Selection and Incentives in Platform Design: Evidence from a Ride-Hailing Platform

(PRELIMINARY DRAFT, PLEASE DO NOT CIRCULATE OR CITE)

Renata Gaineddenova*

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Abstract

Digital gig platforms typically charge workers either an upfront fixed fee or a per-job commission, applying the same structure to workers who differ widely in their desired flexibility and ability to commit. This paper provides the first causal evidence on how fee structure shapes labor supply and equilibrium outcomes on a platform. I study a global ride-hailing platform, inDrive, which transitioned from an upfront fixed-fee model to a commission-based regime in a staggered rollout across cities. Using high-frequency data on hundreds of thousands of drivers, I show that commissions substantially increase participation – by 47–65% in the number of active drivers – but attract more sporadic, lower-effort entrants. At the same time, commissions distort the incentives of incumbents, reducing their effort on the platform. Despite the larger overall labor pool, request-level match rates fall by about 5% and equilibrium prices rise by 2%. A theoretical model explains these patterns: fixed fees screen for more committed workers, while commissions weaken incentives. Additional empirical evidence confirms the theoretical mechanism and underscores a key trade-off in platform fee design.

*Harvard University, USA (e-mail: rgaineddenova@hbs.edu).

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1 Introduction

Digital gig platforms now account for a substantial and growing share of labor market activity: by 2021, more than 16% of U.S. adults had earned income through at least one such platform.[1]

These platforms generate revenue primarily by charging workers for access to jobs and for matching services, and in practice rely on two dominant fee structures: *commission-based contracts*, where workers pay no upfront cost but remit a share of earnings (e.g., TaskRabbit, Uber, Rover, Turo), and *upfront fixed-fee contracts*, where workers pay for access and retain all subsequent revenue (e.g., Thumbtack, TrustedHousesitters, Bark). Some platforms employ hybrid arrangements combining access fees with revenue sharing (e.g., Upwork, Fiverr).

While a classic literature studies how compensation schemes affect worker supply decisions within a single employer (Lazear, 2000*a*; Paarsch and Shearer, 2000), we know remarkably little about how fee structures operate in gig-platform settings. Much like in a traditional setting, platform fees can influence labor supply along both the extensive and intensive margins (Heckman, 1993), that is, through workers' entry decisions and their on-platform effort. However, gig platforms differ fundamentally from conventional firms: they attract highly heterogeneous workers, ranging from full-time earners to highly sporadic participants,[2] whose participation generates externalities for other workers and consumers (Rysman, 2009); entry and exit barriers are minimal; competition on the platform is pervasive; and demand is highly volatile. In a platform environment, intensive and extensive margins of labor supply also shape *equilibrium outcomes*: prices charged to consumers, transacted quantities, equilibrium wages, participants' welfare, and platform's profit.

Understanding how platforms manage labor supply through fee structure raises a central question: what trade-offs do alternative fee structures generate, and how do they affect the platform and its participants? Theoretically, commission-based contracts lower entry barriers and may attract a larger, more flexible workforce, but they can weaken the effort and matching intensity of committed workers. Upfront fixed-fee contracts, by contrast, can screen for more committed workers but deter marginal workers who are especially valuable at peak times. Although central

[1] https://www.pewresearch.org/internet/2021/12/08/the-state-of-gig-work-in-2021/

[2] A growing empirical literature documents that gig platforms attract workers with widely varying opportunity costs and attachment to the market (Chen et al., 2019; Cook et al., 2021).

to debates on platform power and regulation, this platform design trade-off and its equilibrium implications remain unstudied and unquantified.

This paper provides the first quasi-experimental evidence on how fee structure shapes labor supply and propagates to equilibrium outcomes on a platform. I study a global ride-hailing platform, inDrive,[3] that shifted from an upfront fixed-fee contract to a commission-based contract. The platform implemented the new system gradually across cities, affecting hundreds of thousands of drivers. Because a system-wide transition was technically infeasible, the platform migrated cities sequentially and grouped them only by size rather than by local market conditions. This feature generates plausibly exogenous variation in fee structure exposure, enabling identification of the causal effects of fee structures on labor supply and equilibrium outcomes.

Leveraging high-frequency administrative data, I show that moving to a commission-based fee structure raises the number of active drivers who check the platform by 47–65 percent and increases the number of bidding drivers[4] by 25 percent. The entrants drawn in by the commission regime differ sharply from incumbents: they supply far fewer hours, appear more sporadically, and make fewer matching attempts. This shift in the composition of labor supply has meaningful equilibrium consequences. Request-level match rates decline by 5 percent, transaction prices rise by 2 percent, and platform profits increase by 19.7 percent.

To clarify the mechanisms driving the labor supply and equilibrium effects of fee structure, and to guide the empirical analysis, I begin with a model in which heterogeneous workers choose labor supply according to their marginal costs. The model predicts that replacing an upfront fixed fee with a commission increases entry but reduces the effort of incumbent workers when equilibrium wages do not rise. The net effect on aggregate labor supply is therefore ambiguous and operates through three channels. First, the regime change draws in higher-cost workers who, individually, supply fewer hours than any incumbent. Second, the commission distorts incumbents' incentives by effectively acting as an excise tax on earnings, reducing effort whenever expected wages do not increase. Third, equilibrium prices (wages) and quantities adjust, with the direction

[3] www.indrive.com

[4] inDrive uses a decentralized pricing mechanism in which riders propose a price and drivers submit bids to be matched (Gaineddenova, 2022).

of these adjustments — higher or lower wages and smaller or larger quantities – depending on initial demand conditions. These wage adjustments in turn affect the total hours supplied by both incumbents and entrants. If the reduction in incumbents' effort dominates the contribution of new entrants, total hours fall, pushing prices up and reducing the equilibrium quantity. Conversely, if entry is sufficiently strong, aggregate hours rise, putting downward pressure on prices and increasing the equilibrium quantity transacted.

To empirically evaluate the model's predictions, I exploit a quasi-experimental transition in the platform's fee structure. The results provide strong support for the theoretical framework. First, the shift to commission-based contracts leads to a large increase in active drivers: the number of unique drivers checking the platform rises by at least 46.6% per hour, with hourly participation increasing by 46.6% to 64.5% depending on the time of day. Restricting attention to drivers who place a bid in a given hour yields a smaller, though still substantial, increase of 25%. This increase occurs almost immediately, though initially at a smaller magnitude, and remains remarkably stable for at least 30 days after the transition. A decomposition of the entry margin shows that the rise in participation is driven primarily by the reactivation of previously inactive drivers and by the temporal reallocation of labor by already-registered workers, rather than by the registration of entirely new drivers.

I then test the model's prediction concerning selection induced by the change in fee structure. The new entrants differ sharply from incumbents in ways consistent with the theory. They exhibit substantially lower engagement: their probability of being active on a given day is at least 29 percentage points lower; they initiate 1.9 to 2.6 fewer shifts per week; and when they do work, their shifts are shorter, and involve fewer attempts to match with riders. Their working hours are also notably less predictable. These patterns indicate sporadic participation and weaker attachment to platform work, suggesting that commission-based contracts attract more transient workers.

The data also show that incumbents meaningfully reoptimize their labor supply under the new fee structure. Their likelihood of being active on a given day increases by nearly 5 percentage points, and they initiate roughly one additional shift per week. At the same time, each shift

becomes shorter (by about 0.88 hours) and within-shift matching intensity declines by six attempts. Taken together, these patterns indicate a reallocation rather than a uniform increase in effort: incumbents reduce intensity in the markets where they were previously active, yet behave like entrants in other hours of the day. They shift the timing of their participation, becoming less likely to extend ongoing shifts at lower-value times and more likely to begin work during conventionally more attractive periods, such as midday.

Finally, I examine the equilibrium outcomes. Request-level match rates fall by roughly 5% across most hours, while equilibrium prices rise by about 2%, indicating a reduction in consumer surplus and suggesting that increased entry was insufficient to offset the decline in incumbents' effort. Taken together, these results provide rare empirical evidence that, although lowering participation costs can broaden the labor supply pool by attracting more flexible workers, it may simultaneously raise prices and reduce the quantity transacted.

This paper contributes to several strands of research in labor economics and platform design. It extends work on how compensation schemes shape worker selection and incentives (Lazear 2000*b*,*a*; Paarsch and Shearer 2000; Misra and Nair 2011; Biasi 2021) by providing new evidence on sorting and incentive effects in gig markets with strong same-side and cross-side externalities. It also relates to research on fixed costs and participation. Since Cogan (1980), theory has shown that entry costs deter marginal workers, and empirical work highlights heterogeneity and the value of flexibility (Mas and Pallais 2017; Hall and Krueger 2018; Chen et al. 2019; Angrist, Caldwell and Hall 2021). I show that platform-imposed fixed fees function as screening thresholds, selecting lower-cost workers, while commission-based contracts lower entry barriers and broaden participation. The paper connects to the literature on two-sided markets and platform pricing (Rochet and Tirole 2006; Armstrong 2006; Rysman 2009; Reisinger 2014; Bhargava and Rubel 2019; Birge et al. 2021). Despite rich theory, empirical evidence on how fee structures shape equilibrium — especially through supply responses — remains limited; this study helps fill that gap. In addition, it contributes to empirical work on how new entry affects incumbents (Seamans and Zhu 2014; Li and Agarwal 2017; Cao et al. 2021; Farronato and Fradkin 2022; Reshef 2023; Marra 2025). I show that lowering entry costs changes incumbent participation timing,

shift structure, and within-shift effort — spillovers essential for understanding fee design in gig platforms. Finally, the paper adds to empirical research on platform design in high-frequency, two-sided markets (Tucker and Zhang 2010; Benson, Sojourner and Umyarov 2020; Cui, Li and Zhang 2020; Fradkin, Grewal and Holtz 2021; Fradkin and Holtz 2022; Gaineddenova 2022).

Overall, the paper shows that fee structure is a fundamental platform design choice: it shapes worker selection, incentives, and equilibrium performance. Removing fixed fees expands participation but induces adverse selection and reduces the reliability of aggregate labor supply. This reveals a central tension in gig platforms: lowering entry barriers increases flexibility and broadens supply, but can weaken market performance. Fee design is therefore not merely redistributive: it determines the composition of the workforce and the total surplus the platform can generate, with broad implications for platform strategy and welfare.

The remainder of the paper is structured as follows. Section 2 presents a simple theoretical framework that illustrates the role of entry barriers as a screening mechanism. Section 3 describes the institutional background and data. Section 4 outlines the empirical strategy. Section 5 presents the main results. Section 6 discusses underlying mechanisms. Section 7 considers broader implications and concludes.

2 Descriptive Economic Model

This section develops a descriptive theoretical framework to illustrate how the platform's fee structure shapes workers' labor supply decisions. Changes in fees induce shifts in individual behavior that, when aggregated, alter the composition of the active workforce. The model yields intuitive, testable predictions about labor supply at the individual level and shows how these responses propagate to equilibrium market outcomes, affecting aggregate labor supply, quantities traded, and prices.

2.1 Model Setup

I consider a continuum of potential drivers indexed by their marginal cost of participation c, distributed according to $F(c)$ with density $f(c)$ over the support $[\underline{c}, \bar{c}]$. Each driver chooses their hours of work $h \geq 0$ to maximize profits, which depends on the fee structure implemented by the platform. The platform can adopt one of two models: an upfront fixed-fee model, where drivers pay a subscription fee for access to posted jobs, or a commission model, where access is free but the platform taxes each completed transaction.

2.2 Driver's Problem

Let w denote the expected hourly wage in a given market, ϕ the upfront fixed fee (charged only in the fixed fee model), and $\tau \in (0, 1)$ the commission rate (applied only in commission model). The driver's profit is given by:

$$\pi(c) = \begin{cases} wh - \frac{c}{2}h^2 - \phi & \text{(Fixed fee model)} \\ (1-\tau)wh - \frac{c}{2}h^2 & \text{(Commission model)} \end{cases}$$

I normalize the outside option to $u = 0$, so drivers participate only if $\pi(c) \geq 0$.

2.3 Driver's Optimal Hours

Solving the driver's profit maximization problem yields optimal number of hours (effort) supplied by type:

- **Fixed fee model:**

$$h^F(c) = \frac{w}{c}$$

- **Commission model:**

$$h^C(c) = \frac{(1-\tau)w}{c}$$

It follows that, when wages do not increase, switching to a commission model reduces the number of hours supplied by drivers of a given type (characterized by their marginal cost).

2.4 Participation Decisions

By substituting the optimal labor supply decisions back into the driver's profit function, we derive the profits under each fee structure: $\pi^F(c)$ and $\pi^C(c)$.

The participation condition requires these profits to be non-negative:

- **Fixed fee model:**

$$\pi^F(c) = \frac{w^2}{2c} - \phi \geq 0 \quad \Rightarrow \quad c \leq c_F = \frac{w^2}{2\phi}$$

- **Commission model:**

$$\pi^C(c) = \frac{(1-\tau)^2 w^2}{2c} \geq 0 \quad \Rightarrow \quad \text{All types participate}$$

Under the fixed fee model, a participation cutoff arises (i.e., if $c_F \leq \bar{c}$), whereby drivers with marginal costs above c_F choose not to enter the platform. However, after switching to the commission model, all driver types optimally choose to participate and supply a positive number of hours.

Testable Prediction 1. *The commission encourages participation by new drivers who would not enter under the upfront fixed fee model.*

Testable Prediction 2. *New entrants supply fewer hours on average than incumbents, reflecting their higher marginal costs.*

2.5 Aggregate Labor Supply

I characterize total labor supply under each fee structure by integrating over the active driver population, whose cost distribution is given by the density function $f(c)$ with support $[\underline{c}, \bar{c}]$.

- **Fixed fee model:**

$$S_F(w) = \int_{\underline{c}}^{c_F} \frac{w}{c} f(c)\, dc,$$

where drivers participate if their cost c is below the cutoff c_F.

- **Commission model:**

$$S_C(w) = \int_{\underline{c}}^{\bar{c}} \frac{(1-\tau)w}{c} f(c)\, dc,$$

where $\tau \in [0, 1)$ is the commission rate.

Decomposing S_C around the fixed fee cutoff c_F, we have

$$S_C(w) = \int_{\underline{c}}^{c_F} \frac{(1-\tau)w}{c} f(c)\, dc + \int_{c_F}^{\bar{c}} \frac{(1-\tau)w}{c} f(c)\, dc.$$

Rearranging terms gives

$$S_C(w) = S_F(w) - \tau \int_{\underline{c}}^{c_F} \frac{w}{c} f(c)\, dc + \int_{c_F}^{\bar{c}} \frac{(1-\tau)w}{c} f(c)\, dc.$$

This decomposition highlights three components of labor supply under the commission model:

- S_F: Labor supplied by incumbent drivers under the fixed fee model.
- $\tau \int_{\underline{c}}^{c_F} \frac{w}{c} f(c)\, dc \geq 0$: Reduction in incumbent labor supply due to the commission fee at constant wage.
- $\int_{c_F}^{\bar{c}} \frac{(1-\tau)w}{c} f(c)\, dc \geq 0$: Labor supplied by new entrants joining under the commission regime.

Under different distributions of marginal costs, the shapes of $S_C(w)$ and $S_F(w)$ will vary, but the key property remains: for different ranges of w, one supply curve can lie above the other. In some regions $S_C(w) > S_F(w)$, and in others the reverse holds. This implies that, *ex ante*, the direction of the equilibrium adjustment is ambiguous. Figure 1 illustrates the two supply schedules under a representative upfront fixed fee and commission rate when c is uniformly distributed.

2.6 Equilibrium Effects

Assuming a stable demand curve, the direction of changes in equilibrium prices and quantities (measured in this paper by match rates per request) is not uniquely determined and depends on the position of the demand curve relative to the supply schedules.

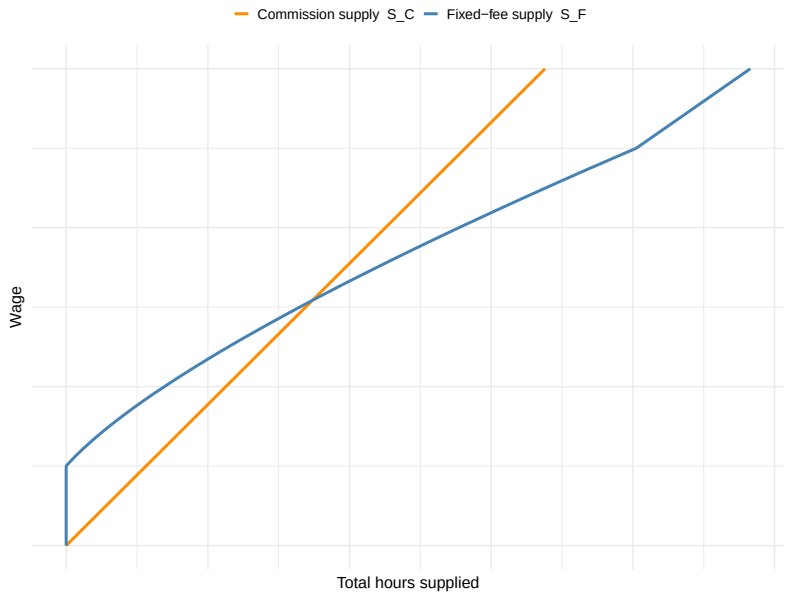


Figure 1: This figure schematically shows the aggregate supply curves under the upfront fixed-fee and commission regimes when c is uniformly distributed.

Under the simplifying assumption that driver availability is evenly distributed across request types — that is, drivers do not systematically favor particular requests — the following comparative statics emerge:

If aggregate labor supply under the commission regime, $S_C(w)$, exceeds that under the fixed-fee regime, $S_F(w)$, for the relevant range of wages (i.e., when w is initially low), then the transition from fixed fees to commissions should lead to lower equilibrium prices and higher match rates.

Conversely, if $S_C(w) \leq S_F(w)$ over the relevant range (i.e., when w is initially high), equilibrium prices are expected to rise and match rates to decline following the switch.

This characterization provides a baseline prediction for how platform-level outcomes should respond to fee-induced shifts in aggregate labor supply.

3 Institutional Context and Data

3.1 Background

inDrive is a global ride-hailing platform that was established in 2013 in Yakutsk, Russia. Since its inception, the platform has experienced substantial growth and currently operates in over 800 cities across 48 countries.[5]

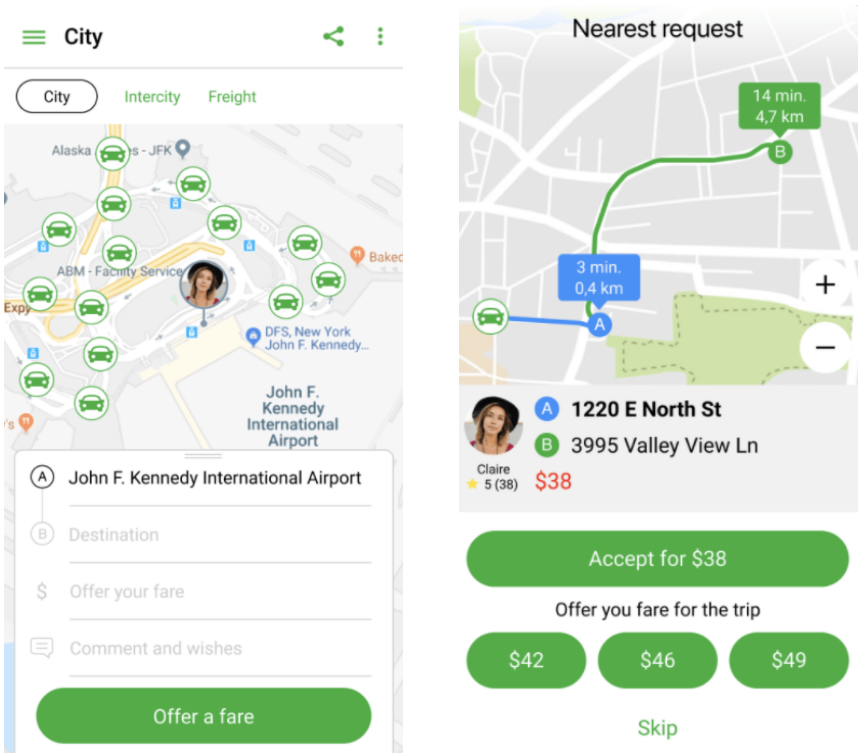
The platform offers a variety of services, including intra-city transportation, inter-city travel, freight, and delivery. This study focuses on the intra-city transportation segment, which parallels the services offered by centralized ride-hailing platforms such as Uber and Lyft. The primary objective of this segment is to facilitate rapid, on-demand matching between riders and drivers. However, in contrast to centralized platforms, inDrive employs a decentralized matching mechanism.

Price negotiation occurs before the rider is matched with a driver. The process begins with the rider submitting an initial price offer through the platform. Idle drivers then choose how to respond: they may accept the offer, submit a counteroffer (requesting a higher fare), or decline the request altogether. For details on the matching mechanisms and their implications for overall efficiency, see Gaineddenova (2022). In earlier iterations of the platform, inDrive itself resolved ties among multiple interested drivers. In more recent implementations, however, this decision has been delegated to the rider. The dataset analyzed in this paper spans both of these operational regimes.

3.2 Platform Interface and Matching Process

To illustrate how the matching works in practice, Figure 2 shows the rider and driver screens at the point of initiating and receiving a ride request, respectively. The interface highlights the active role of both parties in the matching and negotiation process.

[5] https://indrive.com/



(a) Rider's screen. (b) Driver's screen.

Figure 2: User interfaces during the matching stage

3.3 Change in Platform Fee Structure

The institutional change at the core of this study is a transformation in the platform's monetization strategy (fee structure). Initially, inDrive utilized a subscription-based model for drivers, whereby platform access was granted upon payment of a fixed, upfront fee. Drivers could select access durations of 1, 4, or 8 hours[6], and this payment constituted the sole financial obligation to the platform, regardless of how many trips the driver completed during that period. This structure underwent a major revision between late 2018 and early 2019, when inDrive initiated a gradual transition to a commission-based model. Under the new system, drivers were no longer required to pay an upfront fee. Instead, a 10% commission was levied on each successfully completed and negotiated trip.

The new pricing structure was introduced gradually in the 37 original launch cities, because all newer cities had used the commission-based model from the outset. The first cities adopted the

[6]In selected cities, a 14-hour option was available.

commission model in December 2018, while the final transitions occurred by April 2019. A simultaneous, system-wide transition would have posed substantial technical and logistical challenges, including the need for coordinated compliance within each city. Consequently, cities were grouped and migrated sequentially to the commission model. According to conversations with individuals responsible for the transition, the cities were not grouped based on any meaningful criteria other than size; larger cities were transitioned later, once the team was confident that the system was functioning properly and all technical issues had been resolved.

Importantly, riders have never been charged for access to the platform. Throughout the study period, they continued to pay drivers directly in cash (mostly) following each ride, a practice that remained unchanged by the platform's transition into a new fee structure.

Figure 3 presents a schematic illustration of the interface changes associated with this fee structure transformation. The left panel depicts the login screen under the original model, where drivers were prompted to purchase platform access for a specified time period. Hours on the platform were bundled, with quantity discounts offered for longer access times. Once logged in, drivers could view incoming ride requests (right panel) without incurring additional charges, irrespective of the number of rides completed. However, once the prepaid shift expired, the system would lock, and the driver would be required to purchase additional access to continue operating.

Following the transition to the commission model, the initial login screen (left panel) was eliminated. Drivers could immediately access incoming ride requests upon logging in. However, for each completed trip, the platform now deducted a 10% commission, which drivers were required to pay.

3.4 Data Description

This study uses proprietary datasets provided by the ride-hailing platform inDriver. The raw transaction-level data have been transformed into a structured panel dataset, enabling analysis of the platform's hourly operations and changes in driver behavior. All city and user identifiers have been anonymized to ensure confidentiality.

The dataset spans a period beginning 60 days prior to the earliest city-level transition and

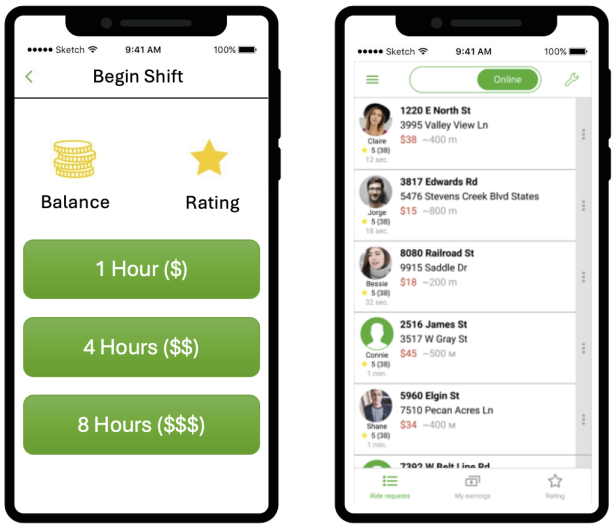


Figure 3: Interface illustration of transition from fixed fee to commission-based pricing

ending 60 days after the final transition, offering a rich panel suitable for event-study analysis. It covers 37 cities in total and includes data on several hundred thousand drivers. The transition from a fixed upfront fee to a commission-based fee structure was implemented gradually over a four-month period, with rollouts occurring on 11 distinct dates. Table 1 provides additional details on the treatment groups, including the number of cities per group, the median number of daily ride requests, and the average number of active drivers prior to the transition. These figures support earlier statements from the people within the organization that larger cities were transitioned later in the rollout process.

The analysis draws on two primary panels:

- **City-level panel:** Aggregated at an **hourly** frequency, this dataset contains platform-wide, city-level metrics. Key variables include the number of requests, proposed prices, matches, equilibrium prices, and other aggregate measures of market activity.
- **Driver-level panel:** Aggregated to the **hourly** level, this dataset includes individual driver data. Key variables capture drivers' online/offline status, number of matching attempts, number of successful matches, and aggregate ride completion metrics.

Both datasets are derived from the platform's internal logs, which include high-resolution timestamps, geolocation data, and action-level detail. This granularity enables precise tracking of behavioral responses to the fee structure change.

Table 1: Pre-transition summary statistics by transition timing group

Group	Switch date	# of cities	Median # of requests	Median # of drivers
Group 1	Date_0+0 days	2	3751.5	374.5
Group 2	Date_0+9 days	3	5185.0	456.0
Group 3	Date_0+33 days	5	3274.0	195.0
Group 4	Date_0+37 days	3	1712.0	123.0
Group 5	Date_0+63 days	1	1899.0	300.0
Group 6	Date_0+113 days	4	7394.0	589.0
Group 7	Date_0+119 days	2	1644.0	115.0
Group 8	Date_0+120 days	2	4604.5	565.0
Group 9	Date_0+121 days	5	12878.0	1617.0
Group 10	Date_0+124 days	5	10036.0	1175.0
Group 11	Date_0+126 days	5	6950.0	686.0

Notes: The table reports the number of cities in each transition group, the scheduled transition date, the median number of daily requests, and the median number of unique drivers active per day in each group.

4 Empirical Strategy

To examine how the transition from a fixed-fee to a commission-based fee structure affects driver behavior and platform performance, I exploit a staggered rollout of the pricing change across 37 cities. The transition occurred over a four-month period, from December 2018 to April 2019. Cities adopted the new fee structure in batches determined primarily by operational constraints — such as city size and internal technical readiness — rather than by economic or market-specific characteristics. This rollout design provides plausibly exogenous variation in treatment timing.

I implement several empirical strategies to evaluate the effects of this pricing change on labor supply and platform-level outcomes. These approaches are organized by the unit of analysis and the temporal resolution of the data.

4.1 Before-and-After Transition Comparison

As a first step, I compare average outcomes before and after the fee structure transition. This reduced-form approach provides an estimate of the overall shift in outcomes associated with the move to a commission-based model.

4.1.1 Daily-Level Platform-Wide Dynamic Specification

To examine the dynamic evolution of treatment effects and assess the plausibility of the parallel trends assumption, I estimate an event study specification using daily-level platform-wide data in a two-way fixed effects (TWFE) framework:

$$y_{c,d} = \alpha_d + \lambda_c + \sum_{k=-30}^{30} \beta_k D_{k(c,d)} + \varepsilon_{c,d} \tag{1}$$

In this specification, $y_{c,d}$ denotes the outcome of interest in city c on calendar day d. The indicator $D_{k(c,d)}$ equals one if city c is exactly k days from its transition date on day d, and zero otherwise. City fixed effects λ_c control for time-invariant city characteristics, and day fixed effects α_d capture common temporal shocks. The coefficients β_k trace dynamic treatment effects relative to the day prior to the transition ($k = -1$), which is omitted and serves as the reference category. Standard errors are clustered at the city level.

4.1.2 Hourly-Level Platform-Wide Static Specification

To investigate heterogeneity in treatment effects across different times of day, I estimate a static TWFE model using high-frequency (hourly) city-level data:

$$y_{c,d,h} = \beta \cdot \text{Post}_{c,d,h} + \alpha_d + \lambda_c + \varepsilon_{c,d,h} \tag{2}$$

Here, $y_{c,d,h}$ denotes the outcome of interest in city c, on day d, during hour h. The indicator $\text{Post}_{c,d,h}$ equals one if the commission-based model is in effect in city c at time (d, h), and zero otherwise. City fixed effects λ_c control for time-invariant differences across locations, and day fixed effects α_d absorb temporal shocks common to all cities. The coefficient β captures the average treatment effect at the hourly level. Standard errors are clustered at the city level.

4.1.3 Driver-Level Static Specification

To analyze responses at the individual level, I estimate a TWFE model using driver-level panel data. The sample is restricted to *active drivers* — those who were registered and attempted to match at least once in the two months preceding the transition:

$$y_{i,t,c} = \beta \cdot \text{Post}_{c,t} + \gamma_i + \alpha_t + \lambda_c + \varepsilon_{i,t,c} \tag{3}$$

In this specification, $y_{i,t,c}$ denotes the outcome of interest for driver i at time period t in city c, where t may refer to a day, week, or other interval depending on the specific outcome considered. The indicator $\text{Post}_{c,t}$ equals one if the commission-based model is in effect in city c at time t, and zero otherwise. Driver fixed effects γ_i control for time-invariant individual characteristics; time fixed effects α_t absorb shocks common across cities at the corresponding temporal resolution; and city fixed effects λ_c capture persistent cross-city differences. The coefficient β measures the average impact of the transition. Standard errors are clustered at the driver level.

4.2 Post-Transition Comparison Across Driver Groups

4.2.1 Driver-Level Static Specification

To explore heterogeneity in post-transition behavior across different types of drivers, I estimate a model comparing outcomes across groups of drivers operating under the commission-based model. While group definitions are introduced later in the paper, the estimation uses *active drivers* — those who were registered and attempted to match at least once in the two months prior to the transition — as the baseline group:

$$y_{i,t,c} = \sum_{k=1}^{K} \beta_k \cdot \mathbb{I}[i \in g_k] + \alpha_t + \lambda_c + \varepsilon_{i,t,c} \tag{4}$$

In this specification, $y_{i,t,c}$ denotes the outcome of interest for driver i at time period t in

city c, where t may refer to a day, week, or other time interval depending on the specific outcome considered. The indicator $\mathbb{I}[i \in g_k]$ equals one if driver i belongs to group g_k, where groups are mutually exclusive and collectively exhaustive. The group of active drivers serves as the baseline category. The coefficients β_k capture differences in outcomes for each group relative to this baseline. The model includes time fixed effects α_t, and city fixed effects λ_c. Standard errors are clustered at the city level.

5 Results

5.1 Evidence on Entry

I begin by presenting evidence on entry following the platform's shift to a commission-based fee structure. Entry can be defined in various ways. While the theoretical framework in Section 2 remains agnostic about the precise definition of a "market", empirically testing its predictions requires a market definition. I demonstrate that the findings are robust across a range of market definitions, although different specifications do lead to some variation in how incumbents and entrants are classified.

5.1.1 Daily-Level Results

The first set of results focuses on *daily* patterns of driver participation (this sample includes data from 7 AM to 11 PM). Using the specification in Equation 1, I estimate dynamic treatment effects around the fee structure transition. For each city, I compute the average number of drivers during the pre-treatment period and normalize all subsequent daily counts relative to this baseline. The resulting outcome variable is a unitless measure interpreted as the percentage change from the city's pre-transition average. In this setup, the regression coefficients represent percentage deviations from the pre-treatment baseline: a coefficient of zero indicates no change, while a coefficient of one corresponds to a 100% increase relative to baseline.

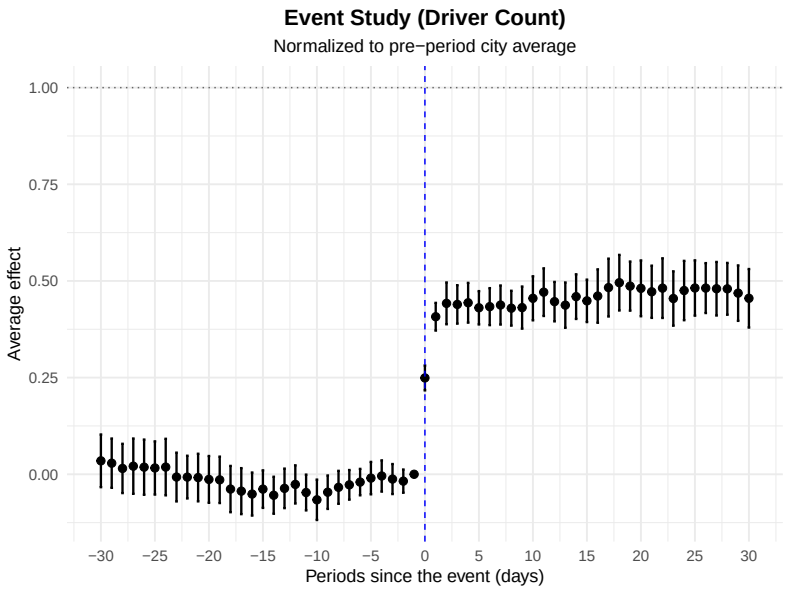


Figure 4: Event Study Estimates: Effect of Transition on Daily Driver Counts (Normalized)

Figure 6 presents the estimated event-time coefficients $\hat{\beta}_k$ and corresponding 95% confidence intervals for a 30-day window around the transition. The estimates indicate a sharp and statistically significant increase in daily driver count beginning precisely at the time of the transition to a commission-based model. This increase persists over time: the estimated effects suggest a sustained rise in daily driver count of approximately 46.9% to 54.8% relative to baseline levels, with an initial jump of around 30%. The pre-treatment coefficients are tightly clustered around zero and are statistically indistinguishable from it, supporting the parallel trends assumption.

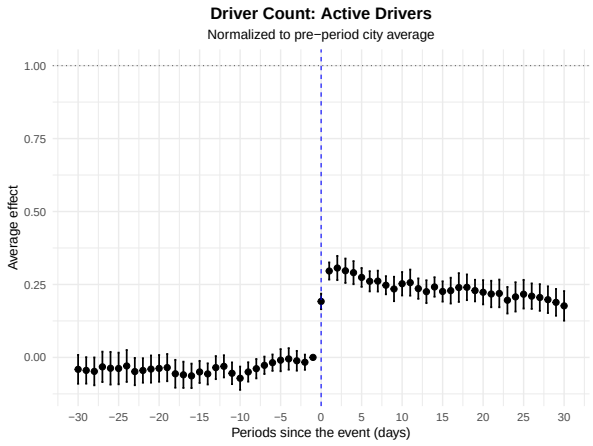
These results are consistent with the theoretical prediction on entry: replacing a fixed upfront fee model with a commission-based model lowers entry barriers, incentivizing broader participation. While these estimates document a substantial increase in the total number of drivers, they do not yet reveal the composition of this entry. To investigate further, I decompose the change in participation into three mutually exclusive groups:

- **Active drivers:** Drivers who registered and attempted to match at least once in the two months preceding the transition in their city.
- **Reactivated drivers:** Previously registered drivers who had been inactive for at least two months prior to the transition.
- **Newly registered drivers:** Drivers who registered and began participating only after the

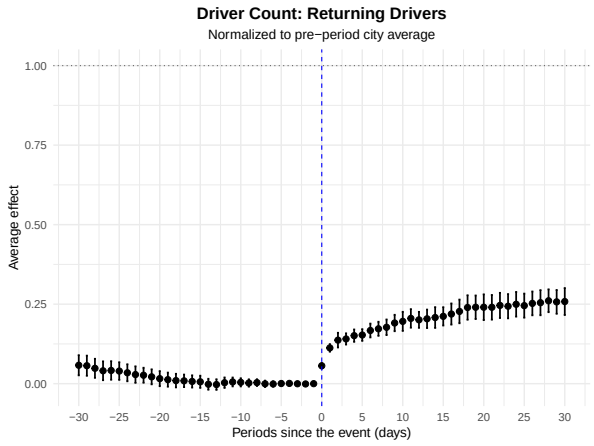
transition.

To assess the relative contribution of each group to the observed entry, I repeat the analysis using Equation 1, normalizing the count of each group by the city-specific pre-treatment average total number of drivers. This approach allows for a direct comparison of group-specific participation dynamics and provides a decomposition of the aggregate increase in entry. In this setup, the regression coefficients represent percentage deviations from the pre-treatment baseline: a coefficient of zero indicates no change, while a coefficient of 1 corresponds to a 100% increase relative to baseline. Interpreted this way, the sum of the group-specific coefficients approximates the total change observed in overall driver participation following the transition.

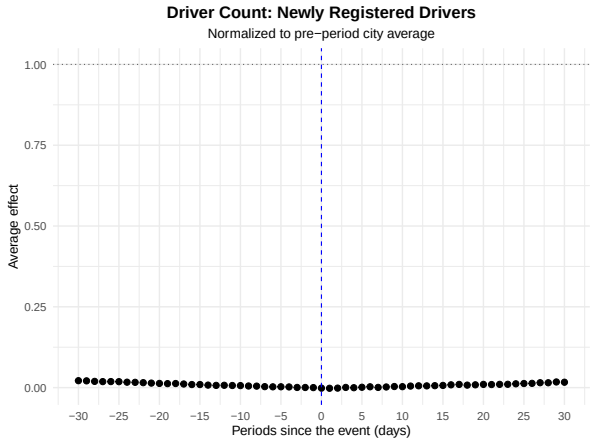
The results are presented in Figure 5. A substantial portion of the observed increase in participation is driven by **reactivated drivers** — workers who had previously registered but were inactive during the recent pre-transition period — as well as by **active drivers** who intensified their platform usage. In contrast, the share of **newly registered drivers** increases gradually over time and does not exhibit an immediate or sharp break in trend, suggesting that the transition did not trigger a short-term surge in new registrations.



(a) Active Drivers



(b) Reactivated Drivers



(c) Newly Registered Drivers

Figure 5: Event Study Estimates by Driver Type. Each panel displays changes in group-specific participation, normalized by the city's pre-period average number of total drivers.

I then repeat the analysis for drivers who were not only active on the platform during a given hour but also placed a bid. The estimated effects are smaller in magnitude, though still substantial – approximately a 25% increase.

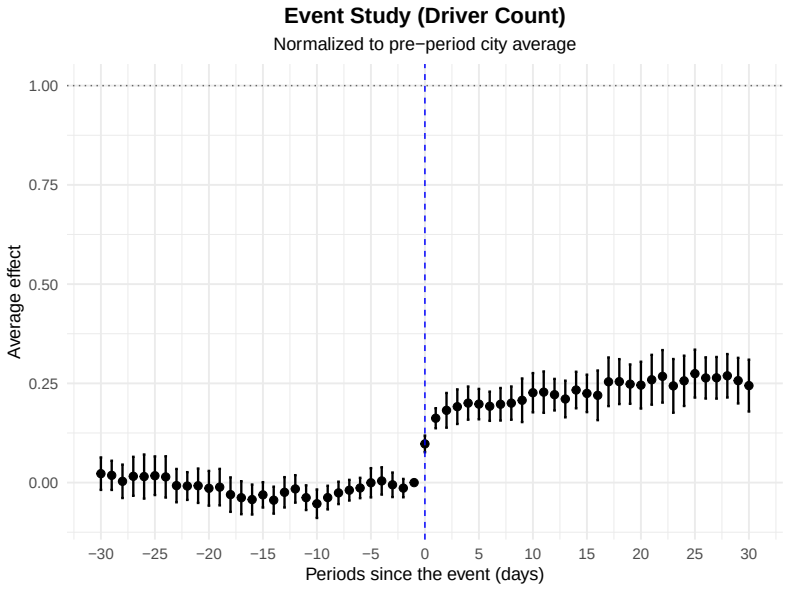


Figure 6: Event Study Estimates: Impact of the Transition on Daily Bidding Driver Counts (Normalized)

5.1.2 Hourly-Level Results

I next examine how the effect of the transition to a commission-based fee structure vary across different hours of the day, recognizing that each hour may represent a distinct market with its own supply and demand dynamics. Due to limitations in sample size at the city-date-hour level, this analysis is restricted to weekdays. To quantify the variation in entry responses by hour, I estimate Equation 2, where the dependent variable is the number of active drivers on the platform during each hour, normalized by the city-hour-specific pre-treatment average—mirroring the approach used in the earlier daily-level analysis. In this specification, the regression coefficients represent percentage deviations from the pre-treatment baseline: a coefficient of zero indicates no change, while a coefficient of one corresponds to a 100% increase in active drivers relative to the pre-transition hourly average.

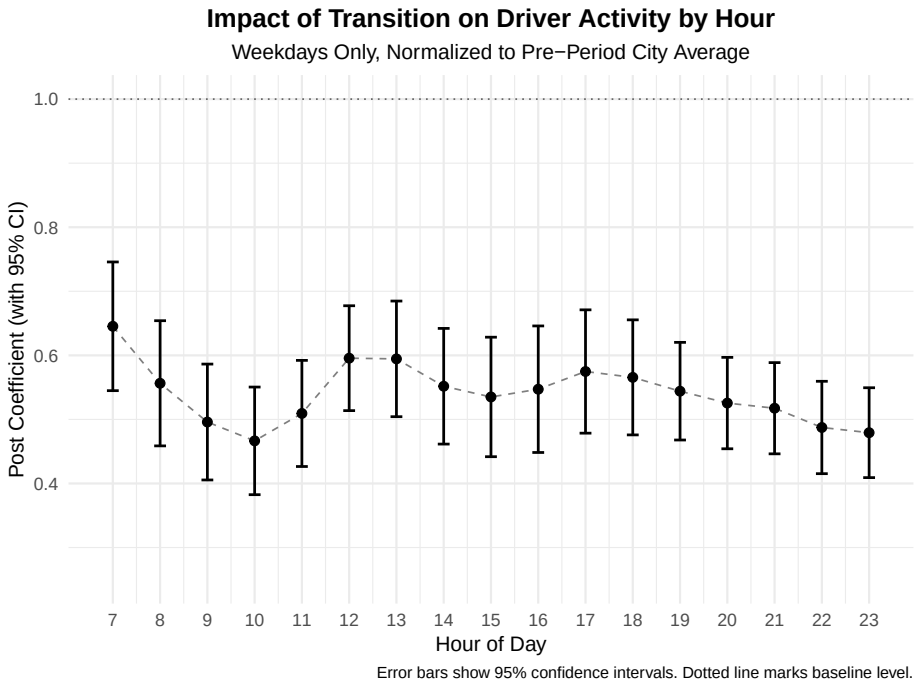


Figure 7: Effect of Transition on Number of Drivers, by Hour of Day (Weekdays)

Figure 7 presents the estimated coefficients from these regressions — separately estimated for each hour — along with 95% confidence intervals. The transition to a commission-based fee structure is associated with a substantial increase in driver count across all hours of the day. The smallest estimated effect occurs at 10 AM, with a 46.6% increase relative to baseline. The largest effects are observed during peak periods: 64.5% at 7 AM, 59% between 12 PM and 1 PM, and 57% between 5 PM and 6 PM. These findings indicate that the policy change had time-dependent effects, with particularly pronounced increases during the morning, midday, and evening demand peaks.

While these results document meaningful increases in the number of drivers present at the hourly level, they do not reveal the composition of this increase. Previous daily-level analyses showed that newly registered drivers played a relatively limited role in driving the aggregate increase in driver count. I therefore turn to other types of entrants, applying a more granular definition of entry tailored to the hourly context. Since each hour is treated as a distinct market segment, the classification of incumbents and entrants must be adjusted accordingly. Specifically, I decompose the population of *active drivers* into the following categories:

- **Stable drivers:** Drivers who consistently operated within the same time block before and after the transition (e.g., morning, afternoon, evening, or night).
- **Shifted drivers:** Drivers who were active prior to the transition but now concentrate their activity in a different time block.
- **Irregular drivers:** Drivers who were active before the transition but without a stable temporal pattern of participation.

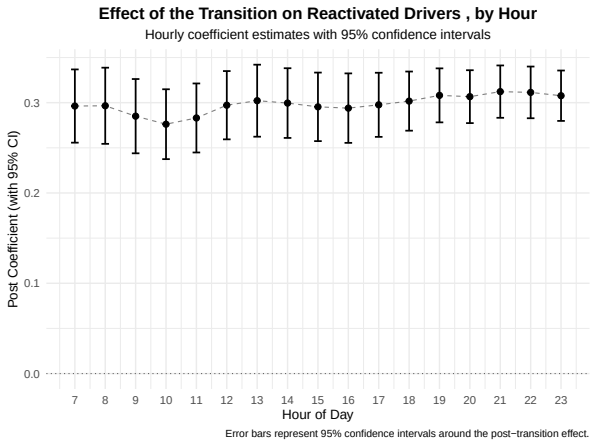
In this hourly context, defining an incumbent is nuanced. Incumbents are identified primarily as a subset of stable drivers, with some inclusion of irregular incumbents — those with a high likelihood of hour-specific participation — and shifted incumbents who occasionally participated in different time blocks. Entrants include reactivated drivers, some shifted drivers, and a portion of formerly stable incumbents who now appear more frequently. Figure 8 presents the estimated coefficients β from the hourly specification in Equation 2, disaggregated by driver group.

This decomposition provides deeper insight into the sources of observed entry. Many stable incumbents concentrate their post-transition participation during peak (rush) hours and show limited changes during off-peak periods; in fact, some reduce their engagement during late morning or late evening hours. By contrast, a substantial share of shifted drivers redistribute their participation across the day, suggesting that drivers who were previously active during specific hours now disperse their activity more broadly. Certain hours — particularly the morning rush, midday, and late evening — see disproportionately large increases from this group.

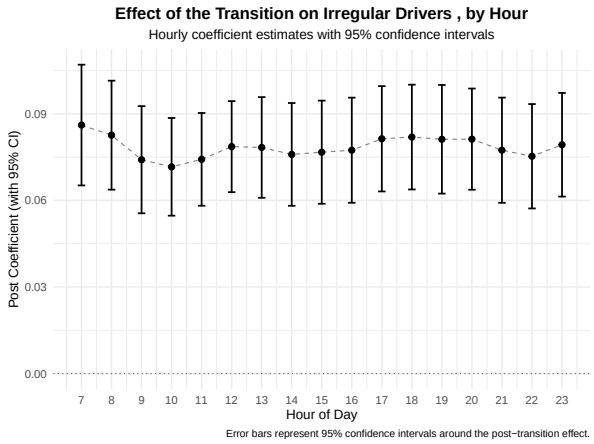
The patterns for reactivated and irregular drivers are more uniform across hours, though they differ in magnitude. Reactivated drivers account for approximately 50% of the total entry—representing a 30% increase relative to the baseline, out of a total increase slightly above 60%. Irregular drivers contribute an additional 8.5% increase relative to the baseline, with relatively consistent presence throughout the day.

The similarity in temporal patterns across these two groups suggests a shared underlying driver profile: both are likely characterized by a preference for flexibility and a non-committal engagement with the platform, rather than strong hour-specific preferences. Irregular incumbents appear behaviorally similar to reactivated drivers, consistent with the interpretation that both

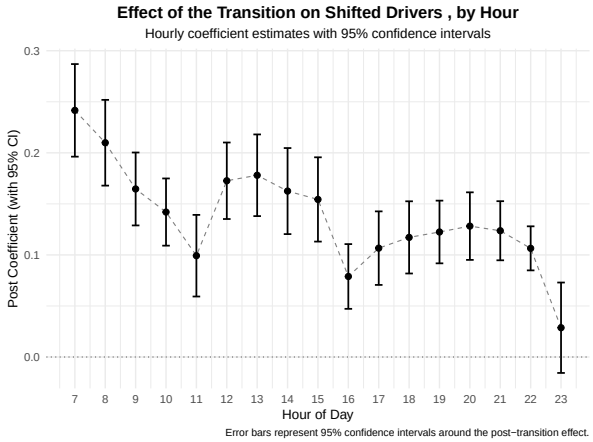
reflect a more flexible segment of the labor supply. In terms of contribution, the largest increases come from shifted and reactivated drivers.



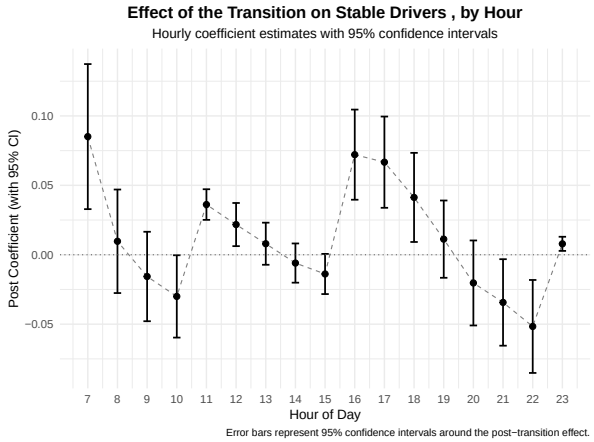
(a) Reactivated Drivers



(b) Irregular Drivers



(c) Shifted Drivers



(d) Stable Drivers

Figure 8: Effect of the Transition on Driver Count by Hour, Across Driver Types

Overall, the empirical results align closely with Theoretical Prediction 1: relaxing entry by shifting from an upfront fixed fee model to a commission-based model leads to increased entry. This finding is robust across a range of market definitions.

5.2 Selection

The second component of the empirical analysis evaluates Theoretical Prediction 2, which posits that entrant drivers supply fewer hours than incumbents, consistent with higher marginal costs. To test this prediction, I compare entrant and incumbent drivers across several key dimensions. For

the analysis below, I define an incumbent as an active driver who registered before the transition and attempted to match at least once in the two months preceding the transition in their city. Reactivated and newly registered drivers are classified as entrants.

5.2.1 Driver-Level Static Outcomes

Following the empirical strategy outlined in Section 4 and using Equation 4, I classify drivers into three groups and estimate differences in behavior across them, using active incumbent drivers as the reference category.

Compared to incumbents (active drivers), both newly joined and reactivated drivers exhibit markedly lower levels of participation. At the weekly level, the probability of participation is 29.8 percentage points lower for newly joined drivers and 32.7 percentage points lower for reactivated drivers. These gaps persist at the daily level, amounting to 16.9 and 21 percentage points, respectively.

Entrants also initiate substantially fewer shifts per week — between 1.99 and 2.58 fewer than incumbents. In addition, reactivated drivers, in particular, work significantly shorter shifts, supplying 0.68 fewer hours per shift. Within each shift, entrants make fewer attempts to match with riders. Notably, reactivated drivers appear even less engaged than newly joined drivers, despite both being classified as entrants: reactivated drivers make 3.27 fewer match attempts per shift, while newly joined drivers make 0.98 fewer, relative to incumbents. This pattern suggests heterogeneity in commitment levels or opportunity costs even within the entrant pool.

Additionally, entrant drivers display significantly greater dispersion in the timing of shift initiation compared to incumbents, as measured by the standard deviation of shift start times. This increased variability indicates more erratic and unpredictable patterns of participation.

Overall, despite some differences in magnitude, reactivated and newly joined drivers appear strikingly similar, suggesting they share latent characteristics, likely a stronger preference for flexibility and less consistent engagement with the platform relative to active incumbents.

Table 2 summarizes these post-transition differences across driver types.

Table 2: Post-transition Heterogeneity by Driver Type

Outcome	β_1 (Newly joined driver)	β_2 (Reactivated driver)	City FE	Time FE
Probability of Weekly Presence	-0.298 (0.011)	-0.327 (0.007)	✓	✓
Probability of Daily Presence	-0.169 (0.006)	-0.21 (0.005)	✓	✓
Total Weekly Work Shifts	-1.985 (0.083)	-2.576 (0.065)	✓	✓
Duration of Each Work Shift (in Hours)	0.042 (0.051)	-0.679 (0.056)	✓	✓
Number of Matching Attempts per Shift	-0.972 (0.204)	-3.272 (0.294)	✓	✓
Std. Dev. of Entry Timing	0.111 (0.036)	0.216 (0.02)	✓	✓

Taken together, this evidence supports theoretical prediction 2: drivers attracted by the commission-based fee structure differ meaningfully from incumbents. They supply fewer hours on average, participate less predictably, and behave in ways consistent with higher marginal costs of labor supply. These patterns validate the model's prediction that the change in fee structure would lead to a compositional shift in the driver pool.

5.3 Active Drivers' Response to Commission-Based Model

5.3.1 Driver-Level Static Outcomes

The model predicts that the transition to a commission-based fee structure affects not only entry dynamics but also the behavior of incumbent drivers, by altering incentives through an effort distortion, where the commission functions similarly to an excise tax. To evaluate these behavioral adjustments, I estimate Equation 3, leveraging variation in the timing of the fee structure transition across markets. For this analysis, I define incumbents as drivers who were active prior to the transition.

Table 3 reports estimates of how these drivers adjust their behavior along several dimensions. On average, incumbents are more likely to be present post-transition, with a 2 percentage point increase in participation observed at the weekly frequency and a 5.1 percentage point increase observed at the daily frequency. They also initiate more shifts, consistent with the idea that some drivers operate as incumbents in familiar markets and as entrants in others under the new

fee structure. However, while participation becomes more frequent, the intensity of participation per shift declines — consistent with the predicted effort distortion. The average duration of a shift decreases by 0.88 hours, and drivers make approximately 6 fewer matching attempts per shift, indicating reduced within-shift engagement.

Table 3: TWFE Estimates: Intensive Margin Effects on Incumbent Drivers

Outcome	Estimate	City FE	Time FE
Probability of Weekly Presence	0.020 (0.009)	✓	✓
Probability of Daily Presence	0.051 (0.005)	✓	✓
Total Weekly Work Shifts	1.001 (0.084)	✓	✓
Duration of Each Work Shift (in Hours)	-0.876 (0.039)	✓	✓
Total Number of Hours Present Each Week	1.425 (0.257)	✓	✓
Number of Matching Attempts per Shift	-6.010 (0.337)	✓	✓

These results suggest that within a given market-hour, total effort — measured in labor hours —supplied by incumbents declines under the commission-based fee structure. Because active drivers may behave as entrants in markets they did not previously serve, the total hours worked by an average driver are not a reliable proxy for aggregate labor supply in a specific market. Instead, the number of matching attempts per shift provides a more accurate measure of effort, capturing the meaningful reduction in labor intensity under the new fee structure.

5.3.2 Hourly-Level Outcomes: Intertemporal Adjustment

While the previous subsection shows that incumbents increase the frequency of participation but reduce effort intensity per shift, another important margin of adjustment lies in their intertemporal work decisions — a dimension that has been only partially explored thus far.

To investigate this further at the hourly level, I estimate the effect of the transition on drivers' continuation probability in each hour (from 7 AM to 11 PM), using the specification in Equation 2. Figure 9 shows that the likelihood of a driver continuing into the next hour declines post-transition across all hours of the day. The drop is particularly pronounced during morning,

early afternoon, and late evening hours, suggesting that drivers increasingly target high-demand periods and are less inclined to remain active across extended time spans.

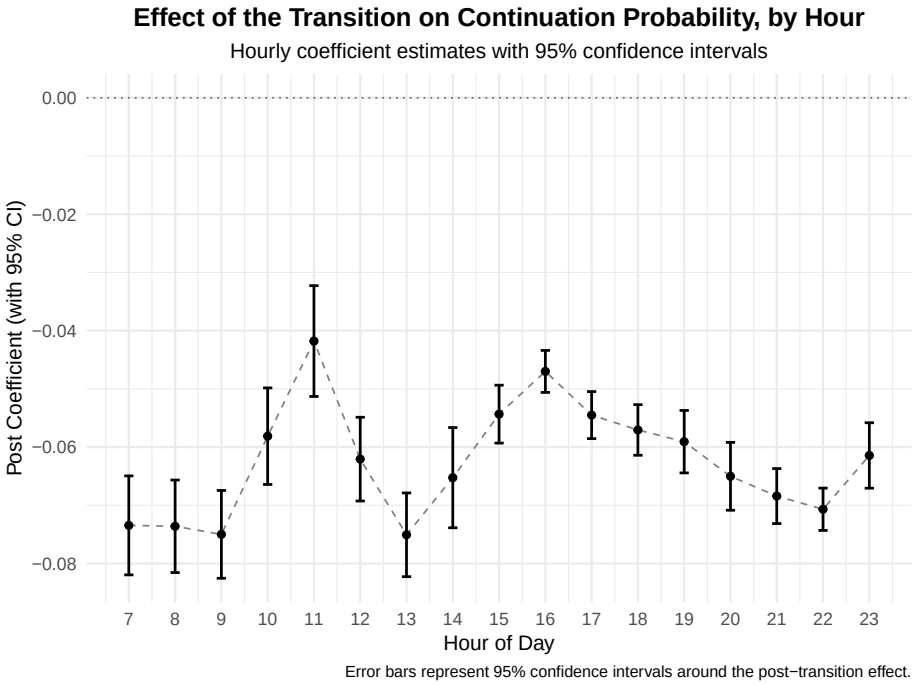


Figure 9: Effect on Continuation Probability by Hour

Given earlier evidence that active drivers expand their participation into new markets following the transition, I also examine how their shift start times adjust. Focusing on drivers with frequent platform use—those initiating at least 30 shifts both pre- and post-transition—I plot the distribution of shift start times. Figure 10 reveals a notable shift toward midday, suggesting that drivers increasingly concentrate their activity during more conventional working hours. This pattern is also consistent with earlier findings on shifted drivers disproportionately selecting midday hours.

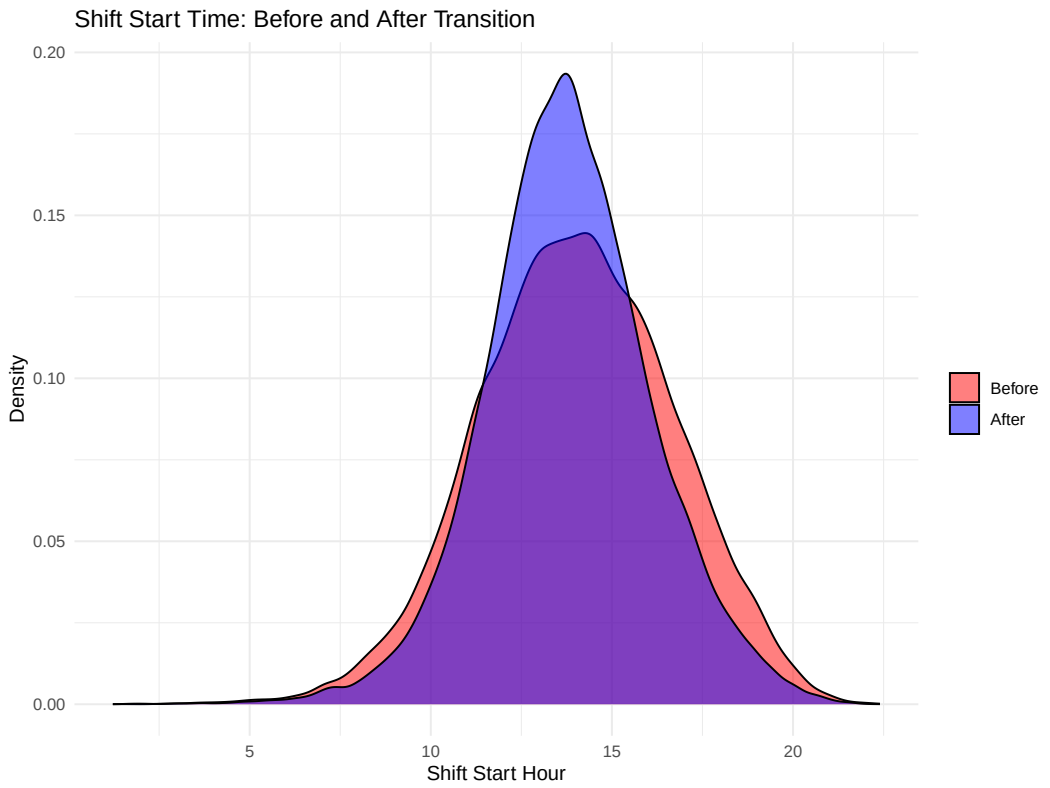


Figure 10: Distribution of Shift Start Times: Before vs. After Transition

These findings highlight substantial changes among incumbent drivers following the shift from an upfront fixed-fee system to a commission-based pricing model. Drivers become more selective about when and how long they work — favoring shorter, better-timed shifts and exerting less effort per unit of time. This response reflects the altered incentive structure under the commission-based regime and underscores the importance of considering both intensive and intertemporal margins when evaluating platform design changes.

5.4 Platform-Level Outcomes

To assess how changes in driver composition and incentives associated with the transition from an upfront fixed-fee model to a commission-based model affected equilibrium outcomes on the platform, I use Equation 2 to estimate shifts in platform-level outcomes.

5.5 Aggregate Measure of Labor Supply

I begin by estimating how total hourly labor supply—proxied by the number of matching attempts—changed following the transition to a commission-based system. Using the specification in Equation 2, I examine variation in the total number of match attempts across different hours of the day. As before, results are normalized by each city's pre-transition baseline.

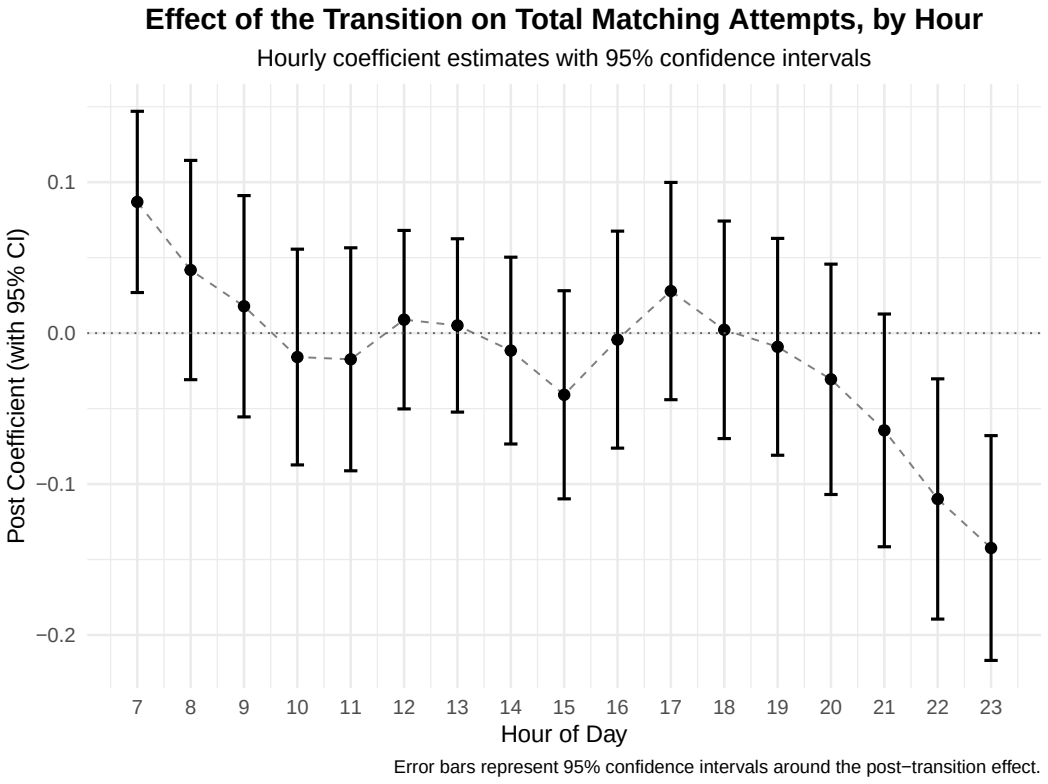


Figure 11: Effect on Total Number of Matching Attempts

Figure 11 shows a modest increase (approximately 10%) in the total number of matching attempts during morning hours, but little change—or even a decline—throughout the rest of the day, with a pronounced drop in the late evening. These patterns suggest that the commission-based fee structure was effective at attracting more workers during specific peak periods, particularly the morning rush hours.

To assess whether this change is driven by the entry of new drivers rather than increased effort among existing ones, I also estimate a set of hourly regressions using Equation 2, where the dependent variable is the mean number of match attempts per driver in a given hour. This variable is normalized in the same way as in the previous analysis.

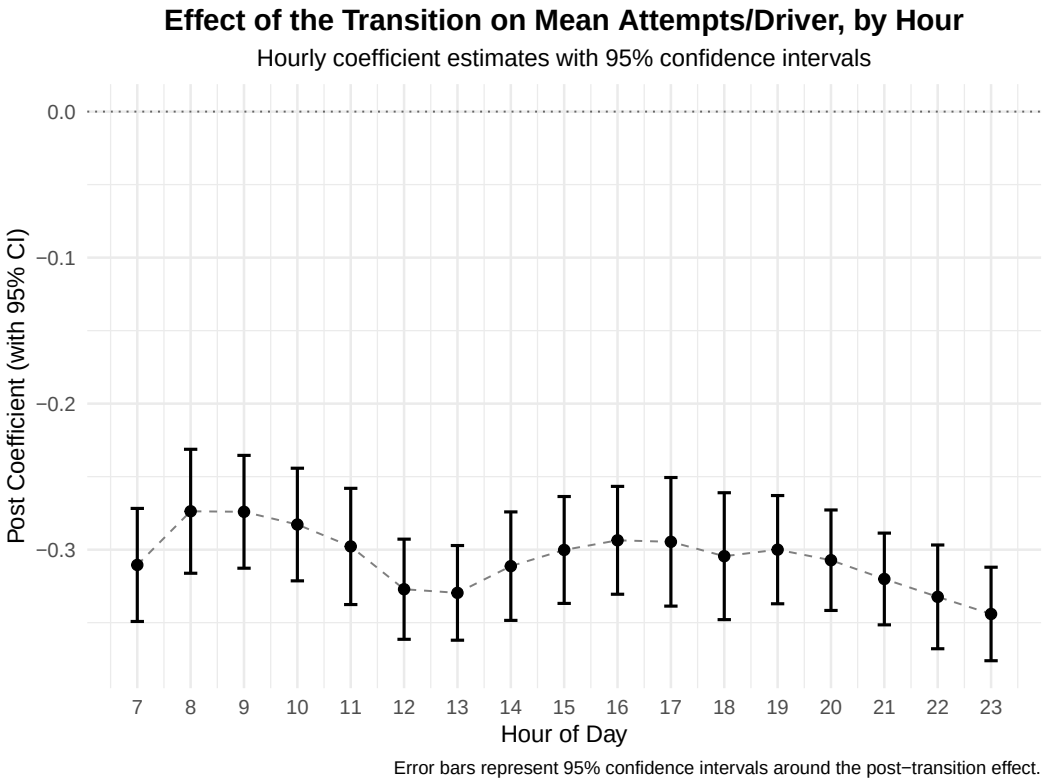
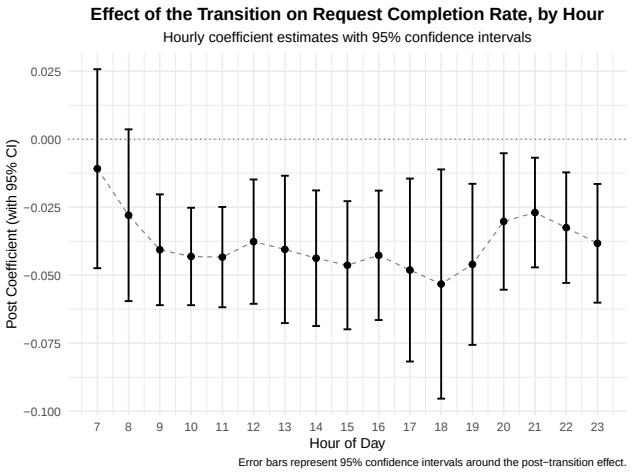


Figure 12: Effect on Mean Attempts per Driver

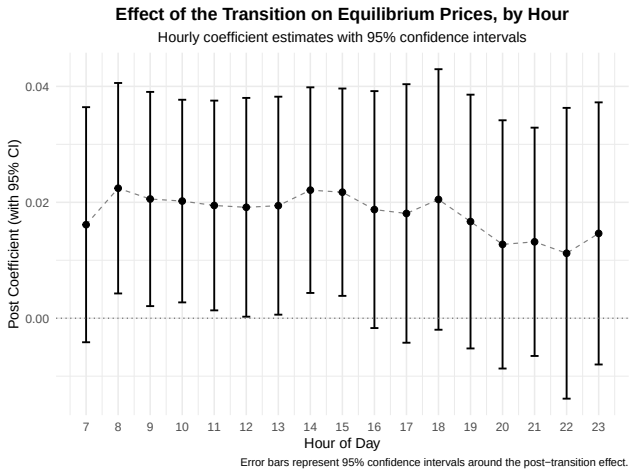
Figure 12 shows that drivers make fewer attempts to get matched following the transition — on average, a reduction of about 30% throughout the day. Thus, the observed increase in total matching attempts in the morning is primarily driven by new entrants to the platform, rather than increased activity by existing drivers, following the shift to the commission-based model.

5.6 Prices and Request Completion Rates

Two key indicators speak to the operational efficiency of the platform under different fee structures: request completion rates and equilibrium prices. I estimate Equation 2 with two dependent variables: first, the request completion rate; and second, the equilibrium transaction price on the platform.



(a) Effect on Request Completion Rates



(b) Effect on Transaction Prices

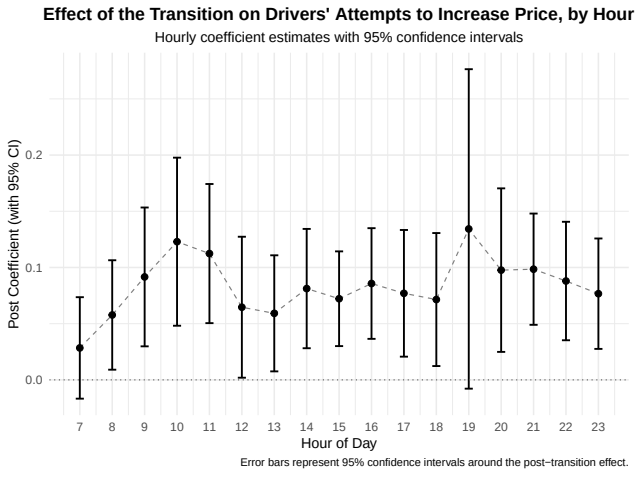
Figure 13: Effects of the Commission-Based Model on Request-level Match Rates and Prices

Figure 13 illustrates two main findings: equilibrium prices increased by approximately 2% (relative to a baseline level), while request completion rates declined by about 5% (relative to a baseline level). These results suggest a deterioration in the platform's operational efficiency following the transition to the commission-based model.

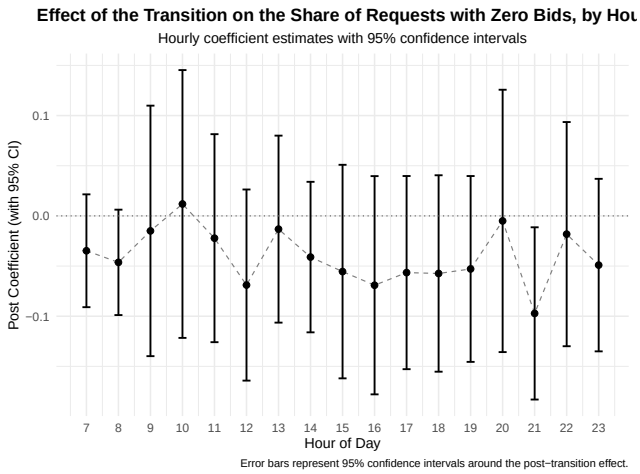
To better understand the mechanisms behind the price increase and the lower request-level match rates, I also estimate Equation 2 with two additional dependent variables: the share of requests in which at least one driver submitted a counteroffer, and the share of requests that did not receive any bids. The results are presented in Figure 14.

The left panel shows that, following the transition, the share of requests with at least one driver asking for a higher price increases in almost all hours, though much less so during the morning rush hours, where we also do not observe a significant price increase or a decline in match rates. This pattern suggests that increased counteroffering may be one of the key mechanisms behind the lower match rates and higher prices observed during most other hours.

Additional evidence comes from the right panel of Figure 14, which shows that for the majority of markets (except around 9 PM) there is no significant change in the share of requests that receive exactly zero bids.



(a) Effect on the Share of Requests Involving Counteroffers



(b) Effect on Share of Requests with Zero Bids

Figure 14: Effects of the Commission-Based Model on Counteroffer Rates and Zero-Bid Request Shares

5.7 Platform's Profit

In addition to examining the equilibrium effects on prices and quantities, the paper also analyzes the platform's profits. I compute daily platform profits at the city level and use equation 1 to study how these profits change following the transition to the commission-based system. The results are presented in Figure 15. On average, the platform's profits increase by 19%, though with substantial variation. A preliminary empirical check suggests that this pattern reflects considerable day-to-day heterogeneity and the degree to which the new fee structure is optimal for the platform. A more detailed analysis is currently underway.

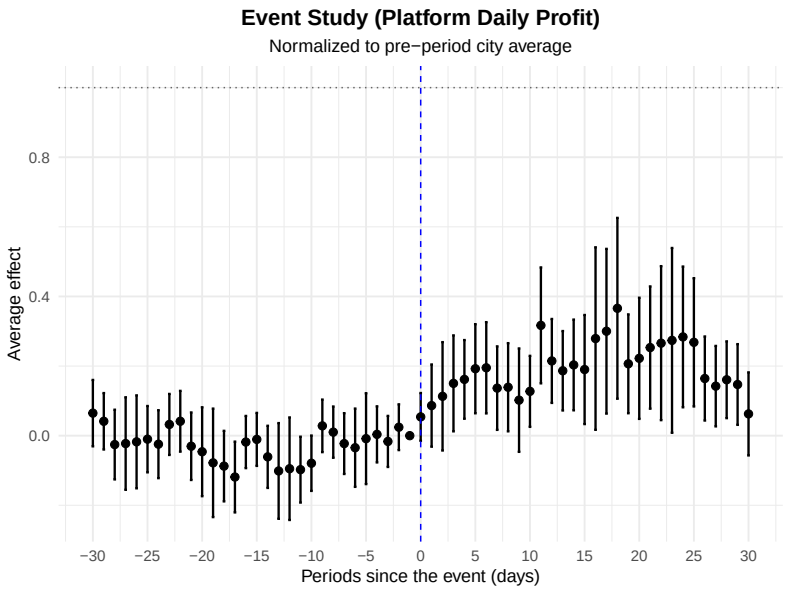


Figure 15: Event Study Estimates: Effect of Transition on Daily Profits (Normalized)

6 Interpretation and Mechanisms

The evidence presented above points to a substantive compositional shift in the driver pool, accompanied by a change in incentives following the introduction of the commission-based fee structure. Although the aggregate number of active drivers increases, particularly during key demand windows such as the morning rush, this expansion coincides with more sporadic participation patterns and lower average effort among drivers. Notably, equilibrium matching rates remain flat during the morning rush and decline during most other hours. Interestingly, while night hours do not exhibit a clear decline in request completion rates, the total number of matching attempts falls.

These outcomes suggest that the commission-based fee structure may increase equilibrium prices and decrease transacted quantity through several distinct channels.

First, the influx of new drivers does not fully compensate for the reduced effort of incumbents. Instead of expanding the platform's capacity to serve new or previously unmet requests – particularly if entrants have different preferences – new drivers appear to replace rather than augment the effort supplied by incumbents. Second, there is a notable increase in counteroffering. This may reflect drivers' attempts to pass the commission on to riders through higher prices, as well as the possibility that new entrants face higher costs and therefore counteroffer more frequently.

A third potential mechanism is that reduced effort among incumbents could leave some requests without any bidding attempts. However, the evidence does not support this channel: the share of zero-bid requests does not increase and, if anything, declines slightly (though this change is not statistically significant).

Taken together, these patterns indicate that the platform may not be successfully attracting incremental supply capable of serving previously unmatched requests. When participation shifts toward more opportunistic or lower-effort drivers, platforms may benefit from reintroducing screening mechanisms—such as fixed-fee schemes—that help ensure a higher-effort, more stable supply of labor.

7 Conclusion

This paper studies how a platform's fee structure shapes both aggregate labor supply and equilibrium outcomes in a gig platform. Exploiting a quasi-experimental transition from an upfront fixed-fee to a commission-based fee structure on a global ride-hailing platform, I document a substantial increase in driver participation following the removal of upfront entry costs. However, this expansion is not unambiguously beneficial: new entrants tend to be less engaged, contribute fewer hours, and participate more sporadically. At the same time, incumbent drivers reduce their effort per shift and alter the timing of their activity.

These behavioral adjustments generate meaningful equilibrium effects. Despite the larger driver pool, request-level match rates decline by approximately 5%, and transaction prices increase by about 2%. The results align with the paper's theoretical predictions: fixed entry costs partially screen for lower-cost, more committed workers, whereas eliminating these costs attracts a more opportunistic and higher-cost supply pool.

By linking fee structure to labor supply composition and market performance, the paper offers new theoretical and empirical contributions to the design of digital labor platforms. It highlights a core tension in platform governance: while reducing entry barriers can promote inclusivity, it also increases the risk of adverse selection, lower engagement, and potential consumer harm. As platforms and regulators seek to balance flexibility, fairness, and efficiency, the findings underscore

the importance of designing fee structures that anticipate adjustments in aggregate labor supply. Fixed fees—often viewed as exclusionary may in fact serve as important instruments for sustaining consumer welfare.

Future research should study the optimal design of fee structures and develop structural models of platform–worker interactions that incorporate heterogeneity in worker types and endogenous behavioral responses. Such models can quantify the trade-offs inherent in platform design and guide the creation of more efficient and resilient digital labor markets.

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