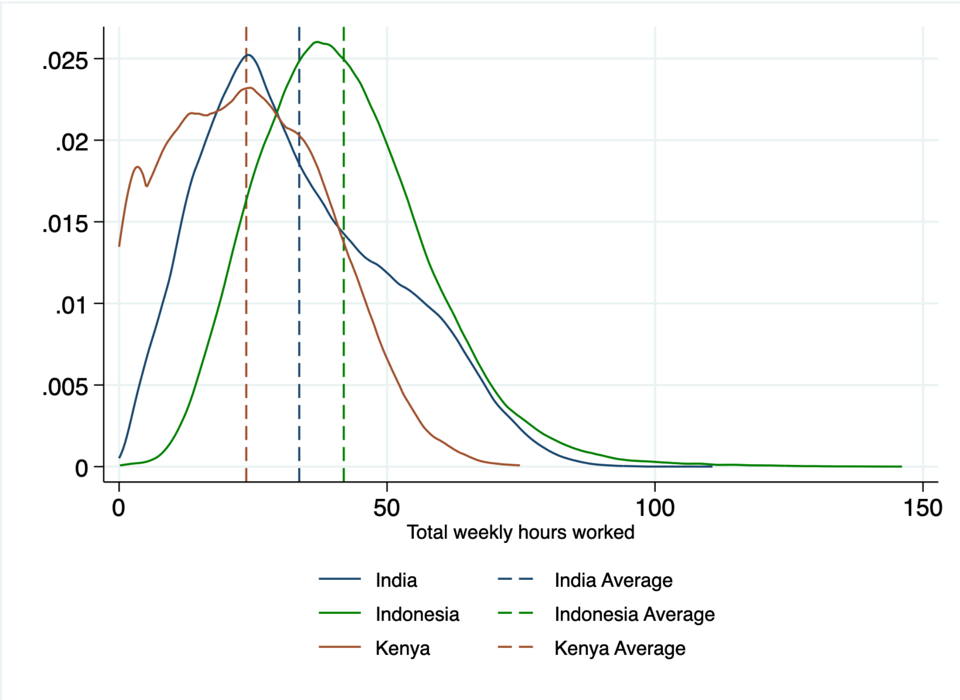

Table 4: Demographic and household characteristics of drivers

	(1)	(2)	(3)	(4)
	India	**Indonesia**	**Kenya**	**q-value**
		Mean		
A. Characteristics				
Age	28.1	37.9	32.2	<0.01
Male	0.99	0.99	1.00	<0.01
Married	0.49	0.80	0.81	<0.01
B. Household				
Head of the household	0.42	0.90	–	<0.01
Household size	4.43	4.11	3.70	<0.01
Dependency ratio	0.23	0.60	0.89	<0.01
C. Education				
High school graduate	0.30	0.69	0.50	<0.01
College graduate and above	0.31	0.12	0.20	<0.01
Currently a student	0.23	0.02	0.13	<0.01
If currently a student, which level they're at:				
Bachelors or post graduate	0.55	0.76	0.13	<0.01
D. Migration				
Migrant to the city of current work	0.49	0.22	0.81	<0.01
If migrant,				
Moved for [platform work]	0.16	–	0.01	<0.01
Moved for other non-platform work	0.77	–	0.61	<0.01
Observations	2,547	3,006	989	

Notes: Weighted means for all of the drivers are presented in columns 1, 2, and 3 for India, Indonesia, and Kenya, respectively. The question of whether the respondent is the head of household was not asked in Kenya; follow-up questions on reasons for migrating were not asked to respondents in Indonesia. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 4.

Table 5: Ownership of necessary assets and work before joining [platform]

	(1)	(2)	(3)	(4)
	India	**Indonesia**	**Kenya**	**q-value**
		Mean		
A. Access to assets before joining [platform]				
National ID	1.00	0.99	0.98	<0.01
Vehicle (two-wheeler)	0.94	0.99	0.89	<0.01
Driver's license	0.82	0.97	0.90	<0.01
Smart phone	0.98	0.96	0.89	<0.01
Bank account	0.99	0.83	0.82	<0.01
B. Previous Work				
Driving offline or online (PT or FT)	0.08	0.05	0.27	<0.01
Full time (non-driving):				
Formal	0.45	0.58	0.30	<0.01
Informal	0.12	0.14	0.21	<0.01
Part time (non-driving):				
Formal	0.04	0.03	0.05	0.05*
Informal	0.11	0.04	0.12	<0.01
Business	0.06	0.11	0.08	<0.01
Unemployed	0.03	0.04	0.02	0.03**
Current income is higher than previous income	0.55	0.38	0.78	<0.01
Observations	2,547	3,006	989	

Notes: Weighted means for all of the drivers are presented in columns 1, 2, and 3 for India, Indonesia, and Kenya, respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 4.

In Panel A, National ID here refers to Aadhar card for India, Kartu Tanda Penduduk for Indonesia, and Kitambulisho for Kenya.

Figure 2: Weekly hours online according to administrative data in India and Kenya (unconditional on logging in)

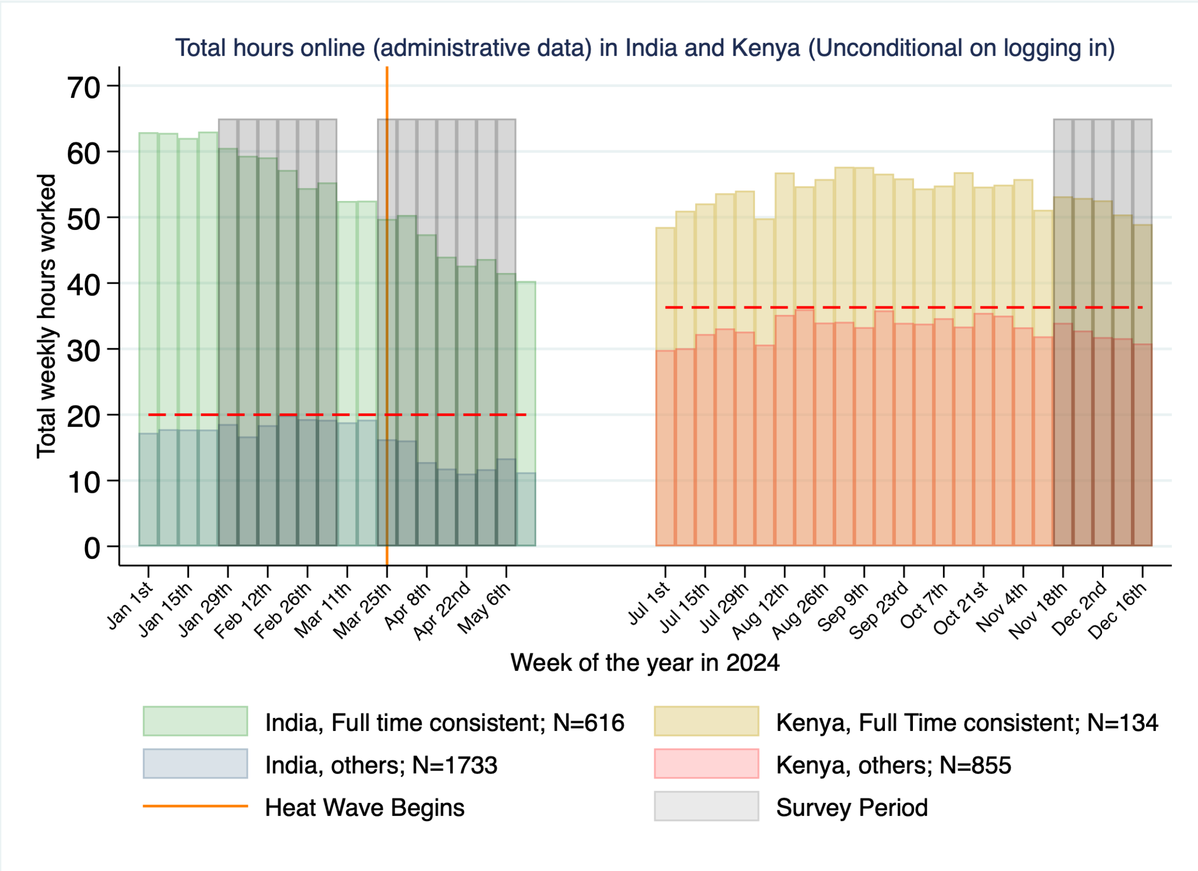

Figure 3: Weekly hours online according to administrative data in India and Kenya (conditional on logging in)

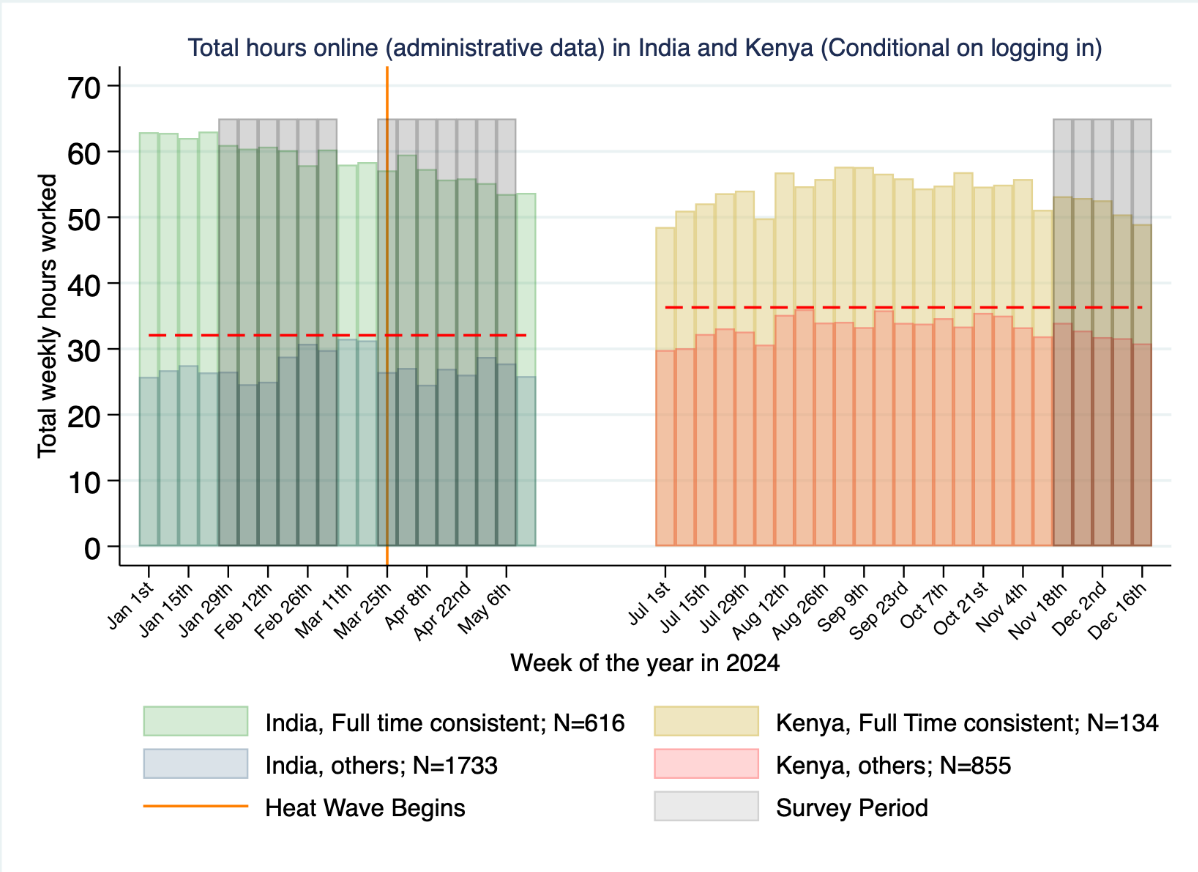

Table 6: Labour supply and decision on working hours

	(1)	(2)	(3)	(4)
	India	**Indonesia**	**Kenya**	**q-value**
		Mean		
A. Earning Sources (in the last 6 months)				
Number of different earning sources	1.74	1.62	2.01	<0.01
[platform]	0.98	1.00	1.00	<0.01
Part-time work (formal or informal)	0.09	0.23	0.13	<0.01
Another driving platform *(multi-homing)*	0.10	0.12	0.41	<0.01
Business	0.06	0.10	0.08	0.01**
Full-time work (formal or informal)	0.30	0.08	0.35	<0.01
B. Weekly Labor Supply				
Weekly working hours across all sources	57.90	76.81	66.16	<0.01
Weekly working hours across on [platform]	32.93	69.21	42.94	<0.01
% of total hours spent working on the [platform]	53%	91%	71%	<0.01
C. Choice of [platform] hours				
How they decide which hours to work on the [platform]				
Work the same working hours everyday full-time	0.29	0.61	0.36	<0.01
Depends on anticipated order volume or prices	0.21	0.26	0.45	<0.01
Based on free time	0.33	0.35	0.15	<0.01
Depends on working hours in other job	0.13	0.08	0.19	<0.01
D. Electric motorcycles				
Drivers using electric vehicles	0.07	–	0.11	<0.01
E. From [platform] data				
Churn (fraction of drivers driving >0 hours after 1 month)	0.84	–	–	–
Utilization rate (all drivers)	0.72	0.60	0.40	<0.01
Utilization rate (full-time drivers who do not multi-home)	0.70	–	0.47	<0.01
Observations	2,547	3,006	989	

Notes: Weighted means for all of the drivers are presented in columns 1, 2, and 3 for India, Indonesia, and Kenya, respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 4.

Figure 4: Utilization rate by week according to [platform] administrative data

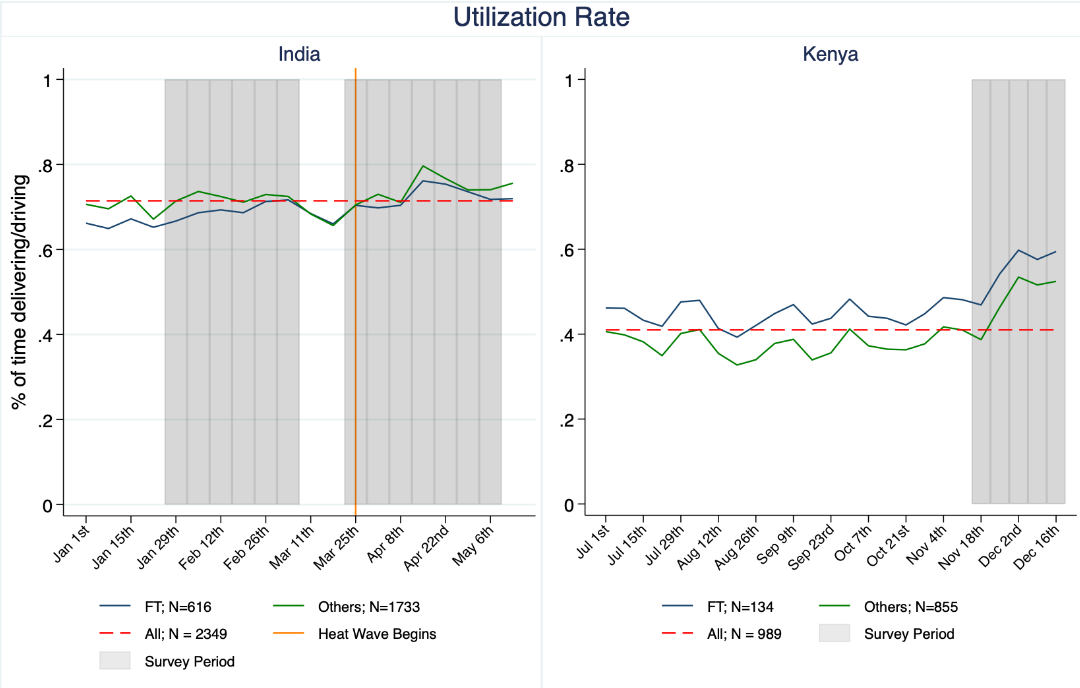

Figure 5: Average nominal gross earnings per hour online (A) and per productive hour (B) by week in India and Kenya

Figure 6: Average gross earnings per order by week in India and Kenya

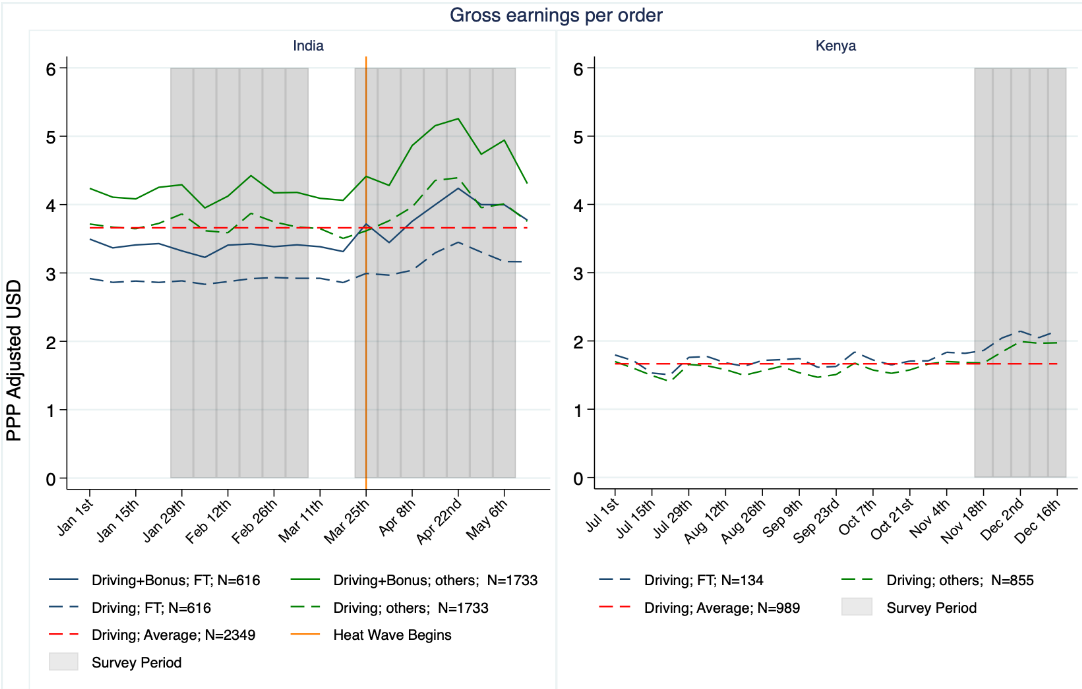

Figure 7: Average self-reported cost per hour by week in India and Kenya derived from drivers surveyed in each week

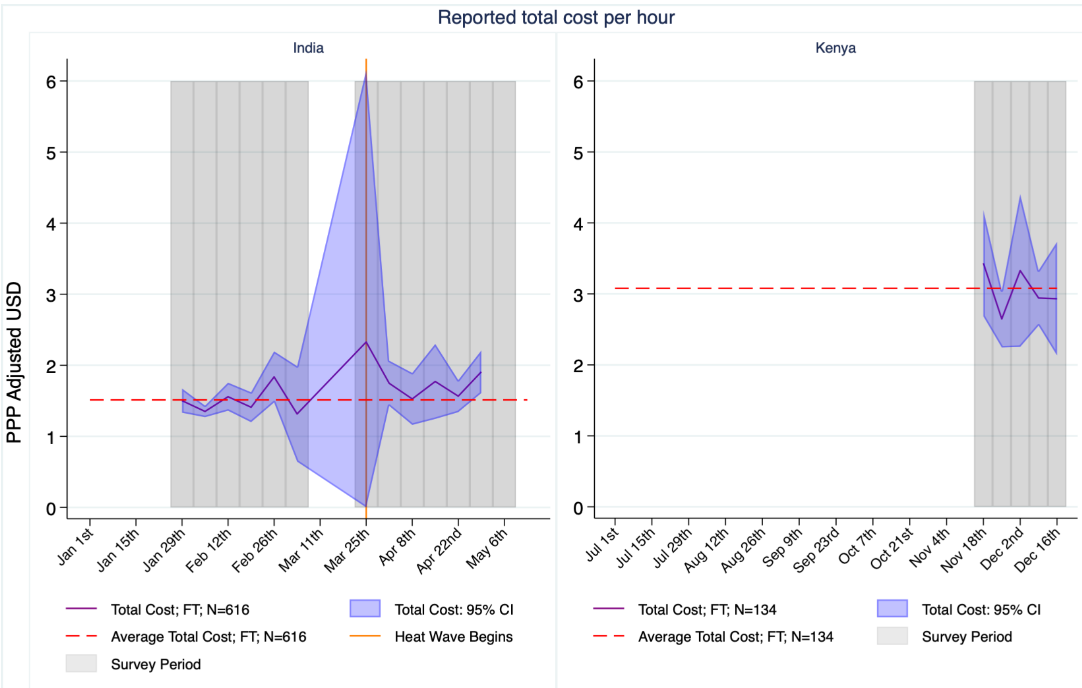

Figure 8: Percentage of FT platform workers logged in each week in India and Kenya

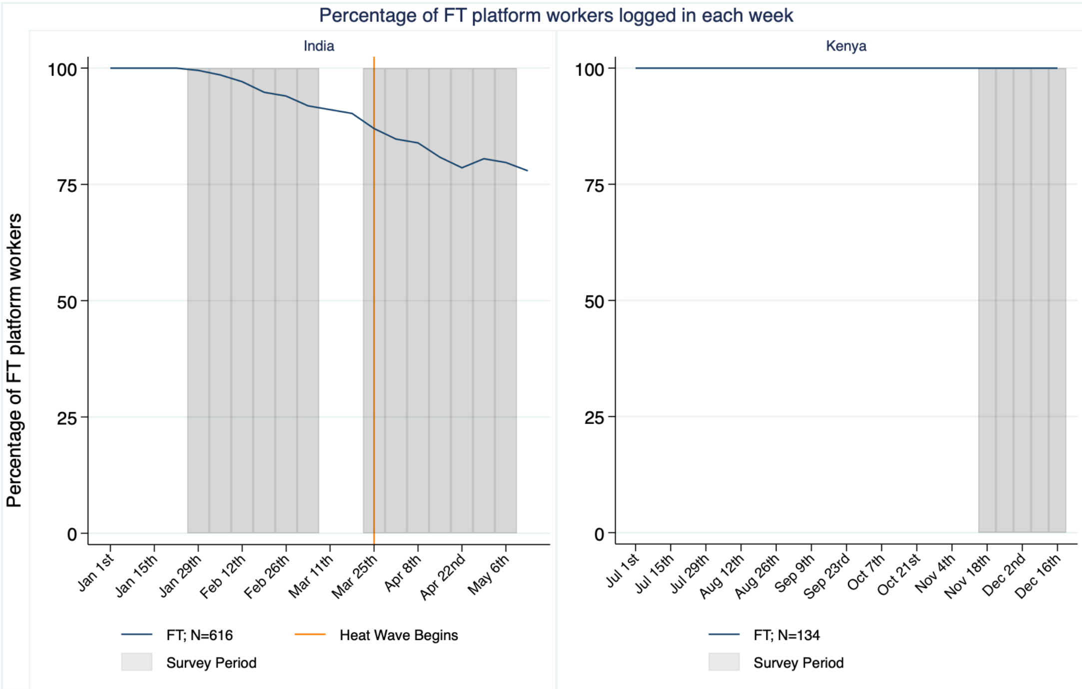

Figure 9: Orders per hour online

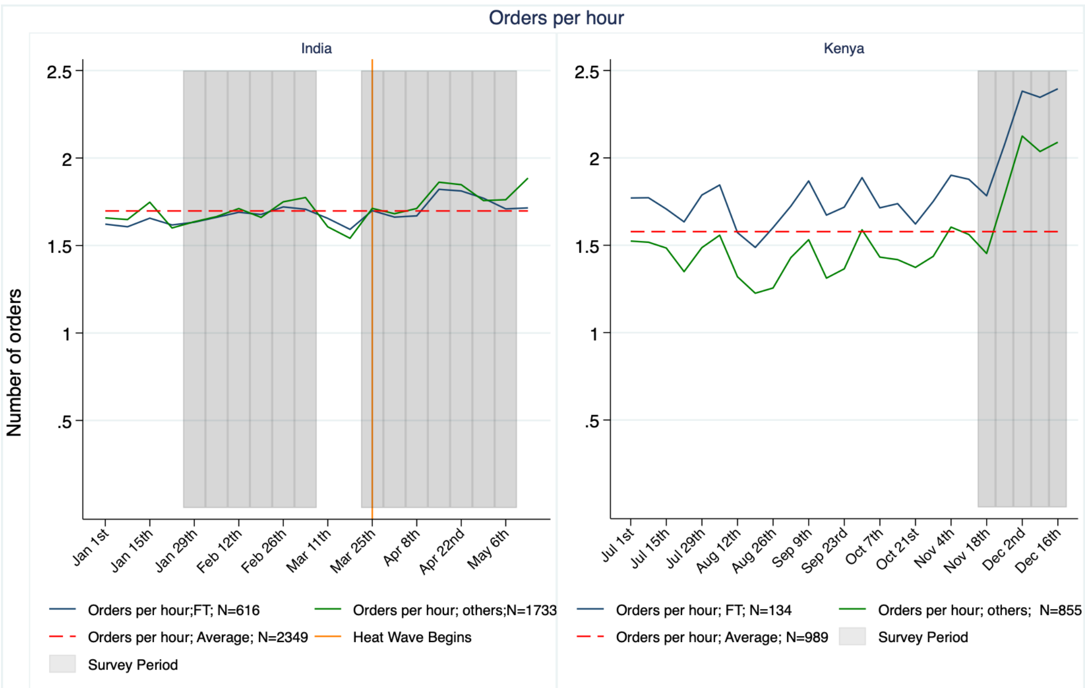

Table 7: Gross and net earnings for full-time 'consistent' drivers

	(1)	(2)	(3)	(4)
	Sub-sample of full time 'consistent' drivers			
	Adjusted to PPP			
	India	**Indonesia**	**Kenya**	**q-value**
A. SURVEYING PERIOD				
1. [platform] Daily Equivalent: Gross and net [platform] earnings estimation				
(1) Gross hourly earnings *(In India for a typical day estimated using admin data, in Indonesia/Kenya for the last working day using survey data)*	5.02	2.96	5.39	<0.01
Expenses (hourly-equivalent)				
Fuel/electricity	1.06	0.59	1.97	<0.01
Parking	0.00	0.04	0.06	<0.01
Repairs	0.27	0.20	0.36	<0.01
2-wheeler loan payment	0.06	0.21	0.04	<0.01
2-wheeler rent payments	0.08	0.02	0.38	<0.01
(2) Total hourly expenses	1.52	1.12	3.08	<0.01
(3) Expenses as % of total earnings	30%	38%	57%	
Net earnings				
Method 1: Calculated hourly equivalent earnings - hourly equivalent expenses [(1)-(2) above]	3.50	1.84	2.32	<0.01
2. [platform] Monthly equivalent				
Method 1: Calculated by scaling daily equivalents in Indonesia/Kenya; in India reporting average [platform] earnings per month before the survey date				
Estimated working hours per week (using self-reports)	72.24	77.27	58.88	<0.01
Gross Earnings	1,491.73	956.88	1,069.01	<0.01
Net Earnings	1,039.86	589.97	465.60	<0.01
3. Total Monthly Equivalent (in the past 30 days)				
Method 1: calculated [platform] earnings + self-reported other earnings	1,103.23	651.55	528.80	<0.01
B. FULL COVERAGE OF ADMINISTRATIVE DATA (Method 2)				
[platform] Per Hour: Gross and net [platform] earnings estimation				
Gross earnings	–	–	3.38	–
Net earnings (gross earnings % taken by expenses).	–	–	1.45	–
[platform] Per Month				
Gross earnings	–	–	764.13	–
Net earnings (gross earnings % taken by expenses).	–	–	328.07	–
Observations	616	1007	132	

Notes: Weighted means for all of the drivers are presented in columns 1, 2, and 3 for India, Indonesia, and Kenya, respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 4. All information was collected in the local currency but has been converted to USD, using the average exchange rate for the period during the survey was conducted in each country.

Table 8: Benchmarking against available types of work

	(1)	(2)	(3)	(4)	(5)	(6)
	In USD, PPP-adjusted					
	India (5 major cities)		Indonesia (Jakarta DKI)		Kenya (Nairobi)	
	Per Hour	Per month	Per Hour	Per month	Per Hour	Per month
A. Survey data:						
Net income (method 1, during the surveying period)	3.72	1109.59	2.15	699.66	2.45	500.39
Net income (method 2, wider time period)	–	–	–	–	1.47	333.71
Offline motorcycle Driver	–	–	1.21	257	–	–
Per hour income for drivers who work full time (formal and informal)	4.08	–	4.07	–	4.95	–
B. Secondary data sources:						
Informal Work						
Casual labour work	3.08	513	2.80	485	–	–
Self-employment	–	–	4.45	770	–	–
Full time salaried/formal work:						
Clerks	6.05	1254	–	–		
Service workers and Shop Sale Workers	3.76	779	–	–	3.34	371
Skilled Agricultural and Fishery Workers	4.47	927	–	–	–	–
Craft and Trade workers	3.75	778	–	–	–	–
Machine Operator And Assemblers	3.98	824	–	–	3.58	389
Machinist, vehicle service worker, other	–	–	–	–	3.99	444
Car driver and other service providers	–	–	–	–	4.17	463
Relevant minimum wage (Jakarta DKI in Indonesia and Top 5 cities in India)	4.09	709.16	6.07	1051		

Notes: For comparisons to other similar work available to this cohort.

(1) For India, we use PLFS 2023 for monthly salaries and average working week for those occupations to derive per-hour estimates. To compare platform income to minimum wages, we calculate the weighted average minimum wage for the top 5 cities, where ∼40% of full-time 'consistent' drivers work, which are New Delhi, Bangalore, Hyderabad, Mumbai, and Pune. For New Delhi, Mumbai, and Pune, we use the minimum wage set for the semi-skilled worker in 2024, available on the state labour website. For Bangalore and Hyderabad, minimum wages are only available by occupation, and we use the figures set for 'Light Vehicle Drivers', under the Transportation category. To make correct comparisons, we only include the earnings of drivers who operated in these 5 cities in India.

(2) For Indonesia, we use means from external sources (Permana et al. (2023), Kusumawardhani et al. (2021), Jakarta Minimum Wage, BPS (2022), and BPS (2023)). For Indonesia, we use Jakarta Minimum Wage, BPS (2022), and BPS (2023) for estimates on salaries and income, and assume 40 hours/week.

(3) For Kenya, we use the KNBS Economic Survey 2024, comparing minimum wages in 2023 for Nairobi, Kisumu, and Mombasa—classified as urban areas. The minimum wages assume a general standard working hours, typically consisting of 45 hours per week—8 hours per day from Monday to Friday and 5 hours on Saturday—under special orders for different sectors, as outlined in the Regulations of Wages and Conditions of Employment Act, Cap 229.

Table 9: Benefits, downsides, and safety challenges on [platform]

	(1)	(2)	(3)	(4)
	India	Indonesia	Kenya	q-value
	Mean			
A. Benefits of working for the [platform]				
Have an extra earnings in the household	0.50	0.58	0.72	<0.01
Have freedom	0.26	0.72	0.44	<0.01
Can save more money for myself	0.35	0.07	0.19	<0.01
Have more of a say in decision making in household	0.09	0.08	0.10	0.47
Gain skills & experiences	0.01	0.03	0.07	<0.01
B. Downsides of working for the [platform]				
No downsides	0.40	0.12	0.11	<0.01
Have to encounter fictional orders sometimes	–	0.52	–	–
Earning are too low	0.06	0.29	0.18	<0.01
Not enough time with family/leisure time	0.15	0.26	0.02	<0.01
Safety risks and traffic problems	0.21	–	0.33	<0.01
Have to work more	0.11	0.21	0.10	<0.01
C. Safety				
Ever experienced unsafe situation	0.45	0.64	0.56	<0.01
Type of situation (out of the full sample)				
Got into a road accident while working	0.24	0.26	0.14	<0.01
Had to deliver in unsafe areas	0.18	0.21	0.27	0.01**
Got into a fight with customer/restaurant/police	0.11	0.26	0.31	<0.01
Valuables got stolen (phone, bike etc)	0.08	0.04	0.12	<0.01
Received fake orders	–	0.41	0.13	<0.01
Observations	670	697	968	

Notes: Weighted means for all of the drivers are presented in columns 1, 2, and 3 for India, Indonesia, and Kenya, respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 4.

Table 10: Financial security and saving behavior

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	India		**Indonesia**		**Kenya**		**q-value**
	Mean	**N**	**Mean**	**N**	**Mean**	**N**	
A. Struggling to meet basic expenses							
Struggling to meet any expenses	0.35	2,541	0.16	775	0.22	969	$<$0.01
B. Saving behavior							
Ability to save							
Able to put away any savings in a typical month	0.39	588	0.47	775	0.63	969	$<$0.01
Savings method (if saving)							
Put money in bank savings account	0.77	172	0.48	379	0.51	614	0.13
Keep as cash	0.13	172	0.31	379	0.05	614	$<$0.01
Put money in digital saving tool	0.01	172	0.10	379	0.27	614	$<$0.01

Notes: Weighted means for all of the drivers are presented in columns 1, 2, and 3 for India, Indonesia, and Kenya, respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 4.

Table 11: Access and usage of various financial instruments

	(1)	(2)	(3)	(4)
	India	Indonesia	Kenya	q-value
		Mean		
Bank account ownership	1.00	0.92	0.93	<0.01
Got before joining [platform]	0.98	0.62	0.82	<0.01
Got because of [platform]	0.01	0.26	0.07	<0.01
Credit card ownership	0.10	0.04	–	<0.01
Got before joining [platform]	0.04	0.03	–	<0.01
Got because of [platform]	0.00	0.00	–	0.08*
Digital money ownership	0.99	1.00	1.00	0.01**
Got before joining [platform]	0.65	0.17	0.98	<0.01
Got because of [platform]	0.04	0.79	0.02	<0.01
Ever taken out a bank loan	0.27	0.16	0.40	<0.01
Got before joining [platform]	0.24	0.05	0.30	<0.01
Got because of [platform]	0.01	0.02	0.05	<0.01
Ever taken out a digital loan	0.19	0.27	0.86	<0.01
Got before joining [platform]	0.11	0.04	0.66	<0.01
Got because of [platform]	0.06	0.13	0.10	0.07*
Ever taken out life insurance (for self)	0.23	0.01	0.06	<0.01
Got before joining [platform]	0.12	0.00	0.03	<0.01
Got because of [platform]	0.01	0.00	0.02	<0.01
Ever taken out health insurance (for self)	0.16	0.03	0.52	<0.01
Got before joining [platform]	0.08	0.02	0.43	<0.01
Got because of [platform]	0.08	0.01	0.05	<0.01
Observations	590	775	952	

Notes: Weighted means for all of the drivers are presented in columns 1, 2, and 3 for India, Indonesia, and Kenya, respectively. Questions on financial inclusion were asked to a subsample of respondents in India and Indonesia, and to all respondents in Kenya. Questions on credit cards were not asked in Kenya, and have been excluded from the results above. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 4.

Table 12: Experiences of inactive drivers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	India			**Indonesia**			**Kenya**		
	Active	**Inactive**	**q-value**	**Active**	**Inactive**	**q-value**	**Active**	**Inactive**	**q-value**
A. Demographics									
Age	28.1	29.0	0.44	37.9	36.3	0.18	32.2	33.6	0.40
Male	0.99	0.99	0.61	0.99	0.96	<0.01	1.00	0.98	0.40
Married	0.49	0.56	0.46	0.80	0.76	0.46	0.81	0.78	0.46
Household size	4.4	4.8	0.46	4.1	4.1	0.75	3.7	3.9	0.41
College graduate and above	0.31	0.39	0.46	0.12	0.21	0.16	0.20	0.24	0.46
Migrated to current place	0.49	0.32	0.05*	0.22	0.20	0.66	0.81	0.88	0.16
B. Exit from [platform]									
Reason for leaving									
Earnings were too low	–	0.38	–	–	0.40	–	–	0.15	–
For personal/health reasons	–	0.22	–	–	0.35	–	–	0.08	–
Wanted to focus on business/other job	–	0.11	–	–	0.15	–	–	0.01	–
Terminated by [platform]	–	0.07	–	–	0.02	–	–	0.48	–
Rejoined the [platform] after quitting	–	0.28	–	–	0.33	–	–	0.31	–
Reasons for rejoining									
During emergencies when money is needed	–	0.28	–	–	0.34	–	–	0.24	–
During lean periods in current work	–	0.25	–	–	0.05	–	–	0.24	–
Realized earnings were better at [platform]	–	0.06	–	–	0.03	–	–	0.26	–
Account got reactivated/ renewed work documen	–	0.00	–	–	0.00	–	–	0.24	–
C. Current Work									
Number of different income sources	1.74	1.26	<0.01	1.62	1.53	0.44	2.01	1.25	<0.01
Full time job (formal or informal)	0.30	0.57	<0.01	0.08	0.59	<0.01	0.35	0.11	<0.01
Offline driving	0.03	0.01	0.41	–	–	–	0.26	0.48	<0.01
Business	0.06	0.17	0.08*	0.10	0.37	<0.01	0.08	0.09	0.71
D. Financial Security									
Current earnings are greater than [platform] earning	–	0.51	–	–	0.57	–	–	0.30	–
Ability to meet expenses									
While working on the platform in the past	–	0.60	–	–	0.25	–	–	0.87	–
Now after quitting	–	0.70	–	–	0.88	–	–	0.65	–
Ability to save									
While working on the platform in the past	–	0.52	–	–	0.49	–	–	0.75	–
Now after quitting	–	0.54	–	–	0.63	–	–	0.53	–
Observations	2,546	114		3,006	196		989	193	

Notes: Weighted means for all active drivers are presented in columns 1, 4, and 7 for India, Indonesia, and Kenya, respectively. Weighted means for all inactive drivers are presented in columns 2, 5, and 8 for India, Indonesia, and Kenya, respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the active and inactive drivers in each country are presented in columns 3, 6, and 9 for India, Indonesia, and Kenya, respectively.

Appendix

Table A1: Comparison of the weighted sample to the sampling frame: India

	(1)	(2)	(3)
		Weighted by sampling weights and IPW within strata	
	Sampling frame	**Sample Reached**	
	Mean	**Mean**	**p-value**
A. Demographics:			
Male	0.99	0.99	0.89
Age	27.92	28.11	0.67
Tenure	383.39	360.77	0.35
Drives motorbike	0.86	0.86	0.87
Drives cycle	0.02	0.01	<0.01
Drives ecycle	0.08	0.07	0.71
Drives multiple	0.04	0.05	0.26
B. Geography			
North and Central	0.41	0.40	0.92
South	0.29	0.33	0.27
Other	0.31	0.26	0.29
Tier: top 7	0.56	0.56	0.98
Tier: top 15 and 30	0.20	0.19	0.73
Tier: emerging	0.24	0.24	0.73
C. Driving Patterns			
Average hours worked per day	5.60	5.56	0.84
Full time	0.22	0.17	<0.01
Part time: fixed	0.39	0.38	0.85
Part time: flexible	0.39	0.44	0.19
D. Driver "quality"			
Platform rating (1=lowest, 4=highest)	2.01	2.06	0.54
Observations	76% of population	2,547	

Notes: Population values (derived from the [platform] administrative data) are presented in column (1), means of the sample taken are adjusted by sampling and inverse probability weights applied within strata and presented in column (2). In column (3), the p-value from a t-test comparing the sample to the population value is presented. The strata definition included driver type, lifetime number of orders, gender, and city tier.

Table A2: Comparison of the weighted sample to the sampling frame: Indonesia

	(1)	(2)	(3)
		Weighted by sampling weights and IPW within strata	
	Sampling frame	Sample Reached	
	Mean	Mean	p-value
A. Demographics:			
Male	0.98	0.98	0.64
Age	38.39	38.42	0.86
Tenure	65.73	65.51	0.71
B. Geography			
Greater Jakarta	0.54	0.55	0.90
Java (Non Greater Jakarta)	0.23	0.23	0.96
Non Java	0.23	0.23	0.92
C. Participation in financial inclusion tools			
Currently participating	0.54	0.54	0.97
Participated in the past 2 years	0.27	0.28	0.27
Never participated	0.19	0.18	0.22
D. Driving Patterns			
Average hours worked per week	41.92	41.98	0.83
Drives passenges	0.90	0.88	0.09
Delivers food	0.86	0.88	0.03
Delivers packages	0.68	0.68	0.67
Number of services	2.44	2.44	0.93
Observations	98.5% of the population	3063	

Notes: Population values are derived from the [platform] company administrative data extract from May 2024. In column 2, weighted means are presented for the sample of drivers reached. Strata definition included: tenure on the platform (higher and lower than median), age (higher and lower than median), and gender.

Table A3: Comparison of the weighted sample to the sampling frame: Kenya

	(1)	(2)	(3)
	Population	**Completed the survey**	
		Weighted	
	Mean	**Mean**	**p-value**
A. Demographics:			
Male	0.99	0.99	0.98
Age	32.30	32.17	0.63
Tenure in days	744.05	750.80	0.77
B. Driving Patterns			
Average hours worked per week	23.73	23.56	0.73
Full time	0.15	0.14	0.56
Part time: fixed	0.21	0.20	0.62
Part time: flexible	0.60	0.62	0.32
Total number of orders	1987.13	2013.58	0.70
C. Driver "quality"			
Average Driver rating	4.86	4.86	0.75
Average number of ratings	826.97	843.03	0.58

Notes: The number of observations represents the maximum size across all variables. Some variables have missing values, resulting in differences between the total population size and the number of completed observations. For example, the variable "Male" has 2470 observations under population but only 234 observations under completed surveys. Unweighted sample means in the attempted sample are presented in column (1). In column(2), we present unweighted means of the participated sample in this study. In column (3), we present p-values comparing means to the means of the sample taken.

Table A4: Research modules and sample size for each country

Themes	Module	India	Indonesia	Kenya
Entry	Demographics (essential)	2,547	3,006	989
	Onboarding and barriers to entry (secondary)	644	763	950
Experiences on Platform	Current Work: Labor Supply & Earnings (essential)	2,547	3,006	989
	Previous and Counterfactual Work: Labor Supply & Earnings (essential)	2,547	3,006	989
	Multi-homing (essential)	2,547	3,006	950
	Financial Health (secondary)	590	775	950
	Financial Inclusion (secondary)	590	775	950
	Working conditions: Work-life Balance (secondary)	670	697	970
	Working Conditions: Safety (secondary)	670	697	970
	Working Conditions: Dignity (secondary)	670	697	970
	Value of Flexibility (essential)	2,547	3,006	–
	Algorithmic management (secondary)	670	672	–
	Social Protection (secondary)	643	771	970
	Questions for female drivers (essential)	404	892	2
Exit	Exit from platform, Feedback to Platform (secondary)	643	771	950
	Collectivization (secondary)	643	771	970

Table A5: Dignity and perception of [platform] work

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	India		**Indonesia**		**Kenya**		**q-value**
	Mean	**N**	**Mean**	**N**	**Mean**	**N**	
A. Perception of the platform work by family							
It's a good job and they approve of my choice	0.45	2,456	0.51	688	0.63	968	<0.01
Good job for now, but not for later	0.39	2,456	0.46	688	0.24	968	<0.01
B. Dignity: Interactions with other people on the job; agreed with statement "Feel respected by..."							
Customers	0.73	669	0.84	697	0.54	968	<0.01
[platform] personnel	0.88	661	0.82	697	0.69	968	<0.01
Merchant	0.65	669	0.77	693	0.61	968	<0.01

Notes: Weighted means for all of the drivers are presented in columns 1, 3, and 5 for India, Indonesia, and Kenya, respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 7.

Table A6: Drivers' exit plan from [platform]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	India		**Indonesia**		**Kenya**		**q-value**
	Mean	**N**	**Mean**	**N**	**Mean**	**N**	
A. How long do you see yourself working for [platform]?							
Less than a year	0.11	625	0.00	748	–	–	<0.01
Less than 3 years	0.10	625	0.02	748	–	–	<0.01
More than 3 years	0.06	625	0.01	748	–	–	<0.01
Undecided	0.73	625	0.28	748	–	–	<0.01
I don't see myself leaving [platform]	–	–	0.69	748	–	–	–
B. Reasons for planning to leave							
Earnings are too low	0.27	80	0.30	229	–	–	<0.01
Want to get fixed monthly income	0.02	80	0.25	229	–	–	<0.01
For health reasons	0.01	80	0.17	229	–	–	<0.01
Need to focus on business/other job	0.16	80	0.14	229	–	–	<0.01

Notes: Weighted means for all of the drivers are presented in columns 1, 3, and 5 for India, Indonesia, and Kenya, respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries are presented in column 7.

Table A7: Gross and net earnings for full-time 'consistent' drivers (in nominal USD)

	(1)	(2)	(3)	(4)
	Sub-sample of full time 'consistent' drivers			
	Nominal in USD			
	India	**Indonesia**	**Kenya**	**q-value**
A. SURVEYING PERIOD				
1. [platform] Daily Equivalent: Gross and net [platform] earnings estimation				
(1) Gross hourly earnings *(In India for a typical day estimated using admin data, in Indonesia/Kenya for the last working day using survey data)*	1.22	0.87	1.84	<0.01
Expenses (hourly-equivalent)				
Fuel/electricity	0.26	0.17	0.67	<0.01
Parking	0.00	0.01	0.02	<0.01
Repairs	0.06	0.06	0.12	<0.01
2-wheeler loan payment	0.01	0.06	0.01	<0.01
2-wheeler rent payments	0.02	0.01	0.13	<0.01
(2) Total hourly expenses	0.37	0.33	1.05	<0.01
(3) Expenses as % of total earnings	30%	38%	57%	
Net earnings				
Method 1: Calculated hourly equivalent earnings - hourly equivalent expenses [(1)-(2) above]	0.85	0.540	0.79	<0.01
2. [platform] Monthly equivalent				
Method 1: Calculated by scaling daily equivalents in Indonesia/Kenya; in India reporting average [platform] earnings per month before the survey date				
Gross Earnings	361.60	281.329	364.57	<0.01
Net Earnings	252.06	173.454	158.78	<0.01
3. Total Monthly Equivalent (in the past 30 days)				
Method 1: calculated [platform] earnings + self-reported other earnings	267.42	191.56	180.34	<0.01
B. FULL COVERAGE OF ADMINISTRATIVE DATA (Method 2)				
[platform] Per Hour: Gross and net [platform] earnings estimation				
Gross earnings	–	–	1.15	<0.01
Net earnings (gross earnings % taken by expenses).	–	–	0.50	<0.01
[platform] Per Month				
Gross earnings	–	–	260.59	<0.01
Net earnings (gross earnings % taken by expenses).	–	–	111.88	<0.01
Observations	616	1007	132	<0.01

Notes: Weighted means for all of the drivers are presented in columns 1, 2, and 3 for India, Indonesia, and Kenya respectively. q-values (p-values adjusted for multiple hypothesis correction) of the differences in means between the countries is presented in column 4. All information was collected in the local currency but has been converted to USD, using the average exchange rate for the period during the survey was conducted in each country.

Table A8: Benchmarking against available types of work (in nominal USD)

	(1)	(2)	(3)	(4)	(5)	(6)
	In Nominal USD					
	India (5 major cities)		Indonesia (Jakarta DKI)		Kenya (Nairobi)	
	Per Hour	Per month	Per Hour	Per month	Per Hour	Per month
A.Survey data:						
Net income (method 1)	0.90	268.96	0.63	205.71	0.83	170.65
Net income (method 2)	1.17	279.75	–	–	0.50	113.80
Offline motorcycle Driver	–	–	0.36	76	–	–
Per hour income for drivers who work full time (formal and informal)	0.99	–	1.20	–	1.69	–
B. Secondary data sources:						
Informal Work						
Casual labour work	0.75	124	0.82	143	–	–
Self-employment	–	–	1.31	227	–	–
Full time salaried/formal work:						
Clerks	1.47	304	–	–		
Service workers and Shop Sale Workers	0.91	189	–	–	1.14	126
Skilled Agricultural and Fishery Workers	1.08	225	–	–	–	–
Craft and Trade workers	0.91	188	–	–	–	–
Machine Operator And Assemblers	0.96	200	–	–	1.22	133
Machinist, vehicle service worker, other	–	–	–	–	1.36	151
Car driver and other service providers	–	–	–	–	1.42	158
Relevant minimum wage (Jakarta DKI in Indonesia and Top 5 cities in India)	0.99	171.90	1.78	309		

Notes: For comparisons to other similar work available to this cohort.
(1) For India, we use PLFS 2023 for monthly salaries and average working week for those occupations to derive per-hour estimates. To compare platform income to minimum wages, we calculate the weighted average minimum wage for the top 5 cities, where ∼40% of full-time 'consistent' drivers work, which are New Delhi, Bangalore, Hyderabad, Mumbai, and Pune. For New Delhi, Mumbai, and Pune, we use the minimum wage set for the semi-skilled worker in 2024, available on the state labour website. For Bangalore and Hyderabad, minimum wages are only available by occupation, and we use the figures set for 'Light Vehicle Drivers', under the Transportation category. To make correct comparisons, we only include the earnings of drivers who operated in these 5 cities in India.
(2) For Indonesia, we use means from external sources (Permana et al. (2023), Kusumawardhani et al. (2021), Jakarta Minimum Wage, BPS (2022), and BPS (2023)). For Indonesia, we use Jakarta Minimum Wage, BPS (2022), and BPS (2023) for estimates on salaries and income, and assume 40 hours/week.
(3) For Kenya, we use the KNBS Economic Survey 2024, comparing minimum wages in 2023 for Nairobi, Kisumu, and Mombasa—classified as urban areas. The minimum wages assume a general standard working hours, typically consisting of 45 hours per week—8 hours per day from Monday to Friday and 5 hours on Saturday—under special orders for different sectors, as outlined in the Regulations of Wages and Conditions of Employment Act, Cap 229.

Validation of self-reported versus administrative data from platforms

We use the detailed platform data ("Admin data 2") to assess the accuracy of the self-reported data for earnings and hours in India, and only hours in Kenya[27]. We did not receive detailed data for drivers in Indonesia and are therefore unable to replicate the analysis there. For this comparison, we use a subsample of drivers surveyed on Monday to ensure maximum comparability between the administrative and survey data recall period. For those drivers, the recall period for hours worked covered 7 days before the survey (Monday to Sunday of last week) and, in India, earnings for the past 30 days (about 4 weeks before the survey). The administrative data on hours online and earnings were also provided weekly, with the week defined as between Monday and Sunday. We use regression without a constant to compare the two reports' correlations and test the coefficient against 1 to assess comparability. We also pay attention to the averages in

[27]We only collected net earnings (after expenses in Kenya) and do not have a survey measure of gross earnings that would be directly comparable to the administrative data. At the start of the study, we planned on comparing daily self-reported data to administrative data, but did not receive administrative data at a required granular level to complete the analysis.

each dataset to make conclusions.

In India (Table A9, columns 1 and 2), self-reported earnings[28] in the survey align closely with administrative data (coefficient is 0.97, p-value testing against 1 is 0.37), suggesting high accuracy of earning data. On average, self-reported weekly working hours are higher than administrative data on hours online (32 hours/week in admin data and 41.58 hours/week in self-reported data), with the regression coefficient being 0.74, statistically different from 1. The difference in means of about 9.3 hours/week (about 1.55 hours/day) may stem from differences in how drivers think of "work", potentially including waiting periods, or breaks, versus actual time logged in on the platform. Overall, the self-reports of earnings are very accurate, while the self-reports of hours are slightly lower than in the administrative data.

In Kenya (Table A9, columns 3-4), we examine the correlation for the full sample of drivers surveyed on Monday (columns 3) and isolate full-time consistent drivers who do not multi-home (columns 4) from the rest of the drivers (columns 5). Simultaneous usage of multiple platforms is very common in Kenya (about 41% of drivers report this), so estimating working hours for a single platform can be more challenging than in India. The correlation coefficient is 0.62 for all drivers, suggesting that self-reported hours are higher than hours recorded on the platform. The discrepancy between platform and self-reported hours is likely driven by the same explanation as in India, and drivers think of work differently than simply logging in/out, despite the questionnaire asking to exclude breaks from the calculation[29]. Zooming in on a sub-sample of drivers who work full-time on the platform and do not multi-home (column 4) reveals a higher correlation between self-reported and survey data of 0.79; however, it is still statistically different from one. The averages (shown at the bottom of the table) in the survey and admin datasets are extremely close for full-time drivers, which is not the case for the rest of the drivers. We believe that these differences are due to the difficulty of attributing work to a single platform. We conclude that data reported by full-time drivers is more accurate than that of other drivers.

[28] Gross self-reported earnings were collected in India

[29] In the past 7 days, how many hours did you spend working on [platform]. Note to enumerator: Ask them to think of the total amount of time spent logging into any platform. For example, if you first logged on at 6 a.m., then logged out at 12 p.m., took a break, and then logged in from 4 pm to 6 pm, that's a total of 8 hours on that day of a full-time

Table A9: Comparison of [platform] earnings and hours between survey and administrative data drivers surveyed on Monday (India and Kenya)

	(1)	(2)	(3)	(4)	(5)
	India [platform] administrative data		**Kenya [platform] administrative data**		
	All drivers		**All drivers**	**Full time Consistent**	**Other drivers**
	Earnings (4 weeks before the week of the survey)	**Hours (1 week before the week of the survey)**	**Hours (1 week before the week of the survey)**	**Hours (1 week before the survey)**	**Hours (1 week before the survey)**
Survey Data					
Gross Earnings (4 weeks before the survey)	0.97		–	–	–
Hours (1 week before the survey)		0.74***	0.62***	0.79**	0.58***
Observations	403	408	235	34	201
R-squared	0.66	0.78	0.67	0.79	0.65
Pvalue testing Beta=1	0.42	<0.01	<0.01	0.01**	<0.01
Mean in administrative data (PPP adjusted USD)	725.5	32.3	29.70	50.18	27.32
Mean in survey data (PPP adjusted USD)	706.9	41.5	42.45	55.33	40.96

Notes: In India and Kenya, the administrative data is available at the weekly level, which spans Monday-Sunday. We do not have survey data on gross earnings in Kenya, but include it in India for earnings in the past 4 weeks. Only a subsample of drivers who were surveyed on Monday is included in the validation to more closely match the observation window in the administrative data. The dependent variable is earnings/hours in the administrative data, independent variable is earnings and hours reported for the platform work. The regression is run without a constant term. p-value testing beta=1 is reported to understand whether the correlation between 2 variables is different from 1.