Driving Electric Rides: Experimental Evidence on Vehicle Access Contracts, Labor Productivity, and Driver-Firm Incidence*

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Abstract

We examine how asset-access contracts shape labor productivity and the distribution of returns between workers and firms, drawing on randomized and natural experiments with motorcycle drivers and electric-vehicle (EV) fleet and battery firms in Nairobi. Offering applicants a fixed-wage opportunity to drive EVs increases daily labor hours by 1.37 hours (17 percent) and earnings by USD 1.8 (27 percent), while reducing gasoline expenditures by USD 1.4 (57 percent). Transitioning drivers from the fixed-wage contract to a lease-to-own (LTO) arrangement raises labor hours by 3.52 hours (38 percent) and earnings by USD 4.2 (33 percent), and lowers gasoline consumption by USD 0.45 (20 percent). Treating energy as an intermediate input, we augment drivers' value-added production function with the labor-effort first-order condition, estimate post-LTO parameters, and backcast them to pre-LTO data to evaluate productivity dynamics and the incidence of returns. Within two months, LTO increases labor productivity by 37 percent through greater income and time flexibility, raises battery-vendor revenues net of grid-electricity costs by USD 1.48 (44 percent), and shifts the fleet supplier toward a more financially sustainable model. Despite longer work hours, drivers' average short-run welfare remains unchanged under LTO, although job-satisfaction and mental-health measures remain stable. A long-term follow-up survey and analysis are underway.

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1 Introduction

Each year, millions of drivers deliver billions of passenger rides (Uber, 2025; Jiang, 2025).[1] These trends reflect a broader global shift in labor markets: the rise of digital marketplaces, which has not only enabled more efficient curation of goods and services, but has also allowed workers to curate their own labor supply through enhanced interpersonal connectivity and algorithmic matching platforms (Cramer and Krueger, 2016; Chen et al., 2019). For instance, more than 200 million workers in China now participate in the gig economy, with analogous trends evident across major African and Asian cities (The Economist, 2025; Nguimkeu, 2025).

Concurrently, transport sector in the globe is undergoing a transition toward electrification, with anticipated gains from cleaner, more energy-efficient transport reshaping urban mobility (Holland et al., 2016; Li et al., 2017; Holland, Mansur, and Yates, 2022; Yu et al., 2023). In 2024, India installed 40,000 new electric-vehicle (EV) charging stations along major highways (International Energy Agency, 2025). Vietnam has begun phasing out gasoline motorcycles in Hanoi and Ho Chi Minh City through circulation and registration bans, and Ethiopia recently prohibited the importation of internal-combustion-engine vehicles (Vietnam Investment Review, 2025; Le Monde, 2024). Notably, these two dynamics—vehicle electrification and the expansion of gig-based labor—are increasingly intersecting in developing-country cities, where urbanization is rapid, formal employment opportunities remain limited, and informal transport systems continues to support the livelihoods of millions.

These intertwined trends make it essential to understand how EV access interacts with gig labor in urban markets like Nairobi, where economic activity relies heavily on informal service work and where electrification is reshaping how workers engage with cleaner, more energy-efficient capital. Yet rigorous evidence remains scarce on how EV access and contract structures jointly affect productivity, earnings, and the incidence of returns—especially in developing-country contexts—and on whether emerging models of EV-enabled gig work create durable economic opportunities or entrench precarious, low-margin labor (Acemoglu et al., 2016; Muehlegger and Rapson, 2022; Juhász and Lane, 2024).

This study examines one of the earliest introductions of electric on-demand transport in Nairobi's motorcycle-taxi market. It analyzes drivers' behavioral responses—and the resulting firm-side and welfare implications—as they transition through successive contract regimes, from fixed-wage employment to flexible, ownership-oriented self-employment, within a unified market environment (Hart and Moore, 2008; Chen et al., 2019; Barker et al., 2025). In doing so, it contributes to broader investigations into labor-market organization, gig-work dynamics, and the role of clean technology in urban economic development.

We evaluate two complementary research designs. The first, an experimental Guaranteed Salary Program (GSP) randomized controlled trial (RCT), assesses how offering an EV-based GSP contract affects labor supply, earnings, and energy use among internal-combustion-engine (ICE) drivers and job seekers. The second design examines the transition from fixed-wage GSP employment to a flexible Lease-to-Own (LTO) contract as a natural experiment, studying how this contractual shift alters driver behavior, productivity, and the allocation of

1. Uber's 2025 Q3 earnings report projects 9.4 million drivers providing 14 billion rides in 2025, and estimates for Didi place it at roughly 15 million and 11 billion rides (Smith, 2021; KrAsia, 2018). Other major platforms, such as Lyft, Grab, Gojek, Bolt, Yango, Kakao T—also operate at substantial scale.

surplus between drivers and firms. To implement these designs, we partner with private-sector fleet and battery operators to collect high-frequency survey data and acquire EV telemetry, enabling empirical and structural estimation of behavioral responses and market dynamics. Using these data, we estimate production, cost, and incidence outcomes to quantify market productivity and to trace how surplus is distributed across drivers, the fleet operator, and the battery vendor. Although the contractual mechanisms we study are not theoretically tied to an EV technology, their empirical viability relies on EVs' substantially lower operating costs and built-in digital traceability (U.S. DOE, 2024; Gertler, Green, and Wolfram, 2024).

Preliminary empirical findings indicate sizable behavioral and market responses. In Experiment 1, offering a GSP contract increases daily labor hours by 1.37 (17%) and daily earnings by USD 1.8 (27%), while reducing gasoline expenditures by USD 1.4 (57%). In Experiment 2, transitioning from GSP to LTO raises labor hours by 3.52 hours (38%) and earnings by USD 4.2 (33%), and lowers gasoline use by USD 0.45 (20%).

To understand the economic benefit and cost implications of these shifts, we treat energy as an intermediate input and conduct structural estimation to identify the mechanisms underlying the observed revenue gains and to examine worker–firm distributional effects across contractual regimes. Our approach builds on a long-standing literature on value-added production-function estimation (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; De Loecker and Warzynski, 2012; Ackerberg, Caves, and Frazer, 2015). While not directly comparable, our model also embeds an agency-based first-order condition—akin in spirit to Gandhi, Navarro, and Rivers (2020)—to capture drivers' labor–effort–cost optimization. We estimate the model using data from the LTO transition and backcast it to pre-transition periods. This structural exercise extends existing approaches by introducing a data-driven workaround to address empirical questions related to asset access, contractual arrangements, and fixed versus flexible wages. The motorcycle-driving context also offers a uniquely clear illustration of energy as an intermediate input and of value-added production under contract-based asset access.

Preliminary results based on this approach indicates that, within two months of the LTO transition, labor productivity increases by 0.32 log points (37%), battery-vendor net revenues ("gross profits") rise by USD 1.48 (44%), and the fleet operator moves from deficit to break-even. Despite these shifts, drivers' average short-run welfare remains constant under LTO: job satisfaction and mental health indicators are stable, while expanded job autonomy and ownership prospects continue to motivate workers. A one-year follow-up survey is forthcoming.

A large literature on labor, contracts, and production function estimation informs our analysis, yet direct evidence on productivity and distributional incidence in the context of EVs and gig work remains scarce (Holmström, 1979; Lazear, 2000; Hall and Krueger, 2018). A core challenge is to analyze the formal contractual entry of informal gig workers and to compare wage-employment and self-employment contractual transitions within a consistent empirical framework—both because such transitions are rarely observed in available data, and because modeling the first-order conditions for fixed-wage workers is not straightforward. This paper contributes to the literature on clean-technology adoption and labor-market organization by documenting one of the first empirical cases of gig-transport electrification in Nairobi, Kenya.

Section 2 introduces the partner firm's contractual models for EV asset access. Section 3 explains the research designs and data construction. Sections 5 and 6 develop the conceptual framework and empirical approaches. Section 7 presents the results. Section 8 offers concluding remarks and policy implications.

2 Two Contractual Structures for EV Asset Utilization

In this study, we evaluate two experiments by partnering with an electric-motorcycle taxi company in Nairobi, Kenya. Established in 2023 and operating its service for a large digital platform's Kenya's EV category in Nairobi, the company operated around five hundred electric motorcycle assets.[2] Two unique features of the company, being a startup and operating the fleets as part of a digital-platform ride-hailing service, introduced unique strengths and limitations to our study.

First, we compared two asset contractual models—limited access through employment and full access through lease-to-own arrangements — as the newborn startup constantly explored different business models. During our field research collaboration, the business model transitioned from the employment-based EV motorcycle operation to LTO asset-based operation for EV ownership transfer. Taking this transition as a natural experiment, we could conduct field data collection and compare the employment-based and leasing EV asset access contracts. On the downside, the business model change overturned our original design of a cohort phase-in randomized controlled trial (RCT) for EV-based employment and paratransit drivers' labor supply, productivity, and gasoline expenditure. We conducted the first experiment with a small cohort. Second, as a digital platform's fleet operator, the company provided drivers with stable passenger demand. Therefore, our study on contracts, labor supply, and worker-firm welfare incidence were minimally affected by demand-side factors.

2.1 Wage Employment for the Firm's EV Asset Operation

At the time the researchers began the experimental partnership, the company was operating the "Guaranteed Salary Program (GSP)," under which it employed volunteers who were qualified to operate motorcycles as EV motorcycle drivers on the digital platform for six days a week, twelve hours a day. To be employed as a driver, candidates had to go through a driver's license check, an onsite driving test, registration on the digital platform as a driver, and company orientation.

Driving the EV asset for 72 hours per week on the digital platform, workers received a monthly compensation package consisting of a base salary, overtime pay, and a housing allowance, totaling about 31,000 Kenyan Shillings (KSh), equivalent to 230 USD. For high performers, the company paid additional incentives of 500 to 1,000 KSh, varying by month. Within the 72-hour weekly shift, 52 hours were compensated at a base salary of 17,750.00 KSh, 20 hours were paid as overtime at 10,340.00 KSh, and a housing allowance of 2,662.50 KSh was provided. Contracted monthly hours and compensation were fixed for all drivers, but the data indicate adjustments through changes in daily shifts and more frequent absences.

The compensation amount was slightly lower than the average earnings of Nairobi motorcycle drivers, who typically earn around 1,000 KSh per day and operate 24 days per month. However, the effective take-home pay for the driver employees was much higher because they

2. The figure reflects the experimental period from late 2024 to early 2025. The company has since expanded rapidly, aiming to reach 3,000 vehicles in the Nairobi market.

did not need to pay for fuel costs except for commuting and other maintenance and operational expenses. Registered as part of the formal workforce, the drivers also enjoyed benefits, including medical insurance, accident coverage, and other social security schemes for formal workforce. In addition, they could provide cash-based paratransit services with the EV asset, taking advantage of the principal–agent relationship on the roads.

The firm conducted monthly performance reviews to screen and lay off low performers and those who acted against laws and social norms in order to maintain high service standards and sustainable business profits.[3] It hired new drivers to fill the resulting vacancies. To detect fraudulent absences and undesirable road behaviors, the company monitored real-time GPS information of drivers and made phone calls to them under suspicious circumstances.

The employment-based EV contract lasted until mid-December 2024, when our three-month RCT period ended, and the firm gradually exited the model until mid-January. The contractual transition began in late October 2024, starting with drivers who were not part of our RCT sample. Participants in the RCT treatment group accounted for about 5% of incumbent drivers in the GSP program.

2.2 Lease-to-Own Arrangement for the EV Asset Ownership Transfer

The firm recognized the need to increase its profit margin to reduce asset-related risks and prepare for future fleet renewal and expansion. As a result, it officially announced a shift to an LTO asset-based contractual model on October 25, 2024. Under this new scheme, independent driver volunteers could operate the company's electric motorcycles without access limits as if they were their own and eventually acquire ownership through a Lease-to-Own (LTO) arrangement. As an exchange, the contract required them to pay a daily lease fee of KSh 399 over 18 to 24 months.[4] During the lease period, drivers could retain and operate the vehicle for as many hours as they wished, provided they met the firm's minimum ride requirements on the digital platform. Unlike in the GSP program, drivers who transitioned to the LTO scheme were considered self-employed, becoming responsible for their own medical insurance and social security contributions[5], as well as EV battery charging and swapping costs, and other maintenance and operating expenses.

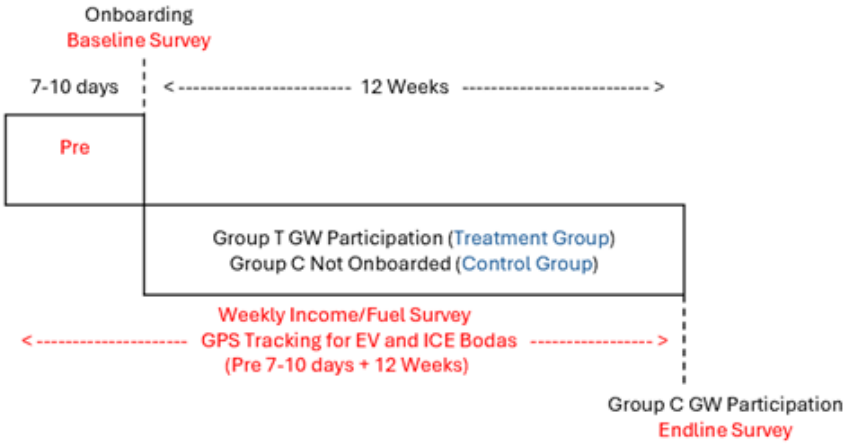
The LTO transition was first offered to existing drivers, commencing on the announcement date and concluding in early January 2025. Thereafter, the company began recruiting new applicants for the LTO contracts with its remaining fleet. Treating the contractual transition of incumbent drivers as a natural experiment, we conducted surveys and other data collection activities over four months, from October 14, 2024, through February 9, 2025. By the end of this period, all incumbent drivers had either transitioned to the LTO scheme or exited the firm.

3. Examples include frequent absentees, individuals who drove under alchohol or other influence, and those who engaged in misconduct towards passengers or society.

4. There exists an initial setup fee of 10,000 KSh, but incumbent drivers in our study were exempted.

5. The vehicle and third-party insurance were covered by the company, and the premium costs were included in the lease fee. After our study, the company is constantly improving the benefits. It recently introduced an optional medical program in which drivers could enroll by paying their own premiums.

Figure 3.1: Randomized Controlled Trial (RCT) Design and Timeline for Hiring Incentives



3 Experimental Design

3.1 RCT Experiment on the Impact of EV Contract on Labor Supply and Productivity

We first conducted a Randomized Controlled Trial (RCT) to evaluate the impacts of employment-based EV asset offerings on paratransit drivers' labor supply, productivity, and gasoline expenditure. [Figure 3.1] shows our RCT experimental design for GSP impact evaluation.

Our target population is potential paratransit drivers when an EV asset is offered through employment. This includes existing independent paratransit drivers without EVs, job switchers, and active job seekers from both the formal and informal labor markets. In the actual sample recruitment, we found that the sample consists of active motorcycle drivers (45.1%), job seekers who were motorcycle drivers for more than a year (43.1%), and job seekers without motorcycle operating experience. There was no job switcher.

Working with a headhunting vendor that listed driver applicants weekly for the partner company, we designed a cohort phase-in RCT with up to 400 candidates. Each week, the vendor listed 30–70 applicants, while the partner firm discharged about 30 drivers based on performance and conduct reviews. We randomly assigned half of the listed applicants to fill these vacancies, forming the treatment group. The control group received smaller yet continuing survey compensation and is waitlisted for the GSP onboarding after the experiment. In the meantime, they remained as self-employed motorcycle drivers or job seekers who were free to seek other jobs.[6]

In close coordination with the field team, a computerized lottery was carried out by researchers in Washington, D.C., immediately after all drivers completed the baseline survey and passed the eligibility screening in Nairobi. The experiment successfully onboard the first cohort of 51 drivers. However, while we were preparing to conduct the baseline survey and random assignment for the second cohort, the company decided to shift its business model to

6. The GSP program disappeared when we finished the experiment. Instead, the control group was offered LTO operational contracts.

the LTO scheme in pursuit of greater profitability.

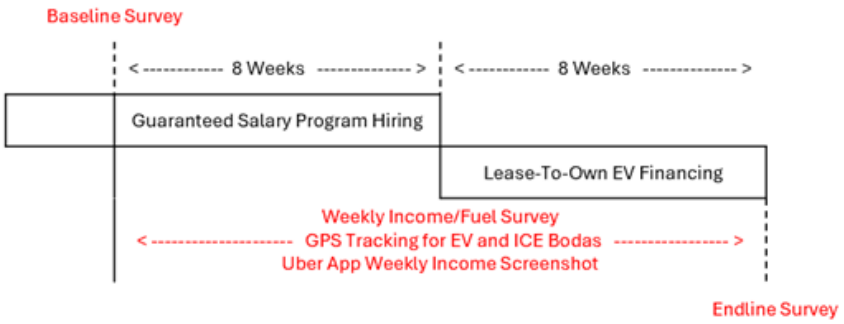
Therefore, the 51 drivers comprised the final sample for the RCT experiment. The analysis results on the first experiment draw on the drivers' baseline and endline survey responses, daily income, work hours, fuel expenditure surveys, and GPS telemetry records collected during the three month experimental period. Two control group drivers dropped out during the study, resulting in a 4% attrition rate.

3.2 Asset Contract Transition as a Natural Experiment

Taking the firm's business model transition as a natural experiment, we conducted a second round of field data collection. This time, the target population was existing EV paratransit drivers. We examined whether the contract transition from employment-based vehicle access to permanent ownership transfer through leasing affected their labor supply, productivity, and the distribution of welfare between drivers and the contracting firm. [Figure 3.2] shows the simplified transition and data collection timeline.

Our sample includes 427 incumbent workers. Despite the redesign and implementation of the experiment over a relatively short period, as well as the collection of additional sensitive data, the attrition rate among drivers remained low at 5%. Data from two drivers who mistakenly failed to submit the baseline survey but participated in all subsequent data collection activities are included in the robustness checks. The research team collected extensive information on worker, firm, and welfare outcomes before, during, and after the transition of incumbent drivers. In this experiment, we specifically gathered data on EV fleet operating costs, including daily battery charging expenses and other maintenance and operational costs.

Figure 3.2: Experimental Timeline for the Contractual Transition



Note: The actual transition of each driver was staggered over the four-month experimental period. The figure presents a simplified version of the design.

4 Data

4.1 Data Collection from Varying Sources

Conducting the above experiments, we collected multiple survey and geospatial field datasets. Recent technological developments—such as cloud-based document version control, mobile

app–based data access, and GPS trackers and telemetry—helped us increase data frequency and precision.

BASELINE AND ENDLINE SURVEYS To evaluate broader labor and asset outcomes from the two experiments, we implemented baseline and endline surveys—comparing treatment and control groups in the RCT and examining drivers before and after the LTO program transition in the second experiment. In the first experiment, the baseline survey was administered on the driver onboarding day, immediately after employment qualification checks (e.g., driver's license verification) and before random assignment. In the second experiment, the baseline survey was conducted over two days with incumbent driver employees, in the order they arrived at the firm's yard to begin work.

The endline survey was administered at the conclusion of each study period—three months for the first experiment and four months for the second—under conditions similar to the baseline, at the partner company's yard. The first experiment's survey instrument included the following sections: (A) demographics, (B) labor conditions, (C) vehicle and asset ownership, (D) road behavior and safety, and (E) mental well-being.

For the transition experiment, we used a baseline survey similar to that of the RCT but expanded the endline questionnaire—particularly Section C, Vehicle and Asset Ownership—to capture changes in drivers' vehicle ownership, operational burdens, and satisfaction with EV motorcycle driving before and after the contractual transition.

VERSION CONTROLLED TABLE SURVEY FOR DAILY SURVEYS Because taxi driving involves day-to-day earning activities, drivers' income and labor costs fluctuate daily. Moreover, paratransit workers are relatively low-skilled and often engage in informal income-generating activities, switching between digital-platform driving, cash passenger rides, and seasonal, temporary, or family jobs to maximize earnings and support household businesses. To capture granular changes in daily income and labor costs, the study team conducted surveys covering Monday through Sunday, recording labor income, work hours, and other expenditures by work type.

Using a cloud-based Excel spreadsheet with timestamped version history, the team created weekly survey tables spanning Monday to Sunday. On baseline days, enumerators assisted drivers in installing the mobile app, linked each driver to an individualized Excel file, and provided instructions. Thereafter, drivers accessed their own survey form through the app and updated the table. Enumerators checked in weekly with the drivers to ensure survey completion, provide compensation, and assist them in transitioning to a new weekly tab.

This cloud-based Excel system enabled the study team to collect approximately 90 daily labor and cost data points from each driver in the RCT sample, and about 120 such data points from each of the 429 drivers in the transition experiment sample. The resulting granularity allowed for more sophisticated causal evaluation of both the smaller RCT sample and the larger transition sample, particularly with respect to labor income, labor supply, and fuel expenditure before and after the EV adoption and business model transition.

GPS AND BATTERY STATUS TELEMETRY Depending on vehicle type and employment status—employed versus self-employed—drivers' road behavior and safety can vary. For exam-

ple, internal combustion engine (ICE) motorcycle drivers in the RCT control group may have spent longer hours on the road or driven at higher speeds to earn additional income to cover fuel costs (Behrens, Chalermpong, and Oviedo, 2021). By contrast, treatment group drivers with a stable base salary may have driven more cautiously. After transitioning to the LTO ownership transfer model, drivers may have reverted to faster and longer driving patterns.

To investigate potential differences in road behavior, we conducted GPS telemetry with nine volunteers from the RCT control group and fourteen incumbent EV employees by attaching trackers to the personal ICE motorcycles.[7] In addition, the EV firm's battery vendor provided GPS and battery telemetry data, which we merged with our tracker data for analysis. Millions of data points from both EV and ICE vehicles allow us to study drivers' road behavior under different contractual and labor conditions. Because the ICE motorcycle telemetry sample represents only a subset of the control group and transition experiment vehicles, we also compare these data with existing Kenyan motorcycle statistics to validate representativeness.

Battery capacity and depletion speed are critical for the productivity of electric motorcycle drivers, particularly in developing economies with limited charging stations. Accordingly, we also utilize real-time battery telemetry data from the EV assets to estimate energy use and carbon emission implications.

PLATFORM EARNINGS INFORMATION FROM DRIVERS The business model transition involves vehicle ownership transfer, enabling company drivers to use EV assets for non-platform driving. With this flexibility, most drivers began offering a portion of services outside the platform, after meeting the ride requirements or activating the app when street demand was low.[8]

To collect both platform and non-platform income, we asked drivers to report their platform earnings. The ride-hailing app allows drivers to view their weekly earnings history, enabling enumerators to collect several months of data at once. Because app-based income information is sensitive, approximately 20% of drivers were reluctant to share it, and we have data from around 80% of our sample.

5 CONCEPTUAL FRAMEWORK

The data assembled so far combine information on revenues, labor hours, energy expenditures, maintenance costs, and asset access fees. These data allow us to examine, in reduced form, how outcomes progress under different contract structures—ranging from no access, to limited access via the GSP program, to full access under the LTO program. At the same time, they motivate a broader question. Is this market's restructuring still in an experimental and uncertain phase, or are the conditions for growth and sustainability becoming increasingly well defined?

To address this latter question, we focus on the core production process, examining how drivers combine labor hours and energy inputs to generate rides and revenues, how they bal-

7. The control group drivers operate it as their main paratransit service vehicle, and the EV employees also utilize the vehicle for commuting and extra hours driving.

8. These outside services are offered through other apps (e.g., Bolt or SafeBoda), or to cash-paying passengers on the street.

ance the marginal benefits and costs of labor, and how the resulting surplus is shared among market participants—drivers, the EV fleet operating startup, and the battery vendor. Once drivers transition to an LTO contract, they gain full autonomy not only over their labor hours but also over their income, taking home the full value of their earnings, while bearing explicit variable and fixed costs for energy and vehicle access. Building on this production framework, we examine how the LTO transition reshapes welfare outcomes for both firm and the broader market.

5.1 The Driver's Problem after the LTO Transition

Each week t, driver i chooses labor hours L_{it} and battery-swap energy E_{it} measured in kilowatt hours (kWh), given information set $\mathcal{I}_{it}$, which includes the vehicle access contract $\mathcal{A}_{it} = \text{LTO}$. Realized service output—equivalently, revenue-weighted trips—is constrained by the bottleneck between time available for work and energy input. Drivers experience disutility of effort from labor supply. They also pay a fixed weekly leasing fee and cover maintenance costs for their vehicle.

5.1.1 Environment and Timing

The information set $\mathcal{I}_{it}$ contains the contemporaneous and lagged realizations of contracts, prices, and productivity shocks that shape the driver's optimal choice of labor hours and energy use. Let p_t^Y denote the effective output price per unit of ride service, reflecting fare levels, demand conditions, and platform commissions; this price varies across weeks but is common across drivers. Driver productivity is subject to an idiosyncratic shock ω_{it}, capturing factors such as skill, location, health, and weather. Productivity follows a first-order autoregressive process,

$$\omega_{it} = \rho\, \omega_{i,t-1} + \xi_{it},$$

where ρ is the persistence parameter and ξ_{it} is an innovation term.

5.1.2 Production

Weekly revenue (before lease and maintenance) is given by

$$R_{it} = p_t^Y \ \min\Big\{ \underbrace{\psi^L\, L_{it}^{\beta^L}}_{\text{labor limb}}\, e^{\omega_{it}},\ \underbrace{\psi^E\, E_{it}}_{\text{energy limb}} \Big\}\, e^{\epsilon_{it}}, \tag{5.1}$$

where p_t^Y is the effective output price, $Y_{it} = \min\{\psi^L\, L_{it}^{\beta^L}\, e^{\omega_{it}},\ \psi^E\, E_{it}\}\, e^{\epsilon_{it}}$ is realized output, ω_{it} is the persistent productivity component, and ϵ_{it} is an unanticipated shock.

5.1.3 Costs

The driver incurs disutility of effort from labor supply, modeled as a power function of hours worked with curvature parameter υ:

$$C_t(L_{it}) = \kappa_t^C\, L_{it}^{\upsilon},$$

where υ governs the curvature of effort costs and κ_{it} is a cost shifter. In particular,

$$\kappa_t^C = \kappa_0^C + \kappa_1^C \cdot \mathbb{1}\{\text{week cluster}\},$$

so that effort costs may differ during salient periods such as holidays, when demand conditions and scheduling constraints may deviate from regular weeks.

Next, we consider energy, maintenance, and leasing-fee costs. Let p_t^E denote the battery-swap price (KSh per kWh). Drivers pay energy costs amounting to $p_t^E E_{it}$. They also incur maintenance costs, modeled as a fixed proportion of weekly revenue, $M_{it} = \kappa^M R_{it}$, where κ^M is exogenously given. Finally, the driver pays a weekly leasing fee set by the EV fleet company, κ_{it}^{LTO}, which can depend on whether the driver meets weekly targets set by the company:

$$\kappa_{it}^{\text{LTO}} = \begin{cases} \kappa^{\text{LTO,l}}, & \text{if } Y_{it} \geq Y^{\text{lb}} \text{ and } L_{it} \geq L^{\text{lb}}, \\ \kappa^{\text{LTO,h}}, & \text{otherwise.} \end{cases}$$

In practice, we assume that drivers always meet their targets and thus set $\kappa_{it}^{\text{LTO}} = \kappa^{\text{LTO,l}}$.

5.1.4 Agency

Driver welfare ("DR") under LTO is given by

$$\Pi_{it}^{\text{DR}} \mid \text{LTO} = R_{it} - C_t(L_{it}) - p_t^E E_{it} - M_{it} - \kappa_{it}^{\text{LTO}}.$$

The production frontier (no slack) implies equality between the labor and energy limbs:

$$\psi^L L_{it}^{\beta^L} e^{\omega_{it}} = \psi^E E_{it}. \tag{5.2}$$

Hence, for each additional expected unit of output, the driver must purchase $\frac{1}{\psi^E}$ units of energy, incurring an effective energy cost of $\frac{p_t^E}{\psi^E}$, which acts as a tax on output. Under the LTO arrangement, the driver's weekly profit can therefore be expressed as

$$\Pi_{it}^{\text{DR}} \mid \text{LTO} = \left(p_t^Y - \frac{p_E}{\psi_E}\right)(1 - \kappa^M)\, Y_{it} - \kappa_t^C L_{it}^{\upsilon} - \kappa^{\text{LTO,l}}.$$

Finally, the driver is assumed to maximize expected weekly profit, $\mathbb{E}\left[\Pi_{it}^{\text{DR}} \mid \text{LTO}\right]$, which implies the first-order condition:

$$\left(p_t^Y - \frac{p_E}{\psi_E}\right)(1 - \kappa^M)\, \psi^L e^{\omega_{it}} \beta^L L_{it}^{\beta^L - 1} = \kappa_t^C \upsilon L_{it}^{\upsilon - 1}. \tag{5.3}$$

5.1.5 Identification

On the production side, the setup corresponds to a value-added specification in the spirit of Ackerberg, Caves, and Frazer (2015), abstracting from capital. This allows the application of their invertibility argument—refining the approaches of Levinsohn and Petrin (2003) and Olley and Pakes (1996)—to establish identification of the production function parameters. Our framework satisfies the five ACF conditions:

1. *Information set.* The driver's information set $\mathcal{I}_{it}$ excludes future productivity shocks $\{\omega_{i\tau}\}_{\tau=t+1}^{\infty}$. The transitory shocks satisfy $\mathbb{E}[\epsilon_{it} \mid \mathcal{I}_{it}] = 0$.

2. *First-order Markov.* Productivity evolves according to $p(\omega_{it+1} \mid \mathcal{I}_{it}) = p(\omega_{it+1} \mid \omega_{it})$, which is stochastically increasing in ω_{it}.

3. *Timing of input choices.* Labor hours L_{it} are chosen at time t.

4. *Scalar unobservable.* Intermediate input demand can be expressed as $m_{it} = f_t(\omega_{it})$, where $f_t(\cdot)$ is a scalar function of productivity.

5. *Strict monotonicity.* The function $f_t(\omega_{it})$ is strictly increasing in ω_{it}.

On the cost side, the first-order condition of the driver's optimization problem identifies the parameters of the effort cost function.

5.2 Firms' Problems after the LTO Transition

In addition to drivers, two firms play a mechanical role in this market: the EV fleet service company ("FL") and the EV battery vendor ("BT").[9] For each driver-week observation, the EV fleet service company receives the leasing-fee payment:

$$\Pi_{it}^{\mathrm{FL}} \mid \mathrm{LTO} = \kappa^{\mathrm{LTO,l}}.$$

The EV battery vendor earns the difference between the price charged for battery swaps and the marginal cost per kWh set by the public utility ("PU"):

$$\Pi_{it}^{\mathrm{BT}} \mid \mathrm{LTO} = \left(p_t^E - p_t^{E,\mathrm{PU}}\right) E_{it}.$$

5.3 Backcasting to the Pre-LTO Period

Contracts in this market can take two forms: the lease-to-own program ("LTO") and the guaranteed-salary program ("GSP")—such that $\mathcal{A}_{it} \in \{\mathrm{GSP}, \mathrm{LTO}\}$. Let w^{GSP} denote the driver's fixed weekly wage under GSP. The driver's problem across contract types is given by

$$\Pi_{it}^{\mathrm{DR}} = \begin{cases} w^{\mathrm{GSP}} - \kappa_t^C L_{it}^{\upsilon}, & \text{if } \mathcal{A}_{it} = \mathrm{GSP}. \\ \left(p_t^Y - \frac{p_t^E}{\psi^E}\right)\left(1-\kappa^M\right) Y_{it} - \kappa_t^C L_{it}^{\upsilon} - \kappa^{\mathrm{LTO,l}}, & \text{if } \mathcal{A}_{it} = \mathrm{LTO}. \end{cases}$$

The EV fleet service company's problem is

$$\Pi_{it}^{\mathrm{FL}} = \begin{cases} \left(p_t^Y - \frac{p_t^E}{\psi^E}\right)\left(1-\kappa^M\right) Y_{it} - w^{\mathrm{GSP}}, & \text{if } \mathcal{A}_{it} = \mathrm{GSP}. \\ \kappa^{\mathrm{LTO,l}}, & \text{if } \mathcal{A}_{it} = \mathrm{LTO}. \end{cases}$$

9. The ride-hailing platform determines the effective output price p_t^Y faced by drivers, capturing demand conditions and platform commissions, but its internal operations and costs are not modeled explicitly.

The EV battery vendor's profit is

$$\Pi_{it}^{\mathrm{BT}} = \left(p_t^E - p_t^{E,\mathrm{PU}}\right) E_{it}, \quad \text{if } \mathcal{A}_{it} \in \{\mathrm{GSP}, \mathrm{LTO}\}.$$

For completeness, we additionally define a third state ("NA") representing the no-EV-contract-access condition for drivers who previously operated their own internal-combustion-engine motorcycles. We model the NA state as

$$\Pi_{it}^{\mathrm{DR}} = \left(p_t^{Y,\mathrm{NA}} - \frac{p^{E,\mathrm{NA}}}{\psi^{E,\mathrm{NA}}}\right)\left(1 - \kappa^{M,\mathrm{NA}}\right) Y_{it} - \kappa_t^C L_{it}^{\upsilon}, \quad \text{if } \mathcal{A}_{it} = \mathrm{NA},$$

with $\Pi_{it}^{\mathrm{FL}} \mid \mathrm{NA} = \Pi_{it}^{\mathrm{BT}} \mid \mathrm{NA} = 0$.

When access contracts are GSP or LTO, we define total market surplus in each driver-week as the sum of profits accruing to the driver, the fleet service company, and the battery vendor:

$$\Pi_{it}^{\mathrm{Total}} = \Pi_{it}^{\mathrm{DR}} + \Pi_{it}^{\mathrm{FL}} + \Pi_{it}^{\mathrm{BT}}, \quad \text{if } \mathcal{A}_{it} \in \{\mathrm{GSP}, \mathrm{LTO}\}.$$

Substituting from the respective component yields

$$\Pi_{it}^{\mathrm{Total}} = p_t^Y \left(1 - \kappa^M\right) Y_{it} - \kappa_t^C L_{it}^{\upsilon} - p_t^{E,\mathrm{PU}}, \quad \text{if } \mathcal{A}_{it} \in \{\mathrm{GSP}, \mathrm{LTO}\}.$$

We leave the driver's agency under the GSP arrangement unmodeled.[10] However, because Y_{it} is directly observed in the pre-LTO period and the parameters of the production and effort-cost functions are identified from the LTO period, these parameters can be backcasted to infer the pre-LTO output residual. This residual captures total driver productivity, up to the unanticipated error term.

Let ζ_{it} denote the logged output residual:

$$\zeta_{it} = \begin{cases} \tilde{\omega}_{it} + \epsilon_{it} & \text{if } \mathcal{A}_{it} = \mathrm{GSP}, \\ \omega_{it} + \epsilon_{it} & \text{if } \mathcal{A}_{it} = \mathrm{LTO}, \end{cases}$$

where $\tilde{\omega}_{it} = (1 - \lambda^{\mathrm{GSP}})\, \omega_{it}$, and λ^{GSP} represents the dampening factor.

6 Estimation Framework

6.1 RCT-based Average Treatment Effect Estimation

Given the RCT setup, we conduct the average treatment effect (ATE) and Two-Way Fixed Effects (TWFE) DID analyses. The RCT sample is assumed to satisfy conditional equivalence with the drivers' random assignment:

$$D_t^{\mathrm{RCT}} = \begin{cases} 0, & \text{if } \mathcal{A}_t = \mathrm{NA}. \\ 1, & \text{if } \mathcal{A}_t = \mathrm{GSP}. \end{cases}$$

10. Why might drivers exert effort under the GSP arrangement? One possible reason is to respond to remote monitoring by the fleet management firm. Another is social preference—such as a sense of reciprocity toward guaranteed wages; see Fehr and Charness (2025) for a review. These non-pecuniary motivations do not lend themselves to straightforward modeling in the present setting.

This implies that the ATE for outcome O_i is given by

$$\widehat{ATE}^{\text{RCT}} = \mathbb{E}[O_i \mid D_i^{\text{RCT}} = 1] - \mathbb{E}[O_i \mid D_i^{\text{RCT}} = 0]$$

We estimate the following standard TWFE estimator with errors clustered at the driver level.

$$O_{it} = \alpha_i + \delta_t + \beta^{\text{RCT}} (D_i^{\text{RCT}} \times Post_t) + \epsilon_{it}^{O}$$

6.2 Staggered Difference-in-Differences Estimation

Drivers switch from the GSP to the LTO contract at different points in time, but within a relatively short window. To measure how this transition affects outcomes, we estimate group-time average treatment effects (ATTs) using the Callaway and Sant'Anna (2021) framework.

At each calendar time t, we compare drivers who have already moved to LTO with those who have not yet switched—treating the latter as valid controls. The staggered rollout of LTO across drivers provides quasi-experimental variation that identifies causal effects under a "conditional parallel trends" assumption: that earlier-treated drivers serve would have followed the same outcome path as later-treated drivers in the absence of LTO.

Let $G_i = g$ denote the period in which dirver i first adopts LTO (with $G = 0$ for those who never adopt). Define $O_{it}(d)$ as the potential outcome under contract status $d \in \{\text{GSP}, \text{LTO}\}$, and $W_{it} = \mathbb{1}\{t \geq G_i,\, G_i > 0\}$ as the treatment indicator. The ATT for the cohort first treated in period g is then

$$ATT(g,t) \;=\; \mathbb{E}[\, O_{it}(LTO) - O_{it}(\text{GSP}) \,|\, G_i = g \,], \quad t \geq g,$$

identified by comparing that cohort's observed outcomes to those of the not-yet-treated drivers $\{i : G_i = g\}$ at time t.

We use the `did` implementation of Callaway and Sant'Anna (2021), which accommodates unbalanced unbalanced panels and produces cluster-robust standard errors at the driver level.

6.3 Production and Cost Function Estimation via GMM

We estimate the structural parameters of the production and cost functions using a two-step Generalized Method of Moments (GMM) procedure with cluster-robust standard errors.

Let lower-case letters denote logged variables, and place drivers on the production frontier. Following Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2015), we invert intermediate input demand $\omega_{it} = \tilde{f}_t^{-1}(l_{it}, e_{it})$, substitute this into the production frontier (eq. (5.2)), and rearrange the production function (eq. (5.1)) as

$$\begin{aligned} y_{it} &= \ln(\psi^L) + \beta_L l_{it} + \tilde{f}_t^{-1}(l_{it}, e_{it}) + \epsilon_{it} \\ &= \tilde{\Phi}_t(l_{it}, e_{it}) + \epsilon_{it}, \end{aligned}$$

treating $\tilde{f}^{-1}$ nonparametrically.

This yields the following first-stage moment condition:

$$\mathbb{E}[\epsilon_{it} \,|\, \mathcal{I}_{it}] = \mathbb{E}\big[y_{it} - \tilde{\Phi}_t(l_{it}, e_{it}) \,\big|\, \mathcal{I}_{it}\big] = 0.$$

We obtain $\hat{\tilde{\Phi}}_t(l_{it}, e_{it})$ by regrssing $y_{it} = r_{it} - \ln(p_t^Y)$ on a higher-order polynomial in (l_{it}, e_{it}) via OLS.[11]

The second-stage GMM step then estimates β_L and the remaining production function parameters using:

$$\mathbb{E}\Bigg[\Big(y_{it} - \ln(\psi^L) - \beta_L l_{it} - \rho\big(\tilde{\Phi}_{t-1}(l_{it-1}, e_{it-1}) - \ln(\psi^L) - \beta_L l_{it-1}\big)\Big) \otimes \begin{pmatrix} 1 \\ l_{it-1} \\ r_{it-1} \end{pmatrix}\Bigg] = 0, \tag{6.1}$$

where $\tilde{\Phi}$ is replaced by its first-stage estimate. In practice, we augment the instrument vector with other components of $\mathcal{I}_{it-1}$, such as l_{it-1}^2, to improve estimation performance and provide overidentifying restrictions.

Finally, we incorporate a cost-function first-order-condition moment based on eq. (5.3):

$$\mathbb{E}\Bigg[\Big(y_{it} - l_{it} - \ln(\beta_L) + \Big(p_t^Y - \frac{p_E}{\psi_E}\Big) + (1 - \kappa^M) - \Big(\ln(\kappa_t^C) + \ln(\upsilon) + (\upsilon - 1) l_{it}\Big)\Big) \otimes \begin{pmatrix} 1 \\ l_{it} \end{pmatrix}\Bigg] = 0, \tag{6.2}$$

which we also augment with additional components of $\mathcal{I}_{it-1}$, such as l_{it}^2, l_{it-1}, l_{it-1}^2, and $\ln(p_{t-1}^M)$, to enhance performance and overidentifying restrictions. While not directly comparable, our reliance on an agency-based first-order condition to strengthen identification is in the spirit of Gandhi, Navarro, and Rivers (2020).

7 Results

This section presents results from the two experiments and the structural estimation. We begin with the RCT evidence on how employment-based EV asset access affects drivers' labor supply, productivity, fuel use, and socioeconomic outcomes. We then examine the consequences of contractual transition from employment-based limited access to lease-based permanent asset ownership. Finally, we introduce the production estimation results, which quantify welfare redistribution between workers and firms.

7.1 Private Sector EV Business and the Paratransit Sector

7.1.1 RCT Balance Test

Table 7.1 reports balance tests for treatment and control groups at baseline, prior to random assignment. Panel A presents sample means for demographics and driving experience, while

11. We first estimate p_t^Y from the data using the production frontier and E_{it} and then proceed with the two-step procedure.

Panel B covers drivers' perceptions of motorcycle work. All variables are balanced across groups, except for reported perceptions of motorcycle earnings. Because the Panel B questions were asked only of 22 drivers who were already working as independent ICE motorcycle drivers, and treatment and control status was evenly distributed within this subgroup, the low p-value likely reflects small sample size and large standard errors. These perception variables are therefore excluded from the joint test in Panel A.

Table 7.1: Balance Test

Means	Control (C)	Treatment (T)	Difference (T – C)	p-value
Panel A: Demographics and Experience				
Age	29.458	29.800	0.342	0.848
Married	1.583	1.760	0.177	0.268
Household head	0.875	0.920	0.045	0.613
Household size	2.958	2.720	-0.238	0.646
Education (years)	11.875	11.240	-0.635	0.627
Years driving motorcycle	4.792	5.480	0.688	0.504
Years as boda driver	3.354	4.168	0.814	0.410
Joint test (p-value)[#]				0.637
Observations	24	25		
Panel B: Opinions on Boda Job				
Use Skills in Boda Taxi (Scale)	1.667	1.400	-0.267	0.511
Earnings from Boda Taxi (Scale)	1.500	1.100	-0.400	**0.039**
Boda Taxi has Safe Env. (Scale)	1.917	1.700	-0.217	0.562
Boda Taxi Unhealthy (Scale)	3.917	4.100	0.183	0.678
Likes Boda Taxi Job (Scale)	1.167	1.700	0.533	0.235
Boda Supports Finan. Needs (Scale)	7.083	7.600	0.517	0.609
Observations	12	10		

Note: The table reports baseline means for the treatment and control groups, along with differences and heteroskedasticity-robust p-values. The sample consists of 25 treatment and 24 control individuals. Questions on BodaBoda work were asked only of those employed as drivers at baseline, representing less than half of the sample. Because of the small number of observations, the joint Wald test excludes these variables. Results are similar when including the two attrited drivers, and the corresponding table will be provided in the appendix.

7.1.2 Wage Employment with EV Access and Drivers' Labor Market Outcomes

Table 7.2 reports the impacts of wage employment with EV access on treated drivers' labor market outcomes. The outcomes include labor hours and earnings by job type—Boda and non-Boda work for and outside the firm contract—as well as energy expenditure.

Panel A of Table 7.2 presents daily labor hours by job type. Column (1) shows firm hours, which are zero for all controls. Thus, the treatment effect corresponds to average daily hours worked by treated drivers, averaged with holidays, and indicates that drivers work slightly fewer hours than their contracted shifts.

Column (2) reports hours in outside motorcycle jobs. As firm hours increase, outside motorcycle hours decline sharply—by about 75 percent for treated drivers. Column (3) shows

Table 7.2: Effects of Firm Offer of Employment on Employment Outcomes

	(1) Hours worked (firm)	**(2)** Hours worked (other boda)	**(3)** Hours worked (non-boda)	**(4)** Total hours worked
Panel A: Hours Worked				
Treatment	6.148***	-4.184***	-0.868	1.095
	(0.726)	(0.847)	(0.583)	(0.676)
Observations	4,151	4,151	4,151	4,151
Control mean	0	5.52	1.79	7.31
	(1) Earning (other boda)	**(2)** Earning (non-boda)	**(3)** Non-firm earnings	**(4)** Fuel costs (Ksh)
Panel B: Earnings and Costs				
Treatment	-771.3***	-71.39	-842.6***	-171.2***
	(159.5)	(49.85)	(149.3)	(48.37)
Observations	4,151	4,151	4,151	4,151
Control mean	925.4	167.0	1,092	296.0

Note: The table shows the effect of the randomized treatment (employment in the firm) on a variety of outcomes. "Firm" refers to the partner firm in the study. The unit of analysis is the driver-day, so the coefficients represent differences in daily means. Robust standard errors are in parentheses.
** p<0.1, ** p<0.05, *** p<0.01*

that non-motorcycle hours also fall, although the effect is statistically insignificant given the number of missing observations. Column (4) aggregates labor hours across all activities and shows no statistically significant change, though the point estimate suggests an increase of roughly one hour, or 15 percent, relative to controls.

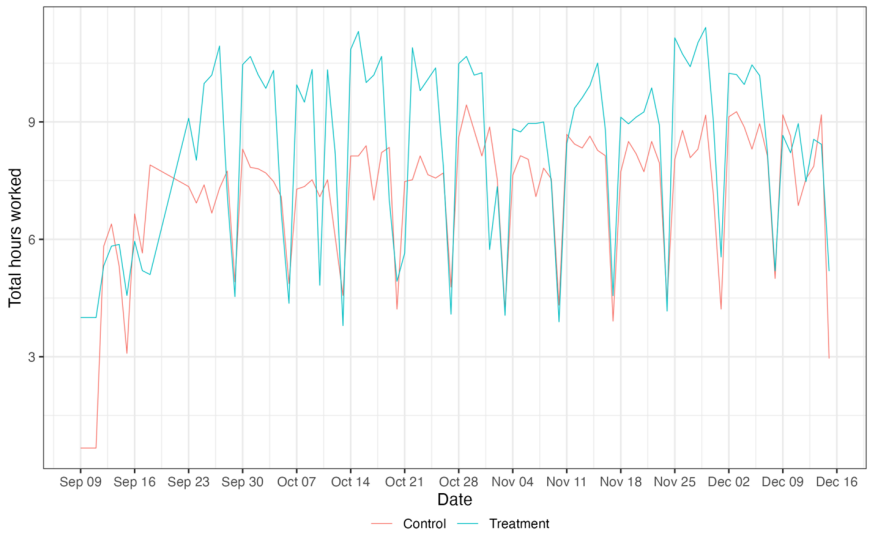
Columns (1)–(3) in Panel B report treatment effects on earnings, and Column (4) presents energy expenditure. Control drivers earned on average 925 KSh per day from non-electric motorcycle work, whereas treated drivers' earnings from this activity fell by about 83 percent to 153 KSh per day. Non-Boda earnings (Column 2) show no statistically significant change. However, when combined, total non-firm earnings (Column 3) decline significantly by about 77 percent, from 1,092 KSh to 249 KSh per day. Column (4) shows fuel expenditure, which fell by 58 percent, from 296 KSh to 125 KSh, as treated drivers used ICE motorcycles only for commuting.

Treated drivers, meanwhile, received a fixed monthly salary of 31,000 KSh from the firm, yielding substantially higher and more stable daily income under the EV employment contract. A simple back-of-the-envelope calculation shows that while non-firm earnings fell by 843 KSh, company wages added about 1,033 KSh per day and fuel savings contributed 171 KSh, raising gross daily take-home income by roughly 361 KSh.

Figure 7.1 plots mean daily labor hours over the three-month experimental period. Two features stand out. First, beginning on the onboarding day of September 19, 2024, labor hours of the treatment and control groups start to diverge. During the first few days, treatment group hours were lower than control hours due to firm registration and job transition. The relatively low hours for both groups before onboarding reflect participants were unemployed or working less hours than they can prior to joining the EV-based employment contracts. Second, both groups show a sharp dip in hours on Sundays, when many drivers paused or reduced work. Excluding these holidays yields even larger treatment effects, as reported in Table 7.2.

Table 7.3 reports estimates excluding Sundays and the initial onboarding days for treated drivers. The results show substantially larger impacts, but in the same direction as Table 7.2.

Figure 7.1: Mean Daily Labor Hours for Treatment and Control Groups



Note: The figure depicts mean total daily labor hours for the control (red) and treatment (blue) group drivers.

Total working hours increased by 1.37 per day, a 17 percent rise relative to the control mean of 7.98 hours. The total earnings from both company-hiring and non-company labor activities increased by 27%, equivalent to USD 1.8. Relative to the estimates in Table 7.2, earnings losses were larger for non-company motorcycle work but smaller for non-Boda activities, leaving the overall decline in non-firm earnings largely unchanged. When restricting the analysis to weekdays, gasoline expenditures among treated drivers decreased by 57%, corresponding to USD 1.4.

The RCT estimation results indicate that employment-based EV paratransit access increases both labor hours and income among Nairobi's paratransit workforce. In addition to the more productive utilization of labor, EV asset access reduces drivers' gasoline expenditures by more than half, presenting a significant opportunity to mitigate urban environmental challenges.

Nevertheless, potential drawbacks emerge from short-term liquidity constraints—since drivers receive a monthly salary instead of daily road-based earnings—as well as from rigid daily shift requirements. In the next section, we present estimation results from the transition experiment that compares employment contracts with lease-to-own (LTO) ownership transfer arrangements, assessing whether easing liquidity constraints and reintroducing gig-style flexible work arrangement can yield additional benefits for drivers.

7.2 Contractual Transitions and Labor Market Outcomes

7.2.1 Balance in Covariates between Early and Late Transitioners

We now turn to the estimation results from the natural experiment, which examines how contractual transitions in EV access affect drivers' outcomes. Because the design does not explicitly assign drivers to treatment and control groups, we implement a staggered Difference-in-Differences (DID) framework, in which drivers who transition later can serve as the control group for those who transition earlier (Callaway and Sant'Anna, 2021).

Table 7.3: Effects of Employment Offer on Employment Outcomes, Weekdays Only

	(1) Hours worked (firm)	(2) Hours worked (other boda)	(3) Hours worked (non-boda)	(4) Total hours worked
Panel A: Hours Worked				
Treatment	7.216***	-4.614***	-1.230*	1.373*
	(0.8511)	(0.8964)	(0.6424)	(0.7122)
Observations	3,282	3,282	3,282	3,282
Control mean	0	5.90	2.08	7.98
	Income (other boda)	Income (non-boda)	Non-firm earnings	Fuel costs (Ksh)
Panel B: Income and Costs				
Treatment	-851.7***	-99.01*	-950.7***	-179.0***
	(170.4)	(56.07)	(160.5)	(51.16)
Observations	3,282	3,282	3,282	3,282
Control mean	999.33	191.92	1,191.25	313.32

Note: The table shows the effect of the randomized treatment (firm employment) on various outcomes. The unit of analysis is the driver-day, meaning the coefficients represent differences in daily means. Robust standard errors are in parentheses. Sundays and the first two weeks of the sample are excluded.
* p<0.1, ** p<0.05, *** p<0.01

Our event-study graphs for the main outcomes—labor hours, earnings, and energy expenditure—do not present notable pre-trends, lending support to the validity of the DID approach. As complementary descriptive evidence, we also compare observable characteristics between earlier and later transition groups to assess balance in covariates.[12] The covariates are balanced except for years of education, which we control for in the subsequent analysis.

7.2.2 The Contractual Transition and Drivers' Labor Market Outcomes

Figure 7.2 presents staggered DID estimates of the contractual transition from employment-based EV access to vehicle leasing under self employment, and the resulting changes in gross weekly platform earnings. The analysis is conducted using the *att_gt()* function from the *did* package in *R*. The Y-axis reports changes in earnings (KSh), and the X-axis measures weeks relative to the transition date, with 0 corresponding to the exact transition week. Because drivers transitioned at different times between October and January, those who had not yet transitioned in a given week serve as the comparison group for drivers who had already transitioned.

We observe substantial increases in drivers' EV paratransit earnings on the platform following their transition to the LTO ownership transfer program-—about 5,000 KSh per week, or roughly 714 KSh per day. Although earnings briefly dip during the transition week, drivers adapt quickly to the new contractual arrangement and soon earn well above pre-transition levels.

Before the transition, platform earnings accrued directly to the company, and drivers received fixed wages of approximately 1,033 KSh per day and small performance-based incen-

12. Among the 331 drivers with complete information, including platform earnings, 174 belong to the later transition group and 157 to the earlier transition group.

Table 7.4: Balance Test of LTO Transition

	(1) Early Mean	**(2)** Late Mean	**(3)** Difference	**(4)** p-value (diff)	**(5)** p-value (reg)
Birth year	1993.2	1994.1	0.898	0.285	0.344
Years of experience (motorcycle)	6.052	5.651	-0.401	0.326	0.799
Years of experience (other jobs)	3.910	3.484	-0.426	0.274	0.502
Married	0.701	0.672	-0.028	0.582	0.935
Head of household	0.968	0.948	-0.020	0.366	0.998
Number of people in household	3.274	3.851	0.577	0.329	0.227
Years of education	10.529	11.879	1.351	0.001	0.001
Number of jobs	2.038	1.977	-0.061	0.067	0.071
Skills (Likert)	1.395	1.461	0.066	0.398	0.412
Income (Likert)	1.421	1.339	-0.082	0.196	0.116
Boda is safe (Likert)	1.618	1.552	-0.067	0.418	0.742
Boda is unhealthy (Likert)	2.914	2.770	-0.145	0.195	0.062
Likes boda job (Likert)	1.421	1.436	0.015	0.822	0.609
Boda supports financial needs (Likert)	6.763	6.873	0.110	0.733	0.930
Joint test (p-value)				0.057	0.040

Note: This table reports means for the early and late treated groups in columns (1) and (2), with "late" defined as being after the median transition date. Column (3) presents the difference (Late – Early). Column (4) reports the p-value for the difference in column (3), and column (5) reports the p-value from a regression using the numeric transition date. The last row gives the joint p-value from a regression including all covariates.

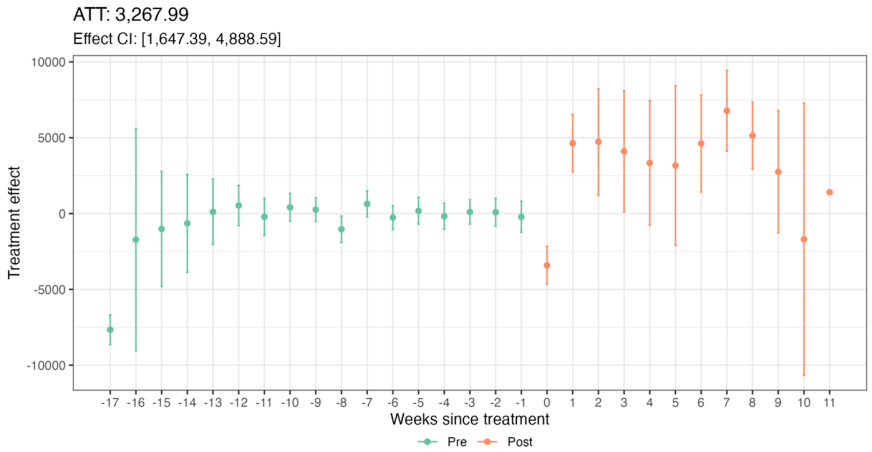
tives (see Section 2). After the transition, however, drivers directly retained all marginal earnings from the platform EV labor. The estimated average treatment effect is sizable. Drivers' gross daily earnings increased by USD 4.2, or roughly 33%, assuming a six-day work week. The shift to the LTO contract, which provides drivers with long-term, 24-hour access to the EV asset with full autonomy in utilization, substantially increased the figure.

Leasing the vehicle under self employment, however, makes the drivers responsible for all operational costs. In addition, they must pay a daily lease fee of 399 KSh. Figure 7.3 presents changes in take-home income from the contract, calculated by deducting fuel expenditures (before and after the transition), the post-transition lease fee, and other fleet maintenance costs from the platform earnings shown in Figure 7.2. Prior to the transition, drivers' net income consisted of fixed remuneration and small performance-based incentives, net of modest commuting fuel costs; hence, variation was relatively limited.

After the transition, there is a noticeable dip in earnings during the transition week, similar to the pattern observed in the gross earnings graph. However, drivers quickly recover their earnings in both cases. A second decline appears around the sixth to seventh week post-transition across both outcome measures, followed by a substantial rebound with high variation. This mid-period dip is likely attributable to year-end work stoppages, as most drivers transitioned between November 12 and 17, and the decline occurred approximately 50 days later—corresponding to late December and early January.

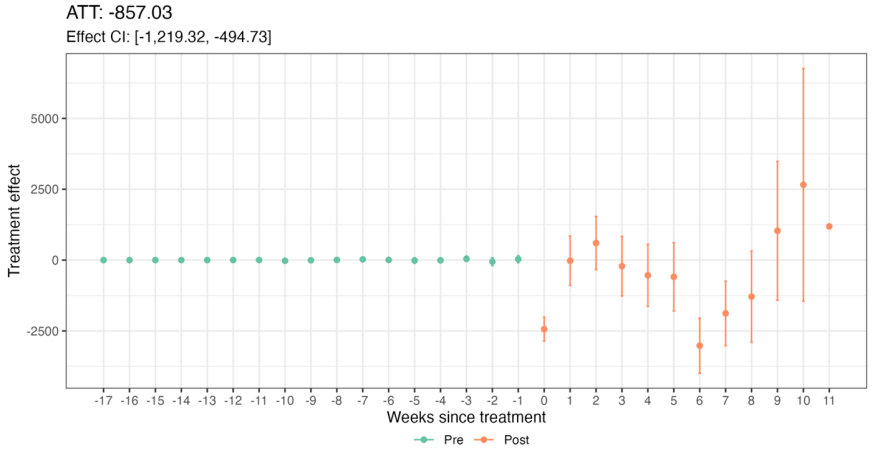
The average treatment effect (ATE) is estimated at approximately -856 KSh per week, or about -143 KSh per day, assuming a six-day work week. While this suggests a reduction in take-home income, it reflects the introduction of lease fee payments and the transfer of vehicle ownership to the drivers. From the perspective of both cash flow and asset accumulation, the transition to self employment represents an overall welfare improvement for the drivers

Figure 7.2: Contractual Transition and Paratransit Earnings at the Firm



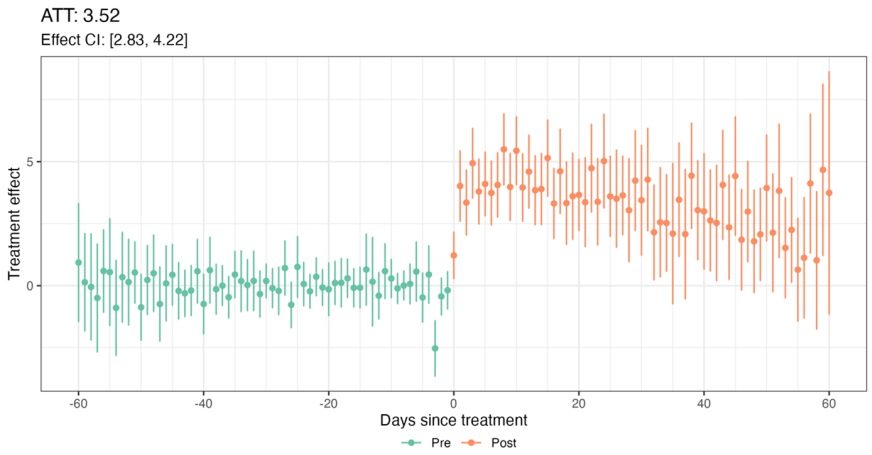
Note: The figure shows the dynamic effects of the contractual change from employment-based limited EV access to LTO contracts providing long-term, 24-hour access. The outcome variable is gross earnings, measured using platform earnings tied to the contractual arrangement with the firm. The ATT reported at the top represents the average treatment effect, and the confidence intervals plotted below correspond to the 95% level.

Figure 7.3: Contractual Transition and Take-Home Income from the Firm Contract



Note: The figure shows the dynamic effects of the contractual change from employment-based limited EV access to LTO contracts providing long-term, 24-hour access. The outcome variable is weekly take-home income from the contracts, calculated by weekly platform earnings from the EV asset contract minus fuel, lease, and other operational costs. The ATT at the top is the average treatment effect, and the CI below it is the 95% confidence interval for the effect.

Figure 7.4: Contractual Transition and the Daily Labor Hours for the Contract



Note: The figure shows the dynamic effects of the contractual change from employment-based limited EV access to LTO contracts providing long-term, 24-hour access. The outcome variable is self-reported daily labor hours for the company, measured first when drivers were employees and later as EV lessees. The ATT at the top is the average treatment effect, and the CI below it is the 95% confidence interval for the effect.

compared to remaining a company employee.

The estimated increase in drivers' labor hours confirms the welfare gains associated with a marked rise in productivity and labor supply. Figure 7.4 plots daily EV motorcycle driving hours self-reported by drivers. Labor hours rise sharply right after the business model transition, with an average treatment effect of 3.52 additional hours per day—equivalent to a 38% increase relative to the pre-transition mean of 8.56 hours. A modest decline appears between 30 and 55 days post-transition, likely reflecting year-end effects, after which the trend recovers with greater cross-driver variation.

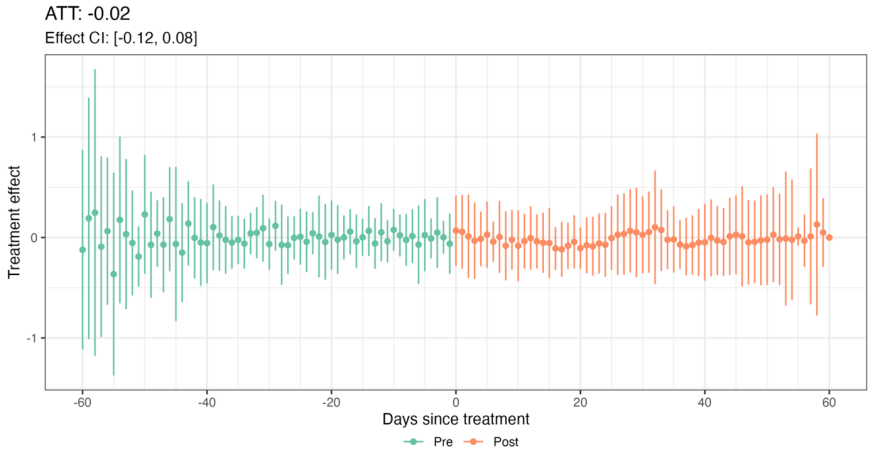
If drivers' labor hours increased, a natural question is whether these hours were reallocated from other jobs or reflected an expansion in total labor supply. In other words, did the increase occur on the intensive margin (substitution across jobs) or the extensive margin (higher overall participation)? To assess this, the survey measured hours outside the firm, including ICE motorcycle driving and non-Boda work. We combined these into a single measure of outside-firm labor hours and tested whether they declined as participation in the company's electric motorcycle program increased.

Figure 7.5 plots changes in outside-firm labor hours. We do not observe a statistically significant decline in these hours or an increase in their variance. This pattern suggests that the additional labor hours and productivity gains from full EV access under lease-to-own contracts arise on the extensive margin—drawing previously untapped leisure into the market rather than substituting from other activities.

7.2.3 Energy Expenditures

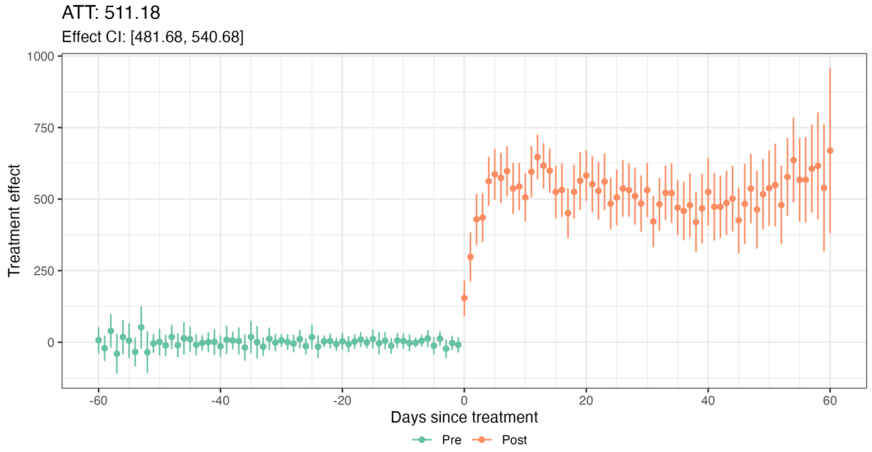
What is the implication of the contractual change for drivers' energy expenditures? Under the LTO contract, drivers were allowed to take their EV motorcycles home, which reduced the need to use ICE motorcycles for commuting to the company lot. At the same time, they

Figure 7.5: Contractual Transition and the Daily Outside-Firm Labor Hours



Note: The figure shows the dynamic effects of the contractual change from employment-based limited EV access to LTO contracts providing long-term, 24-hour access. The outcome variable is a self-reported daily labor hours for ICE motorcycle driving and other jobs. The ATT at the top is the average treatment effect, and the CI below it is the 95% confidence interval for the effect.

Figure 7.6: Contractual Transition and Daily Gross Energy Expenditure



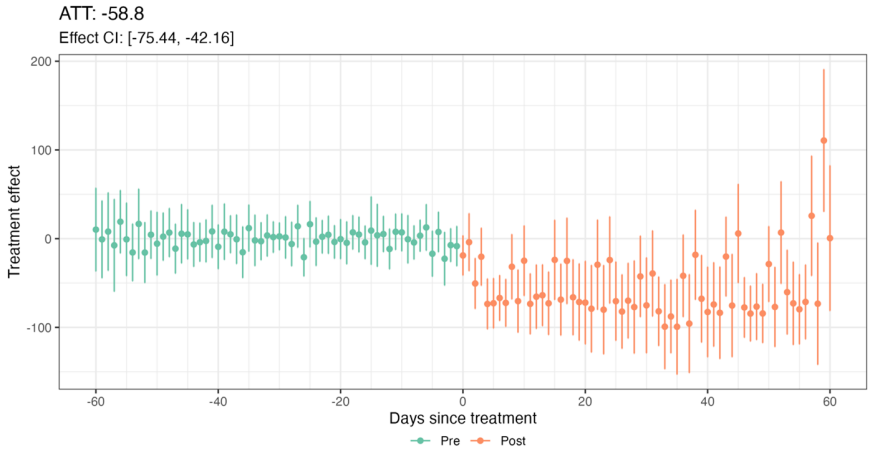
Note: The figure shows the dynamic effects of the change from the guaranteed salary program to the lease-to-own program. The outcome variable is a self-reported daily expenditures for fuel and battery charging, as reported by drivers. The ATT at the top is the average treatment effect, and the CI below it is the 95% confidence interval for the effect.

became responsible for battery charging and swapping costs that had previously been covered by the firm. In other words, while gasoline costs declined, battery-related expenses increased after the transition.

Figure 7.6 reports the combined effect on energy expenditures. Total daily spending on fuel and battery charging rose substantially, increasing by about 511 KSh compared to a pre-transition mean of 147 KSh. This more than triples average energy costs. The evidence in this section suggests that the contractual incentives of the EV asset access and eventual ownership possibilities outweighed the additional cost burden. Drivers increased their work effort rather than being discouraged by the expenses associated with self employment.

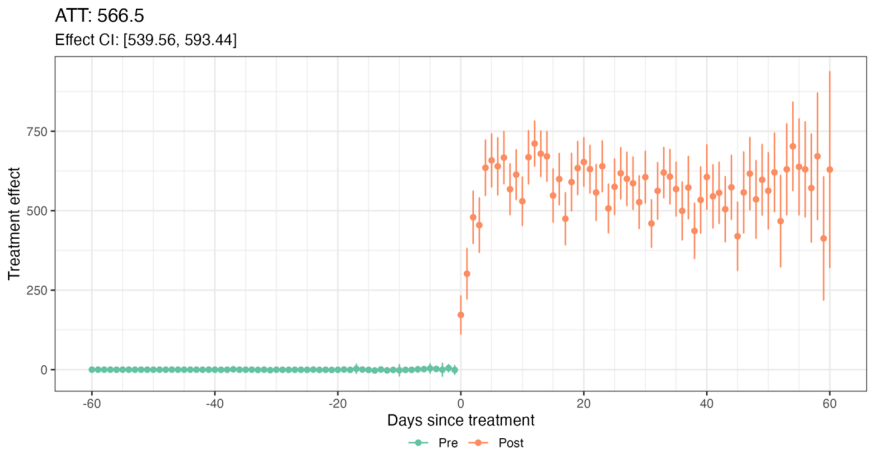
Next, we disaggregate the figures by energy type. As shown in fig. 7.7, gasoline expenditures decline significantly by 20%, corresponding to USD 0.45 per day. This pattern is consistent with earlier findings that drivers with access to ICE motorcycles reduce their ICE usage in favor of EV motorcycles. In contrast, fig. 7.8 shows a marked increase in battery-swapping expenditures, with the rise outweighing the previously observed decline in gasoline spending.

Figure 7.7: GSP to LTO Transition and Changes in Daily Gasoline Expenditure



Note: The figure shows the dynamic effects of the change from the guaranteed salary program to the lease-to-own program. The outcome variable is the daily expenditures on fuel, as reported by drivers. The ATT at the top is the average treatment effect, and the CI below it is the 95% confidence interval for the effect.

Figure 7.8: GSP to LTO Transition and Changes in Daily Battery Expenditure



Note: The figure shows the dynamic effects of the change from the guaranteed salary program to the lease-to-own program. The outcome variable is the daily expenditures on battery/charging, as reported by drivers. The ATT at the top is the average treatment effect, and the CI below it is the 95% confidence interval for the effect.

7.3 EV Access, Productivity, and Reorganization of Market Welfare

So far, we have examined evidence based directly on survey data regarding two developments among young people in Nairobi's urban center who previously did not have access to electric vehicles (EVs): (1) gaining access to EVs through the GSP program, and (2) drivers who previously accessed EVs through GSP transitioning into the LTO program. As seen earlier, both working hours and revenue increased. However, considering factors like maintenance costs, battery-swapping costs, and the effort and opportunity costs of labor compels the econometrician to ask whether this stage of market development remains one of trial and uncertainty or whether prospects for growth are becoming clearer. Then, too, there remain questions about whether public investment or policy intervention in this market development and transition phase is desirable.

More specifically, the following key questions emerge:

1. Did market size—measured in terms of revenues net of maintenance cost, labor cost, and energy cost ("gross profits")—expand with the transition from the GSP to the LTO model?
2. How did market productivity change?
3. How did weekly profits for the EV battery service company change?
4. How did weekly profits for the EV fleet service company change?
5. How did EV driver welfare per week change?
6. How did resource use and climate-related impacts change?

Table 7.5: GMM Estimation of Production and Cost Parameters

Parameter	Coefficient	Std. Error	z
$\ln(\psi^L)$	7.664	(0.246)	31.18***
Labor elasticity (β_L)	0.454	(0.061)	7.41***
Productivity persistence (ρ)	0.147	(0.055)	2.68***
$\ln(\psi^E)$	5.302	(1.160)	4.57***
$\ln(\kappa_0^C)$	4.691	(1.577)	2.98***
$\ln(\kappa^C_{\text{pre-Christmas}})$	-0.443	(0.854)	-0.52
Cost curvature (υ)	0.888	(0.130)	6.84***
Observations	1,505 (198 drivers w/ matched sensors)		
Moments / Parameters	9 / 7		
Hansen J (2 d.f.)	$\chi^2 = 1.958,\ p = 0.376$		

Notes: Two-step GMM with cluster-robust standard errors (198 clusters).
Instruments for AR(1): l_{it-1}, l_{it-1}^2, r_{it-1}, constant.
Instruments for FOC: l_{it}, l_{it-1}, l_{it-1}^2, $\ln p_{it-1}^E$, constant.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Below, we present the main findings from estimating the model outlined in section 5, which quantifies drivers' value-added production function and their income–disutility trade-off frontier, and examines how these parameters shape firm- and market-level welfare outcomes.

While this analysis allows us to address these questions, it is also necessary to clarify its limitations. A key limitation rests in sample selection. This analysis focuses on 206 drivers for whom we have positive values and complete data on revenue, labor time, and battery usage, both before and after the LTO transition. The sample was reduced because battery-swapping data could only be matched to a subset of drivers through their vehicle serial numbers. The CSDID analysis was conducted on 204 drivers for whom data was available across common event-time groups (i.e., driver observations sharing the same event-time distance with respect to their LTO transition week). It should also be noted that even this LTO sample is comprised of drivers who remained in the program until the end of the survey, which may suggest higher productivity than average new entrants to the program; however, attrition was low (below 4%). Moreover, the ArcRide-battery-data matched drivers represent the majority of ArcRide drivers (313 in total), and the technical reason for match failures—battery-log malfunctions that did not otherwise affect battery performance—was plausibly exogenous to driver characteristics.

7.3.1 Parameter Estimates

We begin by presenting the parameter estimates from the joint estimation of eq. (6.1) and eq. (6.2), which together identify the key production and cost parameters.

Table 7.5 reports the two-step GMM estimates of the structural parameters governing drivers' production and cost behavior. The estimated cost curvature parameter, $\hat{\upsilon} = 0.89$, is close to one, indicating an approximately linear cost function in labor—suggesting near-constant marginal costs with respect to driver effort. The baseline fixed cost component, $\ln(\kappa_0^C) = 4.69$, corresponds to an implied daily cost of roughly USD 0.84, comparable to 2025 national minimum hourly wage including overtime. The seasonal adjustment for the week before Christ-

mas, $\ln(\kappa^{C}_{\text{pre-Christmas}}) = -0.44$, is negative but statistically insignificant.

The production-side parameters are economically plausible. The estimated labor elasticity, $\hat{\beta}_L = 0.45$, indicates diminishing returns to labor input across the working week, consistent with increasing effective marginal costs of effort. The productivity persistence coefficient, $\hat{\rho} = 0.15$, suggests modest temporal dependence in driver-specific productivity shocks. The term $\ln(\psi^E) = 5.39$ captures the scale of energy efficiency on the production frontier. With p_Y normalized to 1, this implies an energy toll of 0.46, or roughly half of unit revenue. Overall, the Hansen J-statistic ($\chi^2(3) = 1.96$, $p = 0.38$) fails to reject the overidentifying restrictions, suggesting that the instrument set is valid and the model is well specified.

7.3.2 Market Size and Productivity

A precondition for assessing whether a market can sustain growth is determining whether its size is growing in the first place. In this context, the market "pie" can be understood as comprising four main elements:

1. Revenue from EV ride-hailing services
2. EV maintenance costs
3. Disutility of labor, including effort and opportunity costs
4. Energy costs from batteries

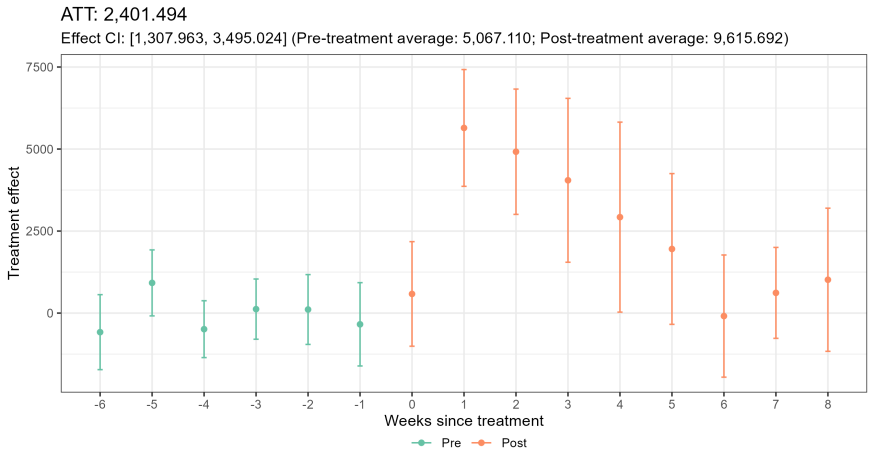
We focus on the following components of each element:

1. **Revenue**: The primary income earned by the driver through the ride-hailing platform. Before LTO, this went to the EV fleet company; after LTO, it went to the driver.
2. **Maintenance cost**: Based on LTO-phase survey data, drivers spent around 4% of their revenue on maintenance after LTO. We assume that maintenance needs were similar also before LTO.
3. **Labor disutility**: Modeled as a flexible power function estimated through the aforementioned exercise.
4. **Energy cost**: Estimated at KSh 22 (USD 0.17) per kWh, based on Kenya's commercial electricity rate.

While there are other cost-relevant factors—such as the EV fleet company's operating costs, battery depreciation, and the EV's fixed costs (e.g., USD 1,500)—we do not focus on these costs, here. These overheads and fixed costs cannot be readily assigned in marginal terms to our main unit of analysis: the EV-driver-week unit. Some of the overheads and fixed costs may also become less significant over time due to economies of scale. We revisit them when discussing 1.5–2 year horizons further below.

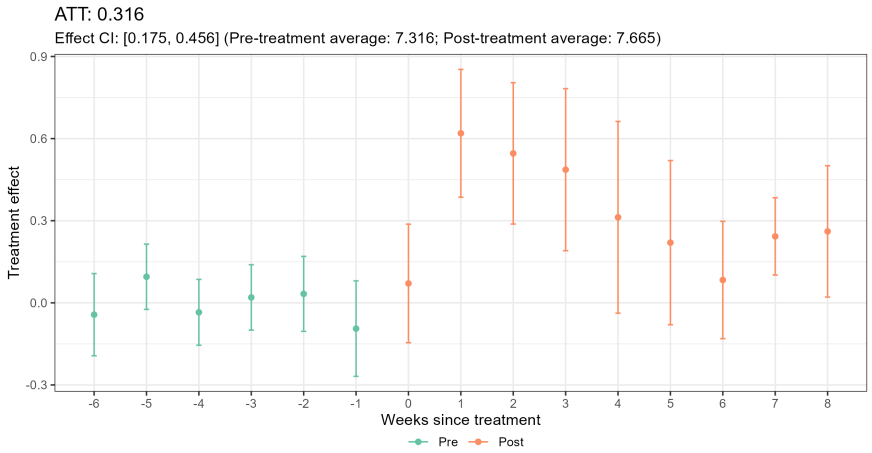
Figure 7.9 illustrates changes in total market size—or gross profits as clarified above—based on data-driven estimates. Prior to the transition, each EV-driver-week generated KSh 5,067 (USD 43.13) in gross profits. After LTO, this figure increased by KSh 2,401 (USD 18.47).

Figure 7.9: Impact of GSP to LTO transition on Gross Profits (KSh)



Note: By gross profits, we refer to revenues net of maintenance cost, labor cost, and energy cost. We exclude overheads and fixed costs.

Figure 7.10: Impact of GSP to LTO transition on Productivity (Log Points)



Note: By productivity, we refer to value-added composite input productivity, which is a function of driving hours in this setting.

Figure 7.10 shows how driver productivity—measured as the residual from a value-added production function per composite input—changed. The average increase was large and statistically significant at 0.32 log points (approximately 37%). Effects remain visibly large up through the final observable post-transition week (week 5) given the segmented sample, with a slightly diminishing trend over time, although the impacts pick back up by weeks 7 and 8.

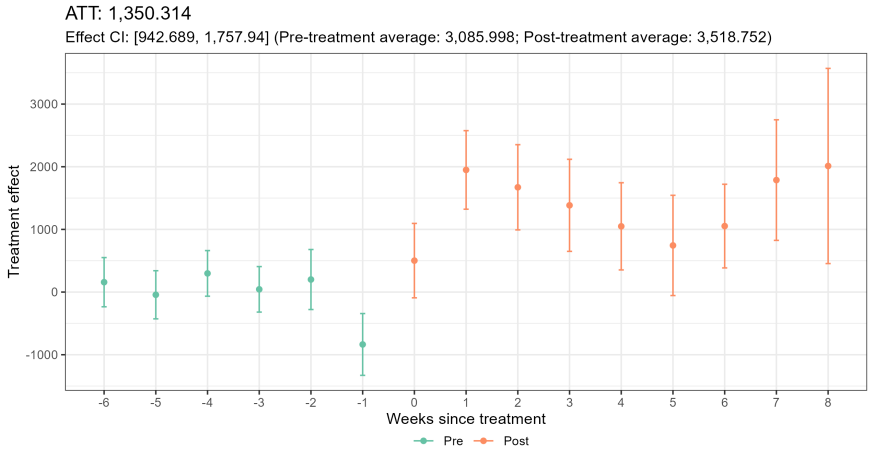
7.3.3 Redistribution of Market Welfare

Beyond total gains, we examine how the distribution of market benefits shifted due to the LTO transition. Specifically:

1. **Revenue**: Before LTO, the EV fleet company earned platform revenue and paid drivers KSh 7,062 (USD 54.66) in wages. After LTO, the company collected KSh 2,793 in leasing fees, and drivers kept all platform earnings.
2. **Maintenance costs**: Paid by the EV fleet company before LTO, by drivers after.
3. **Labor disutility**: Incurred by drivers throughout, as it depends on the hours driven.
4. **Energy cost**: Battery companies charged KSh 99 (USD 0.76) per kWh in 2024 and KSh 92 (USD 0.71) in 2025. Given the electricity cost of KSh 22 (USD 0.17), this represents significant margins. We exclude facility maintenance costs and depreciation.

The following three graphs illustrate how the gross profits of the battery service company and the EV fleet service company, as well as the net welfare levels of the drivers, changed over time.

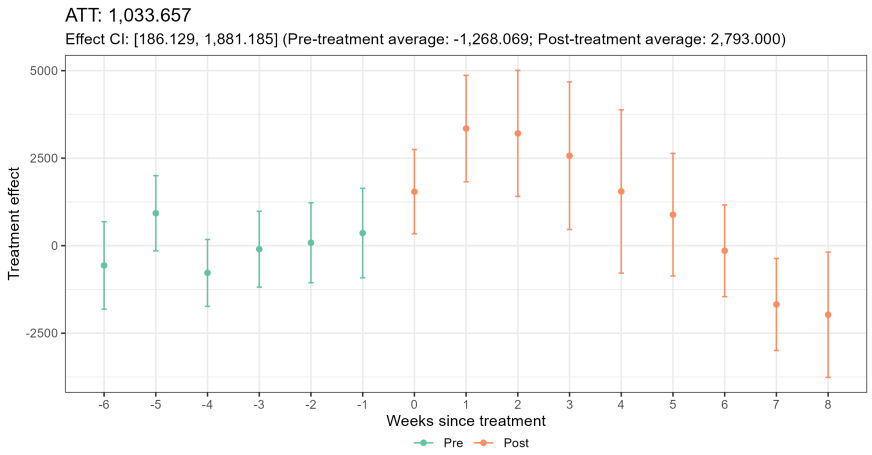
Figure 7.11: Impact of GSP to LTO Transition on EV Battery Firm Gross Profits (KSh)



Note: By gross profits, we refer to revenues net of electricity cost. We exclude overheads and fixed costs.

Figure 7.11 above shows how the battery service company's revenue net of electricity costs changed. It can be seen that even prior to the LTO transition, the battery company was earning a significant gross profit of KSh 3,086 (USD 23.74) per EV-driver-week. After the LTO transition, with a further increase in energy consumption, the company earned an additional profit of KSh 1,350 (USD 10.38).

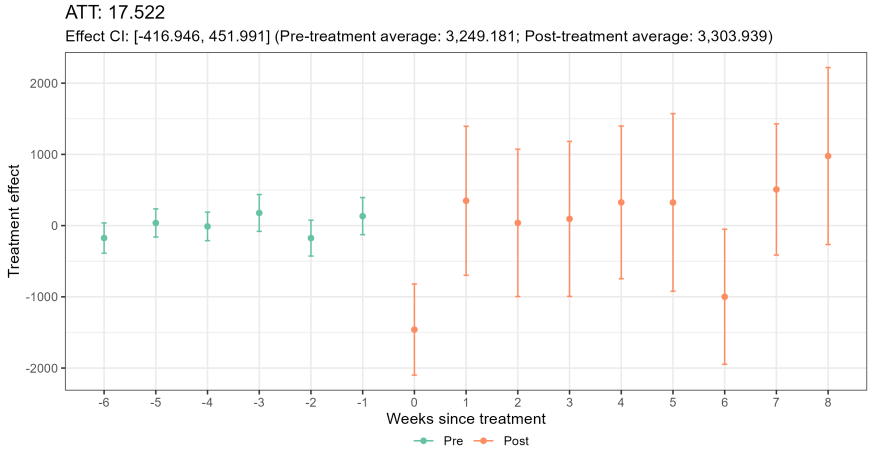
Figure 7.12: Impact of GSP to LTO Transition on EV Leasing Firm Gross Profits (KSh)



Note: By gross profits, we refer to revenues net of maintenance cost, labor cost, and energy cost. We exclude overheads and fixed costs.

Figure 7.12 shows how the gross profits of the EV fleet company changed. Prior to LTO, the company was experiencing a loss of KSh 1,268 (USD 9.75) per EV-driver-week. This figure was calculated over the course of the survey period and averages over a declining trend in losses over time. The LTO transition's impact was a positive KSh 1,033 (USD 7.95), signaling a turnaround into break-even. This change also provides insight into why the EV fleet company may have sought to shift away from the GSP model.

Figure 7.13: Impact of GSP to LTO Transition on Driver Welfare (KSh)



Note: Driver welfare is computed by revenues (salary or platform earnings) minus maintenance, energy, and labor disutility costs.

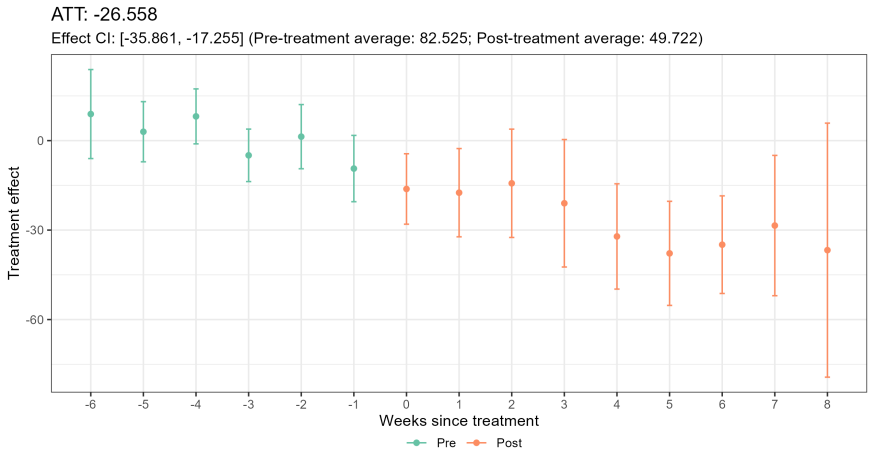
As for the drivers, they had a net welfare level of KSh 3,249 (USD 24.99) before the LTO transition. The transition's impact is KSh 17 (USD 0.13) of that utility, a precisely estimated zero. Nevertheless, they may have chosen to remain in the program because it continued to outperform their outside options. Additionally, the long-term prospect of owning their own EV bike—once they fully repay the leasing fees—may have serve as a continuing motivator. This

incentive could be encouraging them to continue driving with commitment, despite challenging working conditions. In particular, the fact that drivers no longer receive medical insurance or vehicle maintenance coverage for free after the LTO transition make them more vulnerable to road risks. These factors underscore the need to consider not only financial returns but also the broader safety and protection frameworks that shape driver retention and welfare under different mobility models.

7.3.4 Resource and Environmental-Social Implications

As mentioned before, the survey includes data on both gasoline expenditures and battery swapping, which allows us to estimate how total energy consumption has changed. Gasoline spending can be divided by the posted pump prices from the Energy and Petroleum Regulatory Authority to estimate liters consumed, which can then be converted into energy equivalents in kWh. Similarly, battery swapping data can be multiplied by the energy consumed per battery to compute the total energy used.

Figure 7.14: Impact of GSP to LTO Transition on Total Energy Use (kWh)



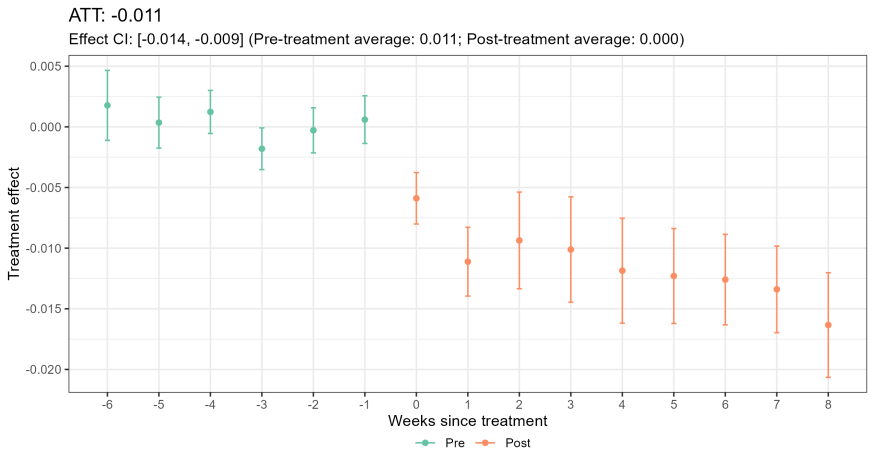
Note: Fuel costs are divided by the posted pump prices from the Energy and Petroleum Regulatory Authority to estimate liters consumed, which is then converted into energy equivalents in kWh. Similarly, battery swapping data is multiplied by the energy consumed per battery to compute the total energy used in kWh.

Figure 7.14 shows that before the LTO transition, drivers consumed about 83 kWh of energy per week. After the transition, energy consumption decreased by approximately 30 kWh. Since productivity increased by 37%, we can calculate that energy efficiency improved by roughly 102%.[13] This illustrates how much more efficient EVs are compared to internal combustion engines and highlights the synergistic effect between increased productivity and the LTO transition. It also offers a glimpse into behavioral changes: before LTO, drivers were not responsible for battery-swapping costs, so they may have managed their swapping frequency more loosely; after LTO, they have tightened control due to the cost burden.

On the other hand, fig. 7.15 shows that while the carbon impact of reduced gasoline usage is statistically significant, it is modest in environmental terms in the particular context of LTO

13. $(1.37/(82.525 - 26.558))/(1/82.525) - 1 = 102\%$.

Figure 7.15: Impact of GSP to LTO Transition on Carbon Footprint (tCO2)



Note: Fuel costs are divided by the posted pump prices from the Energy and Petroleum Regulatory Authority to estimate liters consumed, which is then converted into energy equivalents in tCO2.

transition. The reduction is about 0.01 tons of CO2 per EV-driver-week, meaning one would need 100 weeks to offset one ton of emissions. This limited effect is partly because most drivers were already using EVs full-time even before the LTO transition. Many had been using zero gasoline, so the comparison often involves zeroes. Although this goes beyond the scope of the present analysis, previous studies suggest that full-time drivers using internal combustion engines emit over 3 tons of CO2e annually—indicating that transitioning such drivers to EVs could yield substantial environmental benefits.

8 Conclusion

We have conduct empirical and structural analyses to examine how motorcycle taxi drivers in Nairobi are affected by gaining access to electric vehicles (EVs) through different asset-based business models. By estimating how drivers combine labor hours and energy inputs to produce rides and revenue, we assess the scalability, business sustainability, welfare incidences, and emission implications of the emerging electric two wheeler market.

The key findings are as follows:

- LTO increases driver productivity by 37% and improves energy efficiency by 102%, expanding total market surplus.
- Both the battery vendor and EV fleet company become more profitable; the fleet firm moves from losses to break-even once drivers begin leasing directly.
- Average short-run welfare remains constant, while autonomy and long-term EV ownership appear to continue to motivate drivers.
- Short-term CO_2 savings are modest (drivers were already EV), but scaling ICE to EV transitions could offer larger potential gains.

It would be beneficial for policy interpretation to consider the broader population, including new entrants and those who drop out of the program. Factors such as driver churn, the time and cost of matching firms with suitable drivers, and market fit are all important considerations for assessing the long-term sustainability of the EV mobility market. Interviews with the EV fleet company as well as recruiting agencies suggest recruiting new entrants involve low costs—as low as USD 8 per new driver. Survival rate would be a meaningful area for the next-iteration analysis. The attrition rate was 5% for the duration analyzed in this study, but the drivers were also experienced drivers who have been with the company over a relatively long horizon.

Future studies could strengthen public policy and private investment decisions by examining the long-term sustainability, economies of scale, and other externalities such as air pollution as the market grows. The expanding market size suggests promising potential returns to public investment in this sector. At the same time, the suggested margins in battery swapping—indicative of substantial market power—and gaps in the medical insurance coverage highlight important areas for policy intervention.

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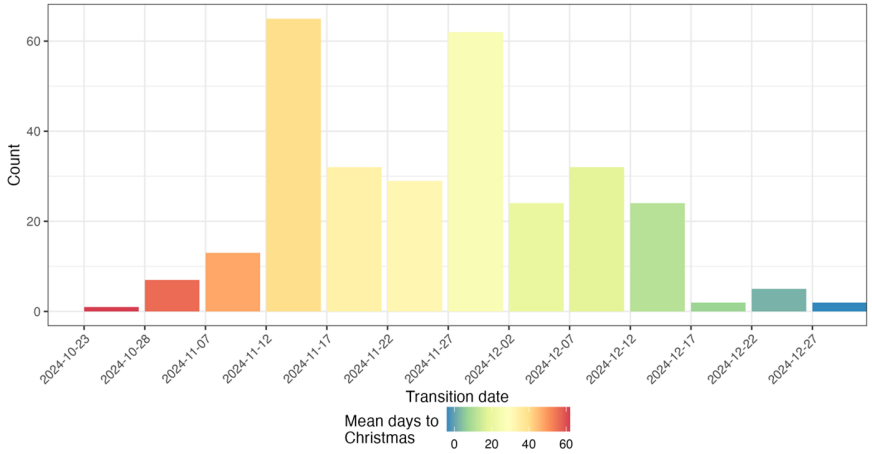
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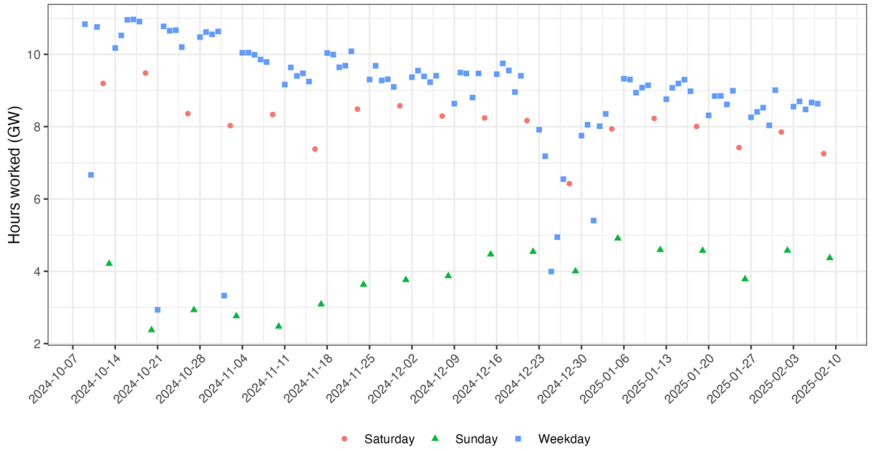
A Appendix.

Figure A.1: Transition Dates and Year-end Holidays



Note: The figure shows the distribution of transition dates for the GSP to LTO contracts, with the y-axis indicating the number of drivers transitioning within a given time frame, shown on the x-axis. The fill is the number of days until Christmas, which is a relatively important holiday in Kenya.

Figure A.2: Working Hours on Weekdays and Weekends



Note: The figure shows the average self-reported hours worked for firm, by day. The color and shape indicate whether the day is a Saturday, a Sunday, or a weekday.