Multihoming and Platform Choice in Online Food Delivery*

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Abstract

This paper examines multihoming in the Philippine online food delivery market using two original cross-sectional surveys of users and delivery riders. We distinguish two margins of platform participation: multihoming as a margin of engagement and single-homing as a margin of specialization. On the user side, multihoming is more common among users with higher delivery demand, as spreading orders across platforms becomes attractive when demand is frequent enough to justify using two apps. Conditional on single-homing, platform choice is shaped by a monetary service dimension: users in areas with larger rider networks are more likely to choose GrabFood, while those in areas with larger restaurant networks are less likely to do so, and loyalty remains a strong sorting device. On the rider side, multihoming is concentrated in thicker local demand environments and is less common among riders who report that other apps provide too few rides, and conditional on single-homing, platform choice reflects how each platform bundles demand, compensation, and administrative requirements rather than simple market-size differences.

keywords: multihoming, binary logit, network effects, online food delivery, platforms, switching costs.
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1 Introduction

The online food delivery market in the Philippines is expanding rapidly, reshaping how consumers access restaurant and prepared meals. Valued at about USD 4.34 billion in 2024, it is projected to reach USD 10.33 billion by 2033, corresponding to a compound annual growth rate of 10.11%.[1] Growth is driven by urbanization, smartphone use, digital payments, and increasing demand for convenience. At the same time, competition among third-party aggregators, restaurant-delivery services, and cloud kitchens has intensified around speed, user experience, and affordability.

Technological change and internet penetration have disrupted the traditional restaurant ordering and delivery process, enabling online food delivery platforms such as FoodPanda and GrabFood to flourish. In these platforms, delivery riders play a pivotal role in linking consumers and restaurants. Platform success depends on maintaining a sufficiently large restaurant base together with a dense rider network that can ensure timely deliveries and reliable service. As in other multisided platform markets, the value created on one side depends on participation on the others, so indirect network effects are central to platform competition.

A central feature of competition in this environment is multihoming, that is, the decision of market participants to join or use more than one competing platform. Consumers may rely on several apps to compare prices, promotions, and delivery times; riders may work across platforms to increase earnings and flexibility; and restaurants may list on multiple platforms to expand demand. Multihoming matters because it affects the extent to which platforms can lock in users and providers, shape entry conditions, and build or defend market power. When multihoming is widespread, platforms face stronger competitive discipline and entry barriers are generally lower. When it is limited, platforms can more easily insulate themselves from rivalry and reinforce their position through switching frictions, loyalty mechanisms, or other forms of lock-in.

Against this background, our paper studies two related empirical questions. First, which observable price, network, switching-friction, and individual characteristics are associated with multihoming among consumers and delivery riders? Second, conditional on single-homing, which characteristics are associated with choosing GrabFood rather than FoodPanda? This distinction separates the diversification margin from the platform-specialization margin and allows the analysis to ask whether the same variables organize both decisions.

To address these questions, we analyze two original survey datasets capturing the preferences and behaviors of both consumers and delivery riders in the Philippines. The empirical analysis uses an economics-first variable selection rule and estimates two sets of side-specific binary logit models: one for multihoming versus single-homing and one for GrabFood versus

[1] Industry Research Group (2024), https://tinyurl.com/54c6ph4f. Accessed online on 12 August 2025.

FoodPanda among single-homers. Because the data are cross-sectional and key regressors are equilibrium outcomes, we interpret the estimates as descriptive conditional associations rather than causal effects, and we discuss the endogeneity problem explicitly in the paper.

This study contributes to the literature on platform economics and multisided markets by providing descriptive evidence on the correlates of multihoming and single-platform specialization in an emerging-market online food delivery setting. Existing work on online food delivery has focused primarily on adoption, usage intention, service quality, and customer satisfaction, whereas direct evidence on homing decisions remains comparatively limited. Our paper adds to this literature by examining users and riders jointly and by distinguishing between the decision to multihome and the decision of which platform to choose when single-homing.

The main empirical patterns reveal two distinct margins of platform participation: multihoming as a margin of engagement and single-homing as a margin of specialization. On the user side, multihoming becomes more attractive when delivery demand is frequent enough to justify maintaining connections with two apps and when the user's outside option set is thin enough that the second connection adds value. In that sense, multihoming reflects both usage intensity and a willingness to keep alternatives open. Conditional on single-homing, GrabFood use is shaped by a monetary service dimension, with users in areas with larger rider networks more likely to choose GrabFood and those in areas with larger restaurant networks less likely to do so; loyalty also remains a strong sorting device. On the rider side, multihoming responds to whether the local market offers enough incremental business to justify keeping a second app active, whereas single-homing reflects how each platform bundles demand, compensation, and administrative requirements. The two decisions are therefore related but distinct: one concerns diversification across competing platforms, while the other concerns specialization on the platform that best matches the rider's expected earnings and working conditions.

Although the analysis is grounded in the Philippine online food delivery market, the distinction between multihoming and conditional platform choice is relevant for a broader set of digital platform markets in which switching costs, indirect network effects, and user lock-in shape competition and contestability.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature on platform competition, with particular emphasis on research related to online food delivery. Section 3 presents the empirical model. Section 4 introduces the survey datasets used in the analysis. Section 5 reports the main empirical findings on multihoming and conditional platform choice. Finally, Section 6 concludes with a discussion of the implications of our findings for theory, practice, and competition policy.

2 Literature review and regulation

Online food delivery (OFD) platforms are multisided intermediaries that coordinate interactions among consumers, restaurants, and delivery workers. As in other platform markets, participation on one side affects the value created on the others, so indirect network effects and price structure are central to market outcomes. The core insight of the economics of platforms is that platforms do not simply choose a single price; they must attract multiple sides simultaneously and determine how total charges are allocated across them. (Rochet & Tirole 2003, Armstrong 2006, Rysman 2009, Weyl 2010) This logic is especially relevant in OFD, where consumer value depends on restaurant variety and delivery performance, restaurant value depends on access to demand and logistics, and rider value depends on order flow and earnings opportunities.

A relevant layer of analysis concerns homing decisions. Platform users may single-homing on one platform or multihome across several platforms, and this choice shapes equilibrium fees, platform differentiation, and market contestability. Seminal work shows why nonexclusive intermediation may emerge, how competitive bottlenecks arise when one side multihomes and the other single-homers, and why exclusivity can become strategically valuable. Subsequent contributions also show that the effects of multihoming on prices, profits, and welfare are not monotonic; they depend on which side multihomes, on homing costs, and on whether homing decisions are endogenous.[2] Empirical work outside OFD confirms that multihoming matters for competition. Studies of video-game consoles, newspapers, and daily-deals platforms show that multihoming affects platform sales, responses to entry, and the effectiveness of information design. More broadly, this literature highlights that multihoming is not just a behavioral residual: it is a market-structuring variable that shapes rivalry and platform incentives (Landsman & Stremersch 2011, Park et al. 2021, Li & Zhu 2021).

The OFD literature has grown rapidly, but systematic reviews show that it remains concentrated mainly on consumer adoption, usage intention, satisfaction, trust, perceived value, and loyalty. Shankar et al. (2022) and Shroff et al. (2022) document that much of this literature relies on survey-based designs and technology-adoption frameworks, including the Unified Theory of Acceptance and Use of Technology, the Theory of Planned behavior, and the Technology Acceptance Model. Similarly, the meta-analysis by Shankar et al. (2024) synthesizes OFD research primarily around consumers' intentions to use delivery platforms and their post-adoption evaluations of service quality and platform value. These contributions provide an important account of why consumers adopt and continue using OFD services. However, they do not place homing decisions at the center of the analysis: whether users, riders, or other platform participants single-homing or multihoming across competing OFD

[2]The literature on the role of homing decisions on market equilibrium is well developed. See Caillaud & Jullien (2003), Armstrong & Wright (2007), Belleflamme & Peitz (2019), Jeitschko & Tremblay (2020), Bakos & Halaburda (2020), Teh et al. (2023) among others

platforms remains comparatively less studied. This paper addresses that gap by centering the analysis on homing decisions, examining the determinants of single-homing and multihoming and their implications for platform competition in a multisided OFD market.

A smaller but growing economics and operations literature studies OFD as a platform ecosystem involving restaurants, logistics, and contractual design. Li & Wang (2025*a*) show that on-demand delivery platforms can increase restaurants' total takeout sales and generate positive spillovers to dine-in visits, although the gains are substantially larger for chains than for independent restaurants. Li & Wang (2025*b*) study commission-fee caps and show that regulations intended to help independent restaurants can backfire once platforms respond by changing recommendations and shifting costs to consumers. Related work examines restaurant-platform conflict and coordination: Feldman et al. (2023) analyze contractual tensions between restaurants and delivery platforms, while Mayya & Li (2025) show that adding noncontracted restaurants can generate positive spillovers for platform growth. Oh et al. (2026) further argue that current commission arrangements can distort restaurant-platform incentives and that broader sharing of delivery costs and fees can improve efficiency. This literature is related to our paper because it treats OFD as a multisided platform ecosystem rather than as a simple delivery service. However, its main focus is the restaurant-platform relationship, commission design, and operational coordination, whereas our analysis shifts attention to the user and rider sides and studies how prices, network density, and loyalty strategies are associated with single-homing and multihoming decisions.

Another stream studies regulation and distributional trade-offs within the OFD ecosystem. Recent models show that wage-floor regulation may improve delivery-worker outcomes under some conditions but at the expense of other stakeholders, whereas commission-cap policies can improve restaurant revenues and, in some settings, ecosystem welfare. Related work also shows that food delivery should often be analyzed as part of a broader multisided mobility and logistics environment because integration with ride-sourcing can alter equilibrium outcomes (Ji et al. 2024, Liu & Li 2023). Relative to these strands, direct evidence on multihoming in OFD remains limited, especially when user-side and rider-side homing decisions are studied jointly. On the demand side, Singh et al. (2022) explicitly describe consumer multihoming on food platforms as underexplored. On the supply side, adjacent ride-sourcing evidence shows that multihoming and switching are shaped by earnings prospects, bonus schemes, waiting and dispatch frictions, and nontrivial switching costs. Passenger-side loyalty work in ridesharing likewise suggests that platform partnerships and loyalty mechanisms can reduce multihoming (Yu et al. 2021, Guo et al. 2023, Valderrama & Cameron 2023). Taken together, this adjacent evidence suggests that OFD multihoming should be studied as a strategic response to local network density, earnings opportunities, switching frictions, and loyalty instruments rather than as a purely residual behavioral outcome.

The preceding discussion also has direct relevance for competition policy. The European

Commission's Digital Markets Act (DMA) of 2022, establishes a regulatory framework aimed at making digital platform markets fairer and more contestable, reflecting a broader policy concern that gatekeeper platforms may use network effects, switching costs, and ecosystem control to entrench their position.[3] In the OFD sector, recent European enforcement illustrates that these concerns are not only theoretical. In 2024, the European Commission opened an investigation into possible anticompetitive agreements between Delivery Hero and Glovo, including concerns related to market allocation, commercially sensitive information, and no-poach arrangements.[4] The subsequent Commission decision in the Food Delivery Services case further confirms the competition relevance of labor-market restraints and coordination between competing food-delivery platforms.[5] In the Philippine context, the Philippine Competition Commission's conditional approval of Mynt's acquisition of ECPay shows that multisided digital ecosystems are also being scrutinized through merger control and behavioral commitments, even outside the OFD sector narrowly defined.[6] These policy developments reinforce the importance of studying how platform strategies affect contestability.

Against this background, our paper contributes by examining multihoming jointly on the user and rider sides of the Philippine OFD market, whereas much of the existing OFD literature focuses either on consumer adoption outcomes or on restaurant-platform relations. By integrating survey data with indicators of local network structure, price and income metrics, and measures of platform loyalty, the paper directly addresses the channels through which platforms influence contestability and lock-in in a rapidly expanding digital market.

3 Empirical model

The empirical analysis is organized around two distinct decisions, which we model within a random utility framework. Agents first decide whether to multihome across online delivery services or instead single-homing on one platform. Conditional on single-homing, they then choose which platform to join. This sequential structure reflects the idea that the determinants of diversification need not coincide with those governing specialization. In particular, the variables that affect the decision to multihome may differ from those that affect platform

[3] Regulation (EU) 2022/1925 of the European Parliament and of the Council of 14 September 2022 on contestable and fair markets in the digital sector (Digital Markets Act), Official Journal of the European Union, available at: https://eur-lex.europa.eu/eli/reg/2022/1925/oj.

[4] European Commission, "Commission opens investigation into possible anticompetitive agreements in the online food delivery sector", press release IP/24/3908, 23 July 2024, available at: https://ec.europa.eu/commission/presscorner/detail/en/ip_24_3908.

[5] European Commission, Commission Decision of 2 June 2025 relating to a proceeding under Article 101 TFEU and Article 53 of the EEA Agreement, Case AT.40795 – Food Delivery Services, C(2025) 3304 final, available at: https://ec.europa.eu/competition/antitrust/cases1/202530/AT_40795_1262.pdf.

[6] Philippine Competition Commission, "PCC clears Mynt's acquisition of ECPay, imposes commitments to safeguard competition", press release, available at: https://phcc.gov.ph/resource-details/pcc-clears-mynt-s-acquisition-of-ecpay-imposes-commitments-to-safeguard-competition.

choice as we explain in the next section.

In the first stage, agent a of type $j \in \{\text{user}, \text{rider}\}$ chooses between multihoming (M) and single-homing (S). Let the latent utilities be

$$U_{ajM} = V_{ajM} + \eta_{ajM}, \qquad U_{ajS} = V_{ajS} + \eta_{ajS}, \tag{1}$$

where the observable components, interacted with their coefficients, are generated by the additive terms,

$$\begin{aligned} V_{ajM} &= \alpha_j^M + P_{aj}\beta_j^M + N_{al}\gamma_j^M + S_{aj}\delta_j^M + X_{aj}\theta_j^M, \\ V_{ajS} &= \alpha_j^S + P_{aj}\beta_j^S + N_{al}\gamma_j^S + S_{aj}\delta_j^S + X_{aj}\theta_j^S. \end{aligned} \tag{2}$$

Here, P_{aj} collects price or expenditure variables, N_{al} captures local indirect network conditions in area l, S_{aj} denotes platform strategy or switching-cost variables, and X_{aj} contains a compact set of individual controls. Importantly, the variables affecting multihoming need not be the same as those affecting the platform-choice margin, and the corresponding coefficients are therefore allowed to differ across the two utilities. The agent chooses to multihome if $U_{ajM} \geq U_{ajS}$.

Conditional on single-homing, the agent chooses between platform G (GrabFood) and platform F (FoodPanda). The latent utilities for the second-stage choice are

$$U_{ajG} = W_{ajG} + \varepsilon_{ajG}, \qquad U_{ajF} = W_{ajF} + \varepsilon_{ajF}, \tag{3}$$

where the observable components correspond to the additive terms,

$$\begin{aligned} W_{ajG} &= \tilde{\alpha}_j^G + \tilde{P}_{aj}\tilde{\beta}_j^G + \tilde{N}_{al}\tilde{\gamma}_j^G + \tilde{S}_{aj}\tilde{\delta}_j^G + \tilde{X}_{aj}\tilde{\theta}_j^G, \\ W_{ajF} &= \tilde{\alpha}_j^F + \tilde{P}_{aj}\tilde{\beta}_j^F + \tilde{N}_{al}\tilde{\gamma}_j^F + \tilde{S}_{aj}\tilde{\delta}_j^F + \tilde{X}_{aj}\tilde{\theta}_j^F. \end{aligned} \tag{4}$$

Again, the covariates relevant for platform choice may differ from those that govern the multihoming decision (hence denoted with tilde), and the coefficients are allowed to vary across platforms. An agent with $U_{ajM} < U_{ajS}$ chooses GrabFood if $U_{ajG} \geq U_{ajF}$.

A useful way to interpret the structure is as a sequential choice tree, as depicted in Figure 1.

This tree highlights that platform choice is only observed for agents who single-home, so the second-stage decision is conditional on the first-stage outcome. The two utilities are also potentially correlated through unobserved components. For instance, an agent with a latent preference for flexibility or a stronger outside option may be more likely to multihome and also have systematically different platform preferences when single-homing. Such correlation suggests that the two equations may not be fully separable in practice.

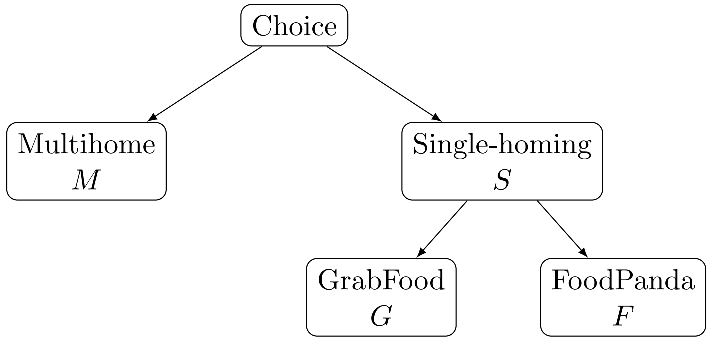


Figure 1: Sequential choice

Empirically, this structure can be estimated in two ways. A first approach is to estimate two independent logit (or probit) models: one for multihoming versus single-homing, and one for the GrabFood versus FoodPanda choice among single-homers. It is easy to implement, but it treats the two decisions as conditionally independent. A second approach is to use a nested logit specification, in which the single-homing alternatives are grouped in a nest. This allows for correlated unobservables within the second-stage choice and offers a more flexible representation of substitution patterns. In both cases, the model should be interpreted as describing conditional associations rather than causal effects. In our main empirical analysis, we use a two-independent-logit approach and report the nested-logit estimates in Appendix A. The main reason is that our data are more consistent with a two-logit specification, as the nested-logit model estimates a correlation of one.

The two independent logit approach does not allow us to identify all coefficients in both the multihoming and single-homing equations, nor in the GrabFood and FoodPanda equations. We therefore normalise the model by setting the coefficients with superscript S in Equation 2 and those with superscript F in Equation 4 to zero and interpret the coefficients and marginal effects with respect to that reference choice.

4 Data

The empirical question is which observable characteristics are associated with the decision to multihome, and, conditional on single-homing and the choice of one platform, which observable characteristics explain the choice of that platform over the other.

4.1 Sample

To study those margins directly, we use two original survey datasets collected in major Philippine cities between December 16 and 24, 2023.[7] The surveys were commissioned by

[7] Appendix B provides details on survey implementation, sampling strategy, and geographic coverage.

the Philippine Competition Commission and were designed to capture the two sides of the platform interaction that are central to the paper: users who place food-delivery orders and riders who supply delivery services. Interviewers completed 700 face-to-face interviews in total, 500 with users and 200 with riders, with response rates among eligible participants of 45.21% and 60.42%, respectively.

The analysis focuses on the online platforms FoodPanda and GrabFood, which define the economically relevant competitive margin in the sample. Starting from the completed interviews, we exclude respondents outside the relevant food-delivery choice set, respondents associated only with niche or rarely observed platforms, and observations missing variables required for the maintained specifications. These restrictions leave 386 users and 156 riders, so the analytic sample retains 77.2% of completed user interviews and 78.0% of completed rider interviews. The resulting samples are large enough to study both multihoming and conditional platform affiliation on the user side, but much thinner on the rider multihoming margin, where only 16 respondents report multihoming behavior. That asymmetry already suggests that the economics of platform participation differ across the two sides of the market and motivates the paper's separate user and rider specifications.

Table 1: Sample composition, regional distribution, and response accounting

	FoodPanda	GrabFood	Multihoming	Total
Panel A: Users				
NCR (Metro Manila)	18	30	16	64
Luzon (other)	29	15	34	78
North Central Luzon	29	13	26	68
South Luzon / Bicol	30	25	27	82
Visayas	35	23	36	94
Total	141	106	139	386
Panel B: Riders				
NCR (Metro Manila)	22	44	7	73
Luzon (other)	7	7	2	16
North Central Luzon	13	8	0	21
South Luzon / Bicol	10	8	3	21
Visayas	15	6	4	25
Total	67	73	16	156
Panel C: Response and sample size				
Group	Completed interviews	Response rate (eligible)	Non-response rate (eligible)	Relevant sample
Users	500	45.21%	54.79%	386 (excluded: 114; 22.8%)
Riders	200	60.42%	39.58%	156 (excluded: 44; 22.0%)

Notes: Panels A and B report sample counts by area and platform status. 'Multihoming' indicates respondents active on more than one online delivery platform. Panel C reports response and non-response rates among eligible participants as well as the completed-interview and relevant-sample size.

Table 1 provides the first stylized fact of the paper. Panel A reports user counts by area, Panel B reports rider counts by area, and Panel C records response and sample-accounting rates. Multihoming is common on the user side but much less common on the rider side.

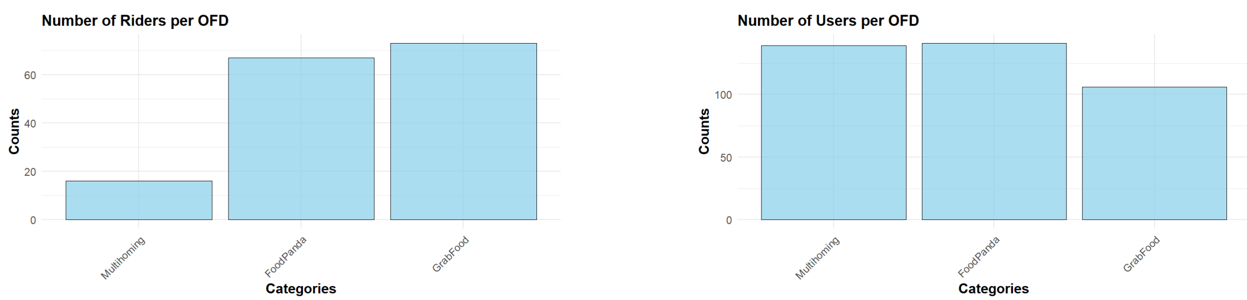
Among users, 139 of 386 respondents, or 36.0%, report active use of both major platforms. Among riders, the corresponding share is 16 of 156, or 10.3%. Conditional on single-homing, users tilt toward FoodPanda: 141 of 247 single-homing users, or 57.1%, report FoodPanda, while 42.9% report GrabFood. The rider side is much closer to parity, with GrabFood accounting for 52.1% of single-homing riders and FoodPanda 47.9%. In economic terms, users appear to rely on multihoming as an active participation margin, whereas riders more often sort into one platform or the other. This difference is central for the empirical design because it implies that the determinants of diversification are likely to differ from the determinants of single-platform affiliation, and that those determinants may differ again across sides.

The regional variation in Table 1 also helps identify the objects the data can speak to. User multihomers appear in every survey area, with especially large counts outside Metro Manila, while rider multihoming remains sparse in every area. That pattern gives the user-side analysis enough dispersion to study both the multihoming margin and the conditional platform-choice margin in a relatively balanced way. On the rider side, by contrast, the thin multihoming cell requires a parsimonious specification and shifts more of the rider-side cross-platform variation to the conditional affiliation margin.

Figure 2 gives a visual summary of the same composition. The user side combines a sizable multihoming group with substantial single-homing on both major platforms, while the rider side is much more concentrated in single-homing. The figure reinforces the paper's core asymmetry: users appear to keep both platforms available more often, whereas riders appear to face a sharper affiliation decision. That is why the empirical analysis does not impose a common reduced-form structure across the two sides.

The unit of observation is the individual survey respondent. We analyze the user sample and rider sample separately because the relevant economic margins differ across the two sides of the market. For both samples, the active variables are organized into four economically motivated groups. First, price or expenditure variables capture monetary incentives: perceived delivery fees and expenditure per order for users, and tips and monthly operating costs for riders. Second, network variables proxy for local indirect network effects through area-level counts of riders, users, and restaurants. Third, platform strategic variables capture mechanisms that may facilitate or impede diversification, such as in-house delivery availability, stated loyalty, uniforms or equipment provision, and pay arrangements. Fourth, a compact set of controls captures demographics and intensity of use or work, including recent ordering, age, gender, and weekly working days. This organization drives the descriptive analysis and the regression design around economically interpretable mechanisms rather than around the full set of available survey responses.

For the broader user-side descriptive table, two variables retain missing values after the sample restrictions: the indicator for continuing to order after a 10% price increase is missing for 33 of 386 users, or 8.5%, and household income is missing for 12 users, or 3.1%. To preserve the full analytic sample in the broader descriptive exhibit, we impute the missing values. Continuous variables are imputed at the median and binary variables at the mode, first within area and multihoming status when at least five observed values are available, otherwise within area, and otherwise in the full user sample. Under this rule, household income is imputed with area-by-status medians and the 10% continuation indicator with area-by-status modes. We do not impute platform-status outcomes, variables that define multihoming, or structurally branch-specific follow-up variables. The rider-side broader descriptive table does not require an analogous new imputation step because the added composition variables are fully observed once the area-level merges are made.



(a) Riders (b) Users

Figure 2: Platform-status composition of surveyed riders and users

4.2 Relevant variables across decision margins

Table 2 and Table 3 convert the raw survey information into stylized facts about the paper's two decision margins. Panel A describes the relevant sample. Panel B in each table compares multihomers with single-homers and therefore speaks to diversification across platforms. Panel C conditions on single-homing and compares GrabFood with FoodPanda, so it speaks to platform affiliation within specialization. The variables in Panel B describe the value and feasibility of keeping both platforms active, whereas the variables in Panel C describe relative platform attractiveness once a respondent has chosen to specialize.

We calculate network size as follows. Suppose we focus on the indirect network size generated by restaurants for users (or riders). For each area, we count the number of restaurants on each platform: P_1 for platform 1, P_2 for platform 2, and P_{12} for restaurants that multihome on both platforms. The total number of restaurants in an area is the sum of these three groups. We then construct a measure of network size by dividing the observed number of restaurants by the maximum possible network size (maximum capacity level), defined as twice the largest number of restaurants observed in any area. For example, in area A_1 there are 5 restaurants on platform 1, 3 on platform 2, and 2 multihoming restaurants, giving 10 restaurant listings in total. If the maximum number of restaurants observed in any area is

Table 2: User-side descriptive evidence for maintained logit variables

Panel A. Summary statistics (all users)				
Variable	Mean	SD	Min	Max
Price and expenditure				
Delivery fee per order (100 of PhP)	0.583	0.28	0.1	1.1
Expenditure per order (100 of PhP)	3.633	2.406	0.208	9.000
Network size				
Share of restaurants	0.116	0.114	0.016	0.5
Share of riders	0.146	0.105	0.055	0.5
Platform strategies				
Considers other platforms	0.803	0.398	0	1
Loyal to preferred platform	0.060	0.237	0	1
Controls				
Age (10 years)	3.178	1.048	1.8	7.1
Female	0.484	0.5	0	1
Household income (100K of PhP)	2.495	2.264	1.250	14
In-house delivery available	0.124	0.330	0	1
No dine-in substitute	0.155	0.363	0	1
Observations	386			
Panel B. Mean differences				
Variable	Multihoming	Single-homing	Difference	Std. error
Network size				
Share of restaurants	0.145	0.099	0.045***	(0.013)
Share of riders	0.184	0.124	0.059***	(0.011)
Platform strategies				
Considers other platforms	0.914	0.741	0.173***	(0.037)
Loyal to preferred platform	0.022	0.081	-0.059***	(0.021)
Controls				
Age (10 years)	3.194	3.169	0.025	(0.11)
Female	0.518	0.466	0.052	(0.053)
Household income (100K of PhP)	2.675	2.392	0.283	(0.250)
In-house delivery available	0.129	0.121	0.008	(0.035)
No dine-in substitute	0.194	0.134	0.061	(0.040)
Observations (multihomers / single-homers)	139 / 247			
Panel C. Mean differences among single-homers				
Variable	GrabFood	FoodPanda	Difference	Std. error
Price and expenditure				
Delivery fee per order (100 of PhP)	0.649	0.551	0.098**	(0.038)
Expenditure per order (100 of PhP)	3.506	3.375	0.131	(0.299)
Network size				
Share of restaurants	0.082	0.112	-0.030***	(0.011)
Share of riders	0.147	0.108	0.039***	(0.013)
Platform strategies				
Loyal to preferred platform	0.047	0.106	-0.059*	(0.033)
Controls				
Age (10 years)	3.172	3.167	0.004	(0.135)
Female	0.434	0.489	-0.055	(0.064)
Household income (100K of PhP)	2.308	2.457	-0.149	(0.283)
Observations (GrabFood / FoodPanda single-homers)	106 / 141			

Notes: The unit of observation is a surveyed online food-delivery user. The table is limited to variables that enter at least one maintained user-side logit specification. Panel A reports means, standard deviations, minima, and maxima using all non-missing observations for each variable, so usable counts can differ across rows because some survey items are branch-specific or unavailable for a subset of respondents. Panel B compares user multihomers with user single-homers; reported differences equal the multihomer mean minus the single-homer mean, and standard errors come from Welch two-sample comparisons when both groups have sufficient support. Panel C restricts the sample to single-homers and compares GrabFood with FoodPanda; reported differences equal the GrabFood mean minus the FoodPanda mean, with Welch standard errors reported in parentheses. Monetary variables are expressed in hundreds of Philippine pesos where noted. The normalized rider- and restaurant-count variables divide each raw area count by twice the largest observed area-level count for that side. Stars denote $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table 3: Rider-side descriptive evidence for maintained logit variables

Panel A. Summary statistics (all riders)

Variable	Mean	SD	Min	Max
Price and expenditure				
Average tip per trip (1K of PhP)	0.068	0.088	0.005	0.6
Monthly operating cost (1K of PhP)	4.935	2.949	0.15	16
Network size				
Share of restaurants	0.160	0.141	0.016	0.5
Share of users	0.280	0.073	0.181	0.5
Platform strategies				
# of required documents at application	3.692	1.189	1	7
Depends on price per order	0.301	0.460	0	1
Uniform and equipment provided	0.250	0.434	0	1
Controls				
Age (10 years)	3.365	0.785	2.1	5.4
Fewer rides on other apps	0.365	0.483	0	1
Working days per week	5.641	1.183	2.5	6.5
Observations	156			

Panel B. Mean differences

Variable	Multihoming	Single-homing	Difference	Std. error
Price and expenditure				
Monthly operating cost (1K of PhP)	4.754	4.956	-0.202	(0.688)
Network size				
Share of restaurants	0.288	0.145	0.143**	(0.05)
Share of users	0.408	0.266	0.142***	(0.018)
Platform strategies				
Uniform and equipment provided	0.250	0.250	0	(0.118)
Controls				
Age (10 years)	3.225	3.381	-0.156	(0.194)
Fewer rides on other apps	0.062	0.4	-0.338***	(0.075)
Working days per week	5.5	5.657	-0.157	(0.277)
Observations (multihomers / single-homers)	16 / 140			

Panel C. Mean differences among single-homers

Variable	GrabFood	FoodPanda	Difference	Std. error
Price and expenditure				
Average tip per trip (1K of PhP)	0.057	0.083	-0.025	(0.016)
Network size				
Share of restaurants	0.112	0.182	-0.070***	(0.021)
Share of users	0.251	0.281	-0.030***	(0.010)
Platform strategies				
# of required documents at application	3.781	3.552	0.229	(0.199)
Depends on price per order	0.233	0.403	-0.170**	(0.078)
Controls				
Age (10 years)	3.477	3.276	0.201	(0.134)
Working days per week	5.815	5.485	0.330	(0.204)
Observations (GrabFood / FoodPanda single-homers)	73 / 67			

Notes: The unit of observation is a surveyed delivery rider. The table is limited to variables that enter at least one maintained rider-side logit specification. Panel A reports means, standard deviations, minima, and maxima using all non-missing observations for each variable, so usable counts can differ across rows because survey branching and sparse support limit some items. Panel B compares rider multihomers with rider single-homers; reported differences equal the multihomer mean minus the single-homer mean, and standard errors come from Welch two-sample comparisons when both groups have sufficient support. Panel C restricts the sample to single-homers and compares GrabFood with FoodPanda; reported differences equal the GrabFood mean minus the FoodPanda mean, with Welch standard errors reported in parentheses. Monetary variables are expressed in thousands of Philippine pesos where noted. The normalized user- and restaurant-count variables divide each raw area count by twice the largest observed area-level count for that side. Stars denote $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

15, then the implied network shares are calculated relative to a maximum capacity of 30. The same construction applies to the number of riders and the number of users for riders.

The decision to Multihome is driven by the benefit of adding an extra platform versus the cost of doing so, while platform choice among single-homers is driven by the relative attractiveness of each platform. That is, market size, compatibility, and multihoming costs matter for the homing decision; whereas platform-specific features matter for the choice among platforms. Some variables like network size may affect both choices as they vary both by platform and by multihome within each area (market).

Variables assigned to the multihoming margin capture whether adding a second platform is worthwhile. We group these variables into four broad categories. First, price and expenditure variables proxy for the economic gains from comparing across platforms. Higher expenditure per order, monthly delivery spending, and delivery fees may increase the value of maintaining access to more than one platform because users can compare prices, promotions, and service terms across platforms. Second, platform strategic variables capture how costly it is for respondents to diversify across platforms. Considering other platforms, loyalty to a preferred platform induced by platform strategies, and value or attachment measures proxy for openness to switching versus attachment to a single platform. For riders, work intensity captures the degree to which delivery work is organized around a regular platform routine. Third, network size variables measure whether a second platform provides meaningful additional access to counterparties. Area-level rider counts, restaurant counts, platform participation, and the number of locally available platforms proxy for the extent to which another platform expands the respondent's effective choice set. Fourth, barriers and frictions capture factors that may reduce the need or ability to multihome. In-house delivery, offline substitution, and the absence of dine-in substitutes proxy for settings in which users are more constrained to one ordering channel or face higher coordination costs.

Variables assigned to the conditional platform-choice margin proxy for factors that affect the relative attractiveness of one platform against another once a respondent has chosen to single-home. Unlike the multihoming decision, which depends on whether maintaining an additional platform is worthwhile, this margin depends on cross-platform differences in the expected utility from affiliation.

Platform-specific price and service variables such as delivery fees, delivery time, reliability, service quality, and promotional intensity capture the direct consumption or operating value of one platform relative to its rival. Better terms on these dimensions should increase the likelihood that a respondent selects that platform when single-homing.

Coverage and local network variables proxy for platform-specific demand- and supply-side network advantages. A platform with greater local rider availability, restaurant density, or market coverage may offer shorter wait times, broader variety, or more reliable matching, which can make that platform more attractive even when the respondent does not multihome.

These variables enter the conditional platform-choice equation rather than the multihoming equation because they primarily govern which platform is preferred conditional on specialization, not whether the respondent finds it worthwhile to maintain access to multiple platforms.

Control variables such as age and gender may enter both regressions. The tables therefore do more than summarize the sample: they indicate which margins the data can discipline and why the same covariates need not matter in the same way across users and riders.

4.3 Descriptive statistics

Tables 2 and 3 summarize the variables used in the maintained logit specifications and organize the raw comparisons around the two empirical margins. The first margin compares multihomers with single-homers. The second margin compares GrabFood and FoodPanda among respondents who single-home. Appendix C and D report the corresponding user- and rider-side variable dictionaries and summary statistics for the broader cleaned survey measures.

The raw comparisons point first to network size. Users who multihome are by definition exposed to larger rider and restaurant networks than users who single-home. The difference is 0.059 in (normalized) rider network size and 0.045 in (normalized) restaurant network size. Riders show the same pattern. Rider multihomers operate in areas with (normalized) user and restaurant network sizes that are 0.142 and 0.143 higher than those of rider single-homers. These gaps are natural in a platform market. A second platform is more valuable when it gives access to a larger local pool of counterparties. For users, this means more riders and restaurants. For riders, this means more potential orders and more restaurants from which orders can originate.

On the user side, Table 2 also shows that multihoming is associated with weaker attachment to a single platform. User multihomers are 17.3 percentage points more likely than single-homers to report considering other alternatives beyond multihoming. They are 5.9 percentage points less likely to report loyalty to a preferred platform. These differences fit the interpretation that multihoming is easier when users face lower attachment switching costs. By contrast, in-house delivery availability, household income, age, and gender show insignificant differences across user multihomers and single-homers. The no-dine-in-substitute measure is somewhat larger, at 6.1 percentage points, but it is also not statistically significant. The main user-side separation is therefore not demographic. It is linked to local network access and to the willingness to keep alternatives open.

Among user single-homers, the relevant comparison changes. The question is no longer whether a user keeps both apps active, but which platform the user relies on. Table 2 shows that GrabFood single-homers report delivery fees that are 0.098 hundred pesos higher than FoodPanda single-homers, or about 9.8 pesos per order. They also live in areas with higher normalized rider network size and lower normalized restaurant network size. Loyalty to a preferred platform is lower among GrabFood single-homers by 5.9 percentage points. Other differences, including expenditure per order, income, age, and gender, are modest. These raw patterns suggest that the single-platform choice margin is more closely related to platform-specific service and local network conditions than to the same factors that separate multihomers from single-homers.

The rider-side evidence in Table 3 has the same two-margin structure, but the economic content is different. Rider multihomers and single-homers have similar operating costs and working days. The largest non-network difference is about outside demand. Only 6.2% of rider multihomers report that other apps provide too few rides, compared with 40% of rider single-homers. The gap is 33.8 percentage points. This comparison is consistent with a simple participation logic: riders are more likely to work across platforms when they believe there is enough demand outside their main app to justify doing so. It shows that the multihoming margin is closely tied to perceived ride availability rather than to observed cost differences.

For rider single-homers, platform affiliation is again linked to platform-specific work arrangements. Table 3 shows that GrabFood single-homers are 17.0 percentage points less likely than FoodPanda single-homers to report being paid by price per order. They also operate in areas with lower normalized user and restaurant network size. Average tips, working days, application document counts, and age differ less sharply in the raw comparisons. Thus, for riders as for users, the descriptive evidence separates the decision to use more than one platform from the decision to specialize on one platform. The former is mainly related to whether the local environment can support activity across apps. The latter is more closely related to the terms and conditions attached to a particular platform.

5 Empirical findings

This section estimates the two empirical margins introduced above. The first margin is whether a respondent multihomes. The second margin is, conditional on single-homing, whether the respondent chooses GrabFood rather than FoodPanda.

Table 4 reports the user-side estimates, and Table 5 documents the rider-side estimates. All entries are average marginal effects from binary logit models, so they are interpreted as percentage-point changes in predicted probabilities rather than as odds ratios. For example, an estimate of 0.10 means a 10 percentage-point difference in the probability of the outcome. For continuous variables, this difference corresponds to a one-unit increase in the units reported in the table. For binary variables, it corresponds to a change from 0 to 1. The estimates are descriptive conditional associations and should not be read as causal effects.

A number of the right-hand-side variables are endogenous, including the price variables, network effects, and platform strategies, among others. This large set of endogenous regressors makes it difficult, if not impossible, to determine the direction of the bias arising from correlations both among the endogenous variables themselves and between the endogenous and exogenous variables. Some endogenous variables, such as network size and loyalty measures, are likely to be positively correlated with the error term, whereas others, such as prices, are likely to be negatively correlated. In Appendix E, we discuss from an econometric perspective how the bias induced by multiple endogenous variables may be signed. Although the problem can be partly decomposed using the Frisch–Waugh–Lovell theorem, the overall direction of the bias remains difficult to establish. In our context, however, if the positive correlations dominate the negative ones, the estimates are likely to be upward biased, as explained in Appendix E. In the discussion of marginal effects below, we therefore caution the reader that these effects may be overstated, although this should be understood only as an intuition, since the true direction of the bias is complex and cannot be determined with certainty.

5.1 User-side results

Table 4 reports average marginal effects from the user-side logit models. Column 1 estimates the probability that a user multihomes. Column 2 uses only single-homing users and estimates the probability that a user chooses GrabFood rather than FoodPanda.

The user-side estimates separate a diversification margin from a platform-affiliation margin. On the first margin, multihoming is concentrated among users whose delivery demand is stronger and with a sizeable number of riders in the area. Monthly delivery spending is a useful benchmark: a 100-peso increase is associated with a 1.3 percentage-point higher probability of multihoming. That magnitude is modest in level terms, but it is meaningful because it moves with behavior that reflects sustained platform use. Users who say they are willing to consider other platforms are 20.4 percentage points more likely to multihome, and users without a dine-in substitute are 11.0 percentage points more likely to multihome. In platform-competition terms, multihoming looks like a margin of engagement: it becomes attractive when delivery demand is frequent enough to justify gaining from two apps and when the user's outside option set is thin enough that the second connection has value.

Network size matters as well, although not symmetrically across all network measures. The rider-network variable is positive and statistically significant, which is consistent with users being more willing to maintain both platforms when the local delivery network is dense enough with a second platform. The restaurant-network measure is not significant in the multihoming equation, so the relevant pattern is not that every counterpart count matters in the same way.

The affiliation margin among single-homers is different. Here the question is not whether a user keeps additional online service apps, but which platform becomes the default. Reported

Table 4: User-side logit models

	Multihoming	GrabFood among single-homers
Price and expenditure		
Delivery fee per order (100 of PhP)		0.283***
		(0.095)
Expenditure per order (100 of PhP)		-0.010
		(0.012)
Monthly delivery spending (100 of PhP)	0.013***	
	(0.003)	
Network size		
Share of restaurant	-0.075	-3.145***
	(0.286)	(0.869)
Share of riders	1.185***	2.498***
	(0.286)	(0.442)
Platform strategies		
Continue after 10 percent price increase	-0.049	-0.099
	(0.060)	(0.085)
Loyal to preferred platform	-0.030	-0.221**
	(0.130)	(0.088)
Controls		
Age (10 years)	0.001	-0.011
	(0.021)	(0.027)
Considers other platforms	0.204***	
	(0.060)	
Female	0.037	-0.084
	(0.045)	(0.057)
Household income (100K of PhP)	0.003	0.010
	(0.010)	(0.014)
In-house delivery available	0.026	
	(0.066)	
No dine-in substitute	0.110*	
	(0.063)	
Orders per month	0.012	-0.044**
	(0.007)	(0.019)
Observations	386	247
Pseudo-R^2	0.149	0.185

Notes: Each column reports average marginal effects from a binary logit model estimated on the imputed user-ready analysis file. Column 1 models the probability of multihoming using the active user-side variables plus the active common controls. Column 2 restricts the sample to single-homers and models the probability of choosing GrabFood rather than FoodPanda using the active Panel C variables plus the active common controls. Variables commented out of the specification are automatically excluded from the model table and average marginal effects output. The analysis is descriptive rather than causal.

delivery fees are strongly associated with choosing GrabFood: a 100-peso increase in the reported fee in both platforms is associated with a 28.3 percentage-point higher probability of choosing GrabFood. Because these fees may reflect basket size, location, service mix, and selection into platform use, the estimate should be read as a sorting gradient rather than a pure price effect. As suggested above, those percentages may be overstated due to endogeneity bias. Even so, the magnitude is large enough to matter, and it indicates that the two platforms segment users along a monetary service dimension. The network variables point in opposite direction: users in areas with larger rider networks are more likely to choose GrabFood, while users in areas with larger restaurant networks are less likely to do so. Loyalty remains a strong sorting device, with loyal users 22.1 percentage points less likely to choose GrabFood, and more frequent orders are also less likely to do so.

5.2 Rider-side results

Table 5 reports average marginal effects from the rider-side logit models. The rider multihoming equation uses ridge penalization because only 16 riders multihome in the maintained sample. For this reason, the rider multihoming estimates should be read with even greater caution.

The rider-side estimates reinforce the idea that multihoming is a scarce margin that becomes viable only when the outside demand pool of users is thick enough. The clearest correlate is the belief that other apps provide too few rides: riders who report that constraint are 9.5 percentage points less likely to multihome. That is the natural sign if a second platform only pays off when expected incremental orders can cover the fixed time and administrative costs of remaining active on multiple apps. The weakly positive user-network gradient is consistent with the same logic. By contrast, operating costs, uniforms or equipment provision, working days, and age do not affect this margin. Rider multihoming is therefore not driven by broad worker demographics; it is tied to whether the local market can supply enough ride opportunities outside the main platform to make diversification worthwhile.

Among single-homing riders, platform affiliation is shaped more by the terms of work than by generic market scale. Riders paid by price per order are 12.7 percentage points less likely to choose GrabFood, while each additional required application document is associated with a 4.6 percentage-point higher probability of choosing GrabFood. Age also matters: a ten-year increase is associated with a 7.8 percentage-point higher probability of choosing GrabFood. These are significant gradients in a market where platform contracts differ in compensation rules and compliance burdens. The network variables are informative: riders in denser user and restaurant markets are less likely to choose GrabFood, which suggests that affiliation is not governed only by market size. A more plausible reading is that the platforms sort riders into different segments of local demand and different work arrangements, with platform choice

Table 5: Rider-side logit models

	Multihoming	GrabFood among single-homers
Price and expenditure		
Average tip per trip (1K of PhP)		-0.421
		(0.369)
Monthly operating cost (1K of PhP)	-0.003	
	(0.009)	
Network size		
Share of restaurants	0.138	-3.726***
	(0.086)	(0.293)
Share of users	0.169*	-10.031***
	(0.098)	(1.108)
Platform strategies		
# of documents application		0.046*
		(0.027)
Depends on price per order		-0.127*
		(0.077)
Uniform and equipment provided	0.000	
	(0.052)	
Controls		
Age (10 years)	-0.025	0.078*
	(0.031)	(0.040)
Fewer rides on other apps	-0.095**	
	(0.042)	
Working days per week	-0.001	-0.033
	(0.022)	(0.030)
Observations	156	140
Pseudo-R^2	0.209	0.516

Notes: Each column reports average marginal effects from a binary logit model. Column 1 models the probability of multihoming and uses a ridge-penalized logit because the rider multihoming margin has few positive observations. Column 2 restricts the sample to single-homing riders and models the probability of choosing GrabFood rather than FoodPanda using the active Panel C variables plus the active common controls. Variables commented out of the specification are automatically excluded from the model table and average marginal effects output. The analysis is descriptive rather than causal.

reflecting how each app packages pay and access to orders.

That pattern fits the broader platform-competition framework used in the paper. Multihoming responds to whether the local market offers enough incremental business to justify keeping a second app live, whereas single-homing reflects how a platform bundles demand, compensation, and administrative requirements. The two decisions are therefore related but distinct: one concerns diversification across competing platforms, the other concerns specialization on the platform that best matches the rider's expected earnings and operating conditions.

6 Conclusions

This paper has examined multihoming in the Philippine online food delivery market from the perspectives of users and delivery riders. Using two original cross-sectional surveys, we document how multihoming and single-platform specialization vary with price or cost measures, network size, switching-friction variables, and individual characteristics. The empirical design separates the decision to multihome from the platform-choice decision among single-homers, which allows the analysis to distinguish diversification across platforms from specialization on one platform.

The descriptive patterns show that multihoming is systematically associated with local market size. On the rider side, multihoming is more common in areas with more users and is less common among riders who report that other apps provide too few rides. Conditional on single-homing, GrabFood affiliation is associated with thinner local networks and with lower reported incidence of platform-provided uniforms or pay-by-price-order arrangements. These conditional platform-choice estimates should be read as sorting patterns, not as causal effects of contract design.

For users, multihoming is positively associated with monthly delivery spending, local rider density, stated willingness to consider other platforms, and the absence of a dine-in substitute. Conditional on single-homing, GrabFood use is more common in areas with more riders and fewer restaurants and among users reporting higher perceived delivery fees. The contrast between the multihoming and conditional platform-choice equations indicates that the correlates of platform expansion are not the same as the correlates of platform specialization.

The findings of this study offer insights for Philippine competition policy, particularly in understanding multihoming behavior in the online food delivery market, a key sector in the country's rapidly expanding digital economy. By examining how users and drivers navigate choices between competing platforms, the study enhances the capacity of antitrust practitioners and policymakers to grasp key factors for platform competition. The results underscore that platform choice and multihoming are shaped not only by costs and fees but also by working conditions, highlighting the need to consider both consumer and worker welfare in the regulation of digital markets.

Methodologically, the paper shows the value of a parsimonious two-margin empirical design for settings in which multihoming is observed but causal identification is limited. This structure is especially useful on the rider side, where only 16 surveyed riders multihome and a highly parameterized platform-choice model would be unstable. The results are therefore best understood as descriptive evidence on significant correlates of multihoming and conditional platform choice.

From a policy perspective, our study underscores the nuanced challenges regulators face in multisided digital markets. Multihoming, by limiting platform lock-in and fostering contestability, can sustain competitive discipline—yet platforms can and do deploy targeted strategies to attenuate these effects. Exclusive partnerships, loyalty-inducing compensation schemes, technological lock-ins, and the calibration of fees and user experience can collectively shape competition.

Although the evidence comes from the Philippine food delivery sector, the empirical distinction between multihoming and conditional platform choice is relevant for other digital marketplaces in which agents decide both whether to maintain access to multiple platforms and which platform to rely on when they single-home. At the same time, the cross-sectional design and the endogeneity of prices, network size, and switching-friction variables limit the strength of causal and welfare claims.

In summary, this study documents systematic correlates of multihoming on both sides of a multisided food delivery market. The results are informative for competition authorities because they identify observable conditions under which multihoming is more or less prevalent, while also showing why cross-sectional survey evidence should be interpreted cautiously. Future research with panel data, experimentally induced variation, or stronger instruments would be needed to estimate the causal effects of fees, network composition, and switching-cost policies on platform participation.

References

Armstrong, M. (2006), 'Competition in two-sided markets', *The RAND Journal of Economics* **37**(3), 668–691.

Armstrong, M. & Wright, J. (2007), 'Two-sided markets, competitive bottlenecks and exclusive contracts', *Economic Theory* **32**(2), 353–380.

Bakos, Y. & Halaburda, H. (2020), 'Platform competition with multihoming on both sides: Subsidize or not?', *Management Science* **66**(12), 5599–5607.

Belleflamme, P. & Peitz, M. (2019), 'Platform competition: Who benefits from multihoming?', *International Journal of Industrial Organization* **64**, 1–26. 2017 EARIE Proceedings.
URL: *https://www.sciencedirect.com/science/article/pii/S0167718718300353*

Caillaud, B. & Jullien, B. (2003), 'Chicken & egg: Competition among intermediation service providers', *RAND Journal of Economics* **34**(2), 309–328.

Feldman, P., Frazelle, A. E. & Swinney, R. (2023), 'Managing relationships between restaurants and food delivery platforms: Conflict, contracts, and coordination', *Management Science* **69**(2), 812–823.

Guo, X., Haupt, A., Wang, H., Qadri, R. & Zhao, J. (2023), 'Understanding multi-homing and switching by platform drivers', *Transportation Research Part C: Emerging Technologies* **154**, 104233.
URL: *https://www.sciencedirect.com/science/article/pii/S0968090X2300222X*

Industry Research Group (2024), 'Philippines online food delivery market forecast and trends'. Market size and CAGR projections.

Jeitschko, T. D. & Tremblay, M. J. (2020), 'Platform competition with endogenous homing', *International Economic Review* **61**(3), 1281–1305.

Ji, X., Li, X. & Wang, S. (2024), 'Balance between profit and fairness: Regulation of online food delivery (OFD) platforms', *International Journal of Production Economics* **269**, 109144.

Landsman, V. & Stremersch, S. (2011), 'Multihoming in two-sided markets: An empirical inquiry in the video game console industry', *Journal of Marketing* **75**(6), 39–54.

Li, H. & Zhu, F. (2021), 'Information transparency, multihoming, and platform competition: A natural experiment in the daily deals market', *Management Science* **67**(7), 4384–4407.

Li, Z. & Wang, G. (2025*a*), 'On-demand delivery platforms and restaurant sales', *Management Science* **71**(7), 5788–5804.

Li, Z. & Wang, G. (2025*b*), 'Regulating powerful platforms: Evidence from commission fee caps', *Information Systems Research* **36**(1), 126–140.

Liu, Y. & Li, S. (2023), 'An economic analysis of on-demand food delivery platforms: Impacts of regulations and integration with ride-sourcing platforms', *Transportation Research Part E: Logistics and Transportation Review* **171**, 103019.

Mayya, R. & Li, Z. (2025), 'Growing platforms by adding complementors without a contract', *Information Systems Research* **36**(3), 1670–1690.

Oh, J., Glaeser, C. K. & Su, X. (2026), 'Food ordering and delivery: How platforms and restaurants should split the pie', *Management Science* **72**(3), 1748–1768.

Park, K. F., Seamans, R. & Zhu, F. (2021), 'Homing and platform responses to entry: Historical evidence from the us newspaper industry', *Strategic Management Journal* **42**(4), 684–709.

Rochet, J.-C. & Tirole, J. (2003), 'Platform competition in two-sided markets', *Journal of the European Economic Association* **1**(4), 990–1029.

Rysman, M. (2009), 'The economics of two-sided markets', *Journal of Economic Perspectives* **23**(3), 125–143.

Shankar, A., Jebarajakirthy, C., Maseeh, H. I., Nayal, P., Kumar, A. & Krishnan, C. (2024), 'Why do consumers choose online food delivery services? a meta-analytic review', *International Journal of Hospitality Management* **123**, 103921.

Shankar, A., Jebarajakirthy, C., Nayal, P., Maseeh, H. I., Kumar, A. & Sivapalan, A. (2022), 'Online food delivery: A systematic synthesis of literature and a framework development', *International Journal of Hospitality Management* **104**, 103240.

Shroff, A., Shah, B. J. & Gajjar, H. (2022), 'Online food delivery research: A systematic literature review', *International Journal of Contemporary Hospitality Management* **34**(8), 2852–2883.

Singh, N., Kumar, N. & Kapoor, S. (2022), 'Consumer multihoming predisposition on food platforms: does gender matter?', *Journal of Retailing and Consumer Services* **67**, 103029.

Teh, T.-H., Liu, C., Wright, J. & Zhou, J. (2023), 'Multihoming and oligopolistic platform competition', *American Economic Journal: Microeconomics* **15**(4), 68–113.

Valderrama, D. X. & Cameron, B. G. (2023), 'Customer loyalty in two sided markets: Rider multihoming in the united states rideshare market', *Research in Transportation Business & Management* **47**, 100950.

Weyl, E. G. (2010), 'A price theory of multi-sided platforms', *American Economic Review* **100**(4), 1642–1672.
URL: *https://www.aeaweb.org/articles?id=10.1257/aer.100.4.1642*

Yu, J., Mo, D., Xie, N., Hu, S. & Chen, X. (2021), 'Exploring multi-homing behavior of ride-sourcing drivers via real-world multiple platforms data', *Transportation Research Part F: Traffic Psychology and Behaviour* **80**, 61–78.

A Nested-logit feasibility and robustness

This appendix reports nested-logit estimates as a robustness check on the maintained two-step binary specification. The platform-affiliation outcome has three mutually exclusive categories: FoodPanda single-homing, GrabFood single-homing, and multihoming. The natural nesting structure places FoodPanda and GrabFood in a single-homing nest and treats multihoming as a separate branch. This structure is intuitive because it separates the decision to single-home from the platform chosen conditional on single-homing. Its limitation is that the multihoming branch is a singleton nest, so the model can identify only the inclusive-value parameter for the single-homing nest.

Table A.1 reports the user-side nested-logit estimates. The model uses the 386-user analytic sample. The estimated inclusive-value parameter is close to one, and the nested-logit likelihood is essentially identical to the multinomial-logit benchmark. This indicates that the nested logit adds little beyond the standard multinomial specification. The main coefficient patterns are nevertheless consistent with the maintained results: rider-network density is positively associated with both GrabFood and multihoming relative to FoodPanda, while restaurant-network density is negatively associated with these margins. Users who report considering other platforms are also more likely to multihome.

Table A.2 reports the corresponding rider-side estimates. These results should be read more cautiously because the rider sample contains only 16 multihomers. The inclusive-value parameter is again close to one, and the fit is nearly identical to the multinomial-logit benchmark. The nested-logit estimates therefore do not provide a separate model of substitution patterns. They mainly show that estimating the three observed affiliation outcomes jointly does not overturn the descriptive interpretation of the main results.

B Survey design

B.1 Survey method

The survey was implemented by a professional field research firm through face-to-face interviews using a standardized questionnaire and visual aids. Tablet-Assisted Personal Interviewing (TAPI) was employed to ensure consistency in data capture. The response rate among eligible interviewees was 45.2% for users and 60.4% for riders. Average interview duration was 22 minutes for users and 19 minutes for riders, including screening questions.

B.2 Survey area

The user survey covered five major regions of the Philippines with an initial total of 500 completed interviews. The user analytic sample used in the main regressions is 386 after ap-

Table A.1: User-side nested-logit robustness model

	GrabFood vs FoodPanda	Multihoming vs FoodPanda
Intercept	-0.364	-2.687***
	(0.982)	(0.824)
Monthly delivery spending (hundreds of PhP)	0.034	0.093
	(0.108)	(0.060)
Delivery fee per order (hundreds of PhP)	1.685***	-0.041
	(0.541)	(0.539)
Expenditure per order (hundreds of PhP)	-0.152	-0.109
	(0.281)	(0.160)
Normalized area rider network size	26.053***	21.200***
	(4.141)	(3.791)
Normalized area restaurant network size	-24.880***	-9.473***
	(4.399)	(2.414)
Considers other platforms	-0.381	0.853*
	(0.413)	(0.471)
In-house delivery available	0.063	0.217
	(0.448)	(0.409)
Loyal to preferred platform	-1.799**	-0.963
	(0.719)	(0.813)
No dine-in substitute	-0.316	0.384
	(0.438)	(0.382)
Continue after 10 percent price increase	-0.368	-0.444
	(0.432)	(0.386)
Orders per month	-0.271	-0.045
	(0.235)	(0.089)
Household income (hundreds of thousands of PhP)	0.074	0.040
	(0.076)	(0.061)
Age (10 years)	-0.005	0.009
	(0.144)	(0.134)
Female	-0.402	0.040
	(0.303)	(0.285)
Inclusive-value parameter	0.999***	
	(0.000)	
Observations	386	
Log-likelihood	-331.911	
AIC	725.823	
BIC	848.454	
MNL log-likelihood	-331.911	

Notes: The table reports a user-side nested logit with 'FoodPanda' and 'GrabFood' inside a single-homing nest and 'Multihoming' as a singleton alternative. FoodPanda single-homing is the base alternative. Because the multihoming branch is a singleton, the only estimable inclusive-value parameter is for the single-homing nest. The sample uses the maintained imputed user-side covariates from the expanded analysis file and complete-case estimation. Estimation-sample shares are FoodPanda: 141 (36.5%); GrabFood: 106 (27.5%); Multihoming: 139 (36.0%). The multinomial-logit benchmark on the same sample has log-likelihood -331.911. Warning summary: estimated nesting parameter is very close to 1, so the nested logit is close to a multinomial logit. Stars denote $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table A.2: Rider-side nested-logit robustness model

	GrabFood vs FoodPanda	Multihoming vs FoodPanda
Intercept	48.908***	-115.352
	(11.149)	(82.188)
Monthly operating cost (thousands of PhP)	0.202	-0.844
	(0.125)	(5.603)
Tip per trip (thousands of PhP)	-7.075	43.824
	(4.420)	(134.015)
Normalized area user network size	-153.249***	272.404***
	(34.009)	(46.096)
Normalized area restaurant network size	-57.621***	88.163*
	(11.636)	(53.049)
Uniform and equipment provided	-3.802***	6.733
	(0.996)	(45.081)
Fewer rides on other apps	-0.531	-2.603
	(0.668)	(28.368)
Paid by price per order	-2.402**	2.608
	(1.070)	(36.301)
Application document count	0.390	-0.682
	(0.345)	(21.252)
Working days per week	-0.766*	-0.702
	(0.399)	(13.547)
Age (10 years)	1.146**	0.005
	(0.509)	(19.056)
Female	-0.039	-11.499***
	(1.414)	(0)
Inclusive-value parameter	0.999	
	0.000	
Observations	156	
Log-likelihood	-34.362	
AIC	118.725	
BIC	194.971	
MNL log-likelihood	-34.442	

Notes: The table reports a rider-side nested logit with 'FoodPanda' and 'GrabFood' inside a single-homing nest and 'Multihoming' as a singleton alternative. FoodPanda single-homing is the base alternative. Because the multihoming branch is a singleton, the only estimable inclusive-value parameter is for the single-homing nest. The sample uses the maintained rider-side covariates and complete-case estimation. Estimation-sample shares are FoodPanda: 67 (42.9%); GrabFood: 73 (46.8%); Multihoming: 16 (10.3%). The multinomial-logit benchmark on the same sample has log-likelihood -34.442. Warning summary: estimated nesting parameter is very close to 1, so the nested logit is close to a multinomial logit. Stars denote $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

plying the maintained exclusions (respondents outside the relevant online food-delivery choice set, respondents associated only with niche or rarely observed platforms, and observations missing key variables). Figure B.1 shows the geographic distribution of user respondents.

AREAS	SAMPLE
NCR	**100**
North/ Central Luzon	**100**
Pangasinan	30
Bulacan	30
Pampanga	40
South Luzon/ Bicol	**100**
Laguna	60
Batangas	20
Camarines Sur	20
Visayas	**100**
Negros Occidental	40
Cebu	60
Mindanao	**100**
Misamis Oriental	40
Davao del Sur	60
TOTAL	**500**

Figure B.1: Survey areas and sample sizes for online delivery users.

For riders, a purposive sampling strategy was adopted to capture active delivery workers in key urban centers. A total of 200 rider interviews were completed, with half of the sample based in NCR. After the same maintained exclusions, the rider analytic sample is 156. Figure B.2 reports the geographic distribution of rider respondents.

AREAS	SAMPLE
NCR	100
North/ Central Luzon	25
South Luzon/ Bicol	25
Visayas	25
Mindanao	25
TOTAL	**200**

Figure B.2: Survey areas and sample sizes for online delivery riders.

B.3 Sampling design

For online delivery users, a multi-stage area probability sampling procedure was implemented to ensure representativeness across regions. For riders, purposive sampling was employed given the absence of a complete sampling frame. Recruiters relied on internal referral networks to identify potential respondents, who were subsequently screened to verify eligibility. This strategy ensured adequate coverage of Foodpanda and GrabFood riders while capturing heterogeneity in demographics, regional location, and platform arrangements.

C Users: supplementary tables and variable definitions

This subsection reports the user-side variable dictionary and summary statistics for the cleaned analytic sample. As with the rider table, it documents the broader set of survey measures available after cleaning, while the maintained empirical specifications use only the compact set of variables motivated by prices, local network conditions, switching frictions, and basic individual characteristics.

Table C.1: User Variable Dictionary and Summary Statistics

Abbreviation	**Detailed Description**	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Channel & Premium						
Preferred: Express	Preferred platform is an express delivery service	386	0.008	0.088	0	1
Premium Member	Premium member on the preferred platform	386	0.008	0.088	0	1
Use: Website	Usual ordering method is via website	386	0.008	0.088	0	1
Demographics & Household						
Age	Age of respondent	386	31.782	10.484	18	71
Female	Female respondent (indicator)	386	0.484	0.500	0	1
Dine-In Deterrents						
No Dine-In: Travel Time	Does not dine in due to travel time	386	0.080	0.272	0	1
Reason: Avoid Crowds	Avoids dine-in to avoid crowds	386	0.047	0.211	0	1
Reason: Dine-In Hours	Avoids dine-in due to limited hours	386	0.044	0.205	0	1
Reason: Full Restaurants	Avoids dine-in because restaurants are full	386	0.003	0.051	0	1
Reason: Hard to Decide	Finds it difficult to choose what to order	386	0.003	0.051	0	1
Reason: Long Queues	Avoids dine-in due to long queues	386	0.003	0.051	0	1
Reason: Slow Service	Avoids dine-in due to slow service	386	0.008	0.088	0	1
Reason: Too Lazy	Avoids dine-in due to convenience/laziness	386	0.010	0.101	0	1
Geography						
Area: NCR	Resides in Metro Manila (NCR)	386	0.166	0.372	0	1

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Area: Luzon	Resides in Luzon (aggregate)	386	0.202	0.402	0	1
Area: N. Central Luzon	Resides in North Central Luzon	386	0.176	0.381	0	1
Area: S. Luzon/Bicol	Resides in South Luzon or Bicol	386	0.212	0.410	0	1
Area: Visayas	Resides in Visayas	386	0.244	0.430	0	1
In-House / Dine-In Attitudes						
No to Dine-In	Would not consider dine-in	386	0.155	0.363	0	1
No to In-House	Would not consider in-house delivery	386	0.166	0.372	0	1
Loyalty / Barriers to Other Options						
Preferred Rest. No In-House	Preferred restaurant has no in-house delivery	386	0.026	0.159	0	1
Reason: Diff. Account	Not using others due to different account sign-in	386	0.003	0.051	0	1
Reason: Difficult Registration	Not using others due to difficult registration	386	0.005	0.072	0	1
Reason: In-House Costly	Not using in-house because it is more costly	386	0.003	0.051	0	1
Reason: In-House Min. Order	Not using in-house due to a minimum order requirement	386	0.041	0.200	0	1
Reason: Loyal to Preferred	Not using others due to loyalty to preferred platform	386	0.060	0.237	0	1
Reason: No App Use	Does not use any app for ordering	386	0.003	0.051	0	1
Reason: Other Platform Cheaper	Not using in-house because another platform is cheaper	386	0.031	0.174	0	1
Reason: Others Expensive	Not using other platforms because they are more expensive	386	0.039	0.194	0	1
Reason: Others' Discounts	Not using others despite vouchers/discounts	386	0.034	0.181	0	1
Restaurant Unavailable Elsewhere	Preferred restaurant unavailable on other platforms	386	0.008	0.088	0	1
Sign-Up Inconvenient	Finds the sign-up process inconvenient	386	0.044	0.205	0	1
Price & Promotions (1–5 scales)						
Reason: Cheap Fee	Cited low delivery fee as a reason	386	4.176	0.735	1	5
Reason: Cheaper Transport	Cited cheaper transport costs as a reason	386	4.158	0.720	2	5
Reason: Premium Perks	Cited premium membership perks as a reason	386	3.863	0.796	1	5
Reason: Promo Frequency	Cited frequency of promotions as a reason	386	4.070	0.781	1	5
Reason: Promos	Cited availability of promotions as a reason	386	4.085	0.770	2	9
Price-Rise Choices (10% scenarios)						
Alt. 10% Dine-In	Would switch to dine-in under a 10% increase	386	0.031	0.174	0	1

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Alt. 10% Express	Would switch to express delivery under a 10% increase	386	0.013	0.113	0	1
Alt. 10% Grab	Would switch to Grab under a 10% price increase	386	0.036	0.187	0	1
Alt. 10% In-House	Would switch to in-house delivery under a 10% increase	386	0.039	0.194	0	1
Alt. 10% None	Would choose none under a 10% increase	386	0.013	0.113	0	1
No to 10% Price Hike	Would not continue if price increased by 10%	386	0.158	0.365	0	1
Price-Rise Choices (5% scenarios)						
Alt. 5% Dine-In	Would switch to dine-in under a 5% increase	386	0.021	0.143	0	1
Alt. 5% Express	Would switch to express delivery under a 5% increase	386	0.008	0.088	0	1
Alt. 5% Grab	Would switch to Grab under a 5% price increase	386	0.023	0.151	0	1
Alt. 5% In-House	Would switch to in-house delivery under a 5% increase	386	0.010	0.101	0	1
Alt. 5% None	Would choose none under a 5% increase	386	0.008	0.088	0	1
No to 5% Price Hike	Would not continue if price increased by 5%	386	0.085	0.280	0	1
Recent Usage & Spending						
Avg. Delivery Fee	Average delivery fee per order (categorical scale)	386	3.417	1.401	1	6
Avg. Spend/Order	Average spend per order (categorical scale)	386	3.531	0.853	2	5
Exp. Last Month	Total food delivery expenditure in the past month (1–5)	386	2.694	1.373	1	5
Use Freq. Last Month	Frequency of food delivery use in the past month (1–5)	386	1.223	0.642	1	5
Used Last Month	Used a food delivery service in the past month	386	0.575	0.495	0	1
Service Quality & Convenience (1–5 scales)						
Reason: Conv. Cooking	Cited convenience relative to cooking as a reason	386	4.174	0.751	2	5
Reason: Conv. Transport	Cited convenient transport as a reason	386	4.394	0.608	1	5
Reason: Customer Service	Cited quality of customer service as a reason	386	4.184	0.620	1	5
Reason: Delivery Time	Cited delivery speed as a reason for use	386	4.262	0.677	1	5
Reason: Ease of Use	Cited ease of app use as a reason	386	4.122	0.679	1	5

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Reason: Restaurant Availability	Cited restaurant availability as a reason	386	4.049	0.721	1	5
Reason: Restaurant Choices	Cited restaurant variety as a reason	386	4.199	0.656	1	5
Switching Intent & Alternatives						
Alt. Dine-In	Alternative: dine-in	386	0.005	0.072	0	1
Alt. Grab	Alternative platform: Grab	386	0.355	0.479	0	1
Alt. In-House	Alternative: in-house delivery	386	0.124	0.330	0	1
Alt. Pickaroo	Alternative: Pickaroo	386	0.003	0.051	0	1
Consider Other	Would consider using another platform	386	0.197	0.398	0	1
Express Delivery (Gen.)	Alternative: general express delivery service	386	0.031	0.174	0	1

D Riders: supplementary tables and variable definitions

This subsection reports the rider-side variable dictionary and summary statistics for the cleaned analytic sample. The table is included for transparency about available survey measures. It should not be read as the covariate list for the maintained regressions, which use the more compact economics-first specification described in the main text.

Table D.1: Rider Variable Dictionary and Summary Statistics

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Demographics & Human Capital						
Age	Rider's age in years.	156	33.647	7.851	21	54
College Graduate	Rider has completed college education.	156	0.026	0.159	0	1
Elementary Graduate	Rider has completed elementary education.	156	0.263	0.442	0	1
Male	Indicator for male riders (1 = male, 0 = female).	156	0.917	0.277	0	1
Some Elementary Education	Rider has completed some elementary education.	156	0.032	0.177	0	1
Some Vocational Education	Rider has completed some vocational education.	156	0.006	0.080	0	1
Vocational Graduate	Rider has completed vocational education.	156	0.013	0.113	0	1
Earnings & Price Variables (Price/Fee-related)						
Average Tip	Average tip received per delivery (hundreds PhP).	156	0.678	0.876	0.050	6

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Fuel (Monthly)	Monthly expenditure on fuel (hundreds PhP).	156	28.650	20.214	0.010	100
Household Income	Monthly household income category.	156	5.474	1.939	1	12
Income: 8,001–11,000	Indicator for HH income 8,001–11,000 PhP.	156	0.038	0.193	0	1
Income: 11,001–15,000	Indicator for HH income 11,001–15,000 PhP.	156	0.115	0.321	0	1
Income: 15,001–18,000	Indicator for HH income 15,001–18,000 PhP.	156	0.141	0.349	0	1
Income: 18,001–20,000	Indicator for HH income 18,001–20,000 PhP.	156	0.160	0.368	0	1
Income: 20,001–30,000	Indicator for HH income 20,001–30,000 PhP.	156	0.205	0.405	0	1
Income: 30,001–40,000	Indicator for HH income 30,001–40,000 PhP.	156	0.205	0.405	0	1
Income: 40,001–50,000	Indicator for HH income 40,001–50,000 PhP.	156	0.071	0.257	0	1
Income: 50,001–60,000	Indicator for HH income 50,001–60,000 PhP.	156	0.026	0.159	0	1
Income: 60,001–75,000	Indicator for HH income 60,001–75,000 PhP.	156	0.013	0.113	0	1
Income: 100,001–130,000	Indicator for HH income 100,001–130,000 PhP.	156	0.006	0.080	0	1
Rent (Monthly)	Monthly expenditure on vehicle/equipment rental (hundreds PhP).	156	3.421	7.516	0.010	40.000
Repairs (Monthly)	Monthly expenditure on vehicle repairs/maintenance (hundreds PhP).	156	14.494	14.220	0.010	100.000
Uniform (Monthly)	Monthly expenditure on uniform (hundreds PhP).	156	2.800	5.464	0.010	30.000
Expense Arrangement (Rent/Uniform Sub-items)						
I Do Not Buy (Equipment)	Rider reports no need to buy equipment.	156	0.006	0.080	0	1
Rentals: Deducted from Salary	Rental expense deducted from salary.	156	0.006	0.080	0	1
Rentals: Everything Provided	Company provides required equipment.	156	0.186	0.390	0	1
Rentals: Own Helmet/Box	Rider owns required helmet and insulated box.	156	0.205	0.405	0	1
Rentals: Paid at Start of Job	Rental paid upfront at job start.	156	0.269	0.445	0	1
Uniform: Deducted from Salary	Uniform expense deducted from salary.	156	0.013	0.113	0	1
Uniform: Everything Provided	Company provides required uniform.	156	0.250	0.434	0	1

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Uniform: No Rent/Change Yearly	Uniform requires no rental or changes yearly.	156	0.006	0.080	0	1
Uniform: Paid at Start of Job	Uniform paid upfront at job start.	156	0.269	0.445	0	1
Geographic Location						
Luzon	Rider is based in Luzon (island group).	156	0.705	0.457	0	1
NCR	Rider is based in the National Capital Region.	156	0.468	0.501	0	1
North/Central Luzon	Rider is based in North/Central Luzon.	156	0.135	0.342	0	1
Region III (Central Luzon)	Work location: Region III.	156	0.103	0.304	0	1
Region IV-A (CALABARZON)	Work location: Region IV-A.	156	0.071	0.257	0	1
Region V (Bicol Region)	Work location: Region V.	156	0.064	0.246	0	1
Region VI (Western Visayas)	Work location: Region VI.	156	0.058	0.234	0	1
Region VII (Central Visayas)	Work location: Region VII.	156	0.077	0.267	0	1
Region XI (Davao Region)	Work location: Region XI.	156	0.160	0.368	0	1
Visayas	Rider is based in Visayas (island group).	156	0.135	0.342	0	1
Motivations for Choosing Platform (Positive Reasons)						
Additional Benefits (Reason)	Chose platform for additional benefits.	156	0.250	0.434	0	1
Better Employer Treatment (Reason)	Chose platform for better treatment by employer.	156	0.212	0.410	0	1
Easy Requirements (Reason)	Chose platform due to easy compliance requirements.	156	0.006	0.080	0	1
Flexible Schedule (Reason—Other)	Other reasons related to flexible schedule.	156	0.006	0.080	0	1
Freelancing (Reason)	Chose platform for freelancing flexibility.	156	0.013	0.113	0	1
High Demand (Reason—Other)	Other reasons related to high demand.	156	0.006	0.080	0	1
High Demand / Higher Earnings (Reason)	Chose platform due to high demand or higher earnings.	156	0.801	0.400	0	1
Lower Expenses (Reason)	Chose platform to reduce expenses.	156	0.179	0.385	0	1
More Orders (Reason)	Chose platform for more ride/order opportunities.	156	0.583	0.495	0	1
No Boss/Autonomy (Reason)	Chose platform for autonomy ('no boss').	156	0.026	0.159	0	1
No Employer (Reason)	Chose platform for self-employment.	156	0.038	0.193	0	1
No Startup Cost (Reason)	Chose platform due to no startup cost.	156	0.013	0.113	0	1
Time Management (Reason)	Chose platform for better time management.	156	0.051	0.221	0	1
Well-Known App (Reason)	Chose platform because the app is well-known.	156	0.006	0.080	0	1
Pay Structure & Performance Factors						

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Fare Matrix (Pay Factor)	Pay is influenced by the fare matrix.	156	0.455	0.500	0	1
Fake Bookings (Pay Factor)	Pay is affected by fake bookings.	156	0.026	0.159	0	1
Incentives (Pay Factor)	Pay is influenced by incentives.	156	0.167	0.374	0	1
Length of Travel (Pay Factor)	Pay is influenced by travel length.	156	0.596	0.492	0	1
Order Cancellations (Pay Factor)	Pay is affected by order cancellations.	156	0.019	0.138	0	1
Order Processing Speed (Pay Factor)	Pay is affected by order processing speed.	156	0.019	0.138	0	1
Price per Order (Pay Factor)	Pay is influenced by price per order.	156	0.301	0.460	0	1
Rating (Pay Factor)	Pay is influenced by rider rating.	156	0.135	0.342	0	1
Traffic (Pay Factor)	Pay is affected by traffic conditions.	156	0.013	0.113	0	1
Platform Requirements (Documentation)						
Authorization Letter	Authorization letter required.	156	0.032	0.177	0	1
Barangay Clearance	Barangay clearance required.	156	0.006	0.080	0	1
Business Permit	Business permit required.	156	0.038	0.193	0	1
CI Documents	Certificate of inspection (CI) required.	156	0.096	0.296	0	1
College Graduate (Requirement)	Platform requires college education completion.	156	0.026	0.159	0	1
Deed of Sale	Deed of sale required.	156	0.032	0.177	0	1
Drug Test	Drug test required.	156	0.038	0.193	0	1
Elementary Graduate (Requirement)	Platform requires elementary education completion.	156	0.263	0.442	0	1
Health Card	Health card required.	156	0.013	0.113	0	1
ID Photo	Identification photo required.	156	0.199	0.400	0	1
Medical Certificate	Medical certificate required.	156	0.013	0.113	0	1
NBI Clearance	NBI clearance required.	156	0.865	0.342	0	1
Non-Pro Driver's License	Non-professional driver's license required.	156	0.968	0.177	0	1
OR/CR Documents	Official Receipt / Certificate of Registration required.	156	0.872	0.335	0	1
Police Clearance	Police clearance required.	156	0.032	0.177	0	1
Resume	Resume required.	156	0.006	0.080	0	1
SSS ID	Social Security System ID required.	156	0.032	0.177	0	1
Some Elementary Education (Requirement)	Platform requires some elementary education.	156	0.032	0.177	0	1
Some Vocational Education (Requirement)	Platform requires some vocational education.	156	0.006	0.080	0	1
TIN ID	Taxpayer Identification Number ID required.	156	0.032	0.177	0	1
Vaccine Card	COVID-19 vaccination card required.	156	0.006	0.080	0	1
Vocational Graduate (Requirement)	Platform requires vocational education completion.	156	0.013	0.113	0	1
Reasons for Not Multihoming (Barriers)						

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Bad Experience on Other Apps (Reason)	Did not multihome due to bad experiences on other apps.	156	0.109	0.313	0	1
Daily Wages (Reason)	Did not multihome due to daily wage arrangement.	156	0.006	0.080	0	1
Exclusive to Company (Reason)	Did not multihome due to exclusive company arrangement.	156	0.013	0.113	0	1
Fewer Benefits/Incentives (Reason)	Did not multihome due to fewer benefits/incentives.	156	0.192	0.395	0	1
Fewer Rides on Other Apps (Reason)	Did not multihome due to fewer rides on other apps.	156	0.365	0.483	0	1
Had Previous Job (Reason)	Did not multihome because rider had another job.	156	0.006	0.080	0	1
Loyal to Company (Reason)	Did not multihome due to loyalty to current company.	156	0.032	0.177	0	1
Lower Earnings on Other Apps (Reason)	Did not multihome due to lower earnings on other apps.	156	0.455	0.500	0	1
Many Requirements (Reason)	Did not multihome due to many requirements.	156	0.006	0.080	0	1
Negative Employer Treatment (Reason)	Did not multihome due to negative employer treatment.	156	0.096	0.296	0	1
Not Caused by the Pandemic (Reason)	Reason for not multihoming was unrelated to the pandemic.	156	0.006	0.080	0	1
Others Not Hiring (Reason)	Did not multihome because other companies were not hiring.	156	0.019	0.138	0	1
Requires Complete Education (Reason)	Did not multihome because complete education was required.	156	0.006	0.080	0	1
Satisfied with Current Company (Reason)	Did not multihome due to satisfaction with current company.	156	0.006	0.080	0	1
Target/Quota (Reason)	Did not multihome due to target/quota.	156	0.006	0.080	0	1
Trouble Holding Multiple Jobs (Reason)	Did not multihome due to difficulty managing multiple jobs.	156	0.013	0.113	0	1
Work Intensity & Operations						
Daily Deliveries	Average number of deliveries per day.	156	3.545	0.712	1	4
Daily Working Hours	Number of hours worked per day.	156	3.224	0.563	2	4
Motorcycle (Vehicle)	Indicator for using a motorcycle as the delivery vehicle.	156	0.981	0.138	0	1
Trip Distance 10–14 km	Typical delivery trip distance is 10–14 km.	156	0.064	0.246	0	1
Trip Distance 15–19 km	Typical delivery trip distance is 15–19 km.	156	0.019	0.138	0	1
Trip Distance 5–9 km	Typical delivery trip distance is 5–9 km.	156	0.231	0.423	0	1

Abbreviation	Detailed Description	N	Mean	St. Dev.	Min	Max
Trip Distance < 5 km	Typical delivery trip distance is less than 5 km.	156	0.468	0.501	0	1
Working Days/Week	Number of days worked per week.	156	3.571	0.591	2	4

E Multiple variables endogeneity bias

The identification of a least squares estimator relies on the conditional independence assumption $E[\varepsilon \mid X] = 0$. Consider $y = X\beta + \varepsilon$ where $X \equiv [X_1, X_2]$, with X_1 containing exogenous variables but X_2 containing multiple endogenous variables correlated with ε. The least squares estimator simultaneously estimates both β_1 and β_2 via $\widehat{\beta} = (X'X)^{-1}X'y$.

While our empirical specification relies on a nonlinear logit model estimated by maximum likelihood, the identification intuition carries over. In the logit case, parameters are obtained by solving a score equation that enforces orthogonality between regressors and a nonlinear transformation of the error term. Although the estimator is nonlinear in parameters, the key identifying condition remains analogous: violations of exogeneity, i.e., correlation between regressors and unobservables, distort this orthogonality and generate biased estimates. As a result, the direction of bias induced by endogenous regressors in the logit model follows the same logic as in the linear case, even though the functional form differs. Hence, below we explain identification for OLS models.

The moment matrix partitions of $\widehat{\beta}$ can be written as:

$$X'X = \begin{pmatrix} X_1'X_1 & X_1'X_2 \\ X_2'X_1 & X_2'X_2 \end{pmatrix}.$$

The inverse then has the complete block structure:

$$(X'X)^{-1} = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix},$$

where

$$\begin{aligned}
A_{11} &= (X_1'M_{X_2}X_1)^{-1}, \\
A_{12} &= -(X_1'M_{X_2}X_1)^{-1}(X_1'X_2)(X_2'X_2)^{-1}, \\
A_{21} &= -(X_2'X_2)^{-1}(X_2'X_1)(X_1'M_{X_2}X_1)^{-1}, \\
A_{22} &= (X_2'X_2)^{-1} + (X_2'X_2)^{-1}(X_2'X_1)(X_1'M_{X_2}X_1)^{-1}(X_1'X_2)(X_2'X_2)^{-1},
\end{aligned}$$

and $M_{X_2} = I - X_2(X_2'X_2)^{-1}X_2'$ is the annihilator that orthogonalizes X_1 with respect to X_2.

The bias vector is $E[\widehat{\beta}] = \beta + (X'X)^{-1}X'\varepsilon$. Partitioning gives:

$$
\begin{aligned}
E[\widehat{\beta}_1] &= \beta_1 + (X_1'M_{X_2}X_1)^{-1}X_1'\varepsilon + (X_1'M_{X_2}X_1)^{-1}(X_1'X_2)(X_2'X_2)^{-1}X_2'\varepsilon, \\
E[\widehat{\beta}_2] &= \beta_2 + (X_2'X_2)^{-1}X_2'\varepsilon.
\end{aligned}
$$

Even with $X_1 \perp \varepsilon$, the $\mathrm{Cov}(X_1, X_2) \neq 0$ term transmits $X_2'\varepsilon$ bias to $\widehat{\beta}_1$.[8] The direction depends on $\mathrm{sign}(\mathrm{Cov}(X_2, \varepsilon))$: positive correlation yields upward bias for $\widehat{\beta}_2$ and (if $X_1'X_2 > 0$) also for $\widehat{\beta}_1$; negative correlation yields downward bias.

If $X_1'X_2 = 0$ (block diagonal $X'X$), then $\widehat{\beta}_1$ remains unbiased despite X_2 endogeneity, a rare identifying assumption. Otherwise, simultaneity in X_2 contaminates all coefficients through the full matrix structure.

Instrumental variables with valid $Z \perp \varepsilon$ eliminates this bias via $(Z'X)^{-1}Z'y$, breaking the problematic $X'\varepsilon$ correlation regardless of the $X'X$ block structure.

Example: Consider X_1 = age of the user (exogenous), X_2 = [cross-network effect of restaurants, cross-network effect of riders] (both endogenous). The moment matrix becomes 3×3:

$$
X'X = \begin{pmatrix} X_1'X_1 & X_1'X_{21} & X_1'X_{22} \\ X_{21}'X_1 & X_{21}'X_{21} & X_{21}'X_{22} \\ X_{22}'X_1 & X_{22}'X_{21} & X_{22}'X_{22} \end{pmatrix}.
$$

Suppose $\mathrm{Cov}(X_{21}, \varepsilon) > 0$ (restaurant network effects) and $\mathrm{Cov}(X_{22}, \varepsilon) < 0$ (rider network effects). Then $\mathrm{Bias}[\widehat{\beta}_1] \propto (X_1'X_{21})\mathrm{Cov}(X_{21}, \varepsilon) + (X_1'X_{22})\mathrm{Cov}(X_{22}, \varepsilon)$, where positive correlation with restaurant effects pushes the age coefficient upward while negative correlation with rider effects pulls it downward, net direction indeterminate without knowing the relative magnitudes.

Since in our case most of the bias is positive, then the effect of the bias is to systematically overstate both the direct network effects ($\widehat{\beta}_2$) and, through positive cross-correlations with user age ($X_1'X_2 > 0$), the age effect ($\widehat{\beta}_1$) in the OLS estimates.

[8] By applying the annihilator matrix $M_{X_2} = I - X_2(X_2'X_2)^{-1}X_2'$, we invoke the *Frisch-Waugh-Lovell (FWL) Theorem*, which demonstrates that the coefficient estimate $\widehat{\beta}_1$ is numerically identical to the regression of the 'cleaned' variables $\widetilde{Y} = M_{X_2}Y$ and $\widetilde{X}_1 = M_{X_2}X_1$. This transformation is powerful because it renders the first term, $(X_1'M_{X_2}X_1)^{-1}X_1'\varepsilon$, innocuous: the operator M_{X_2} ensures that $\widetilde{X}_1$ is orthogonal to X_2, effectively purging the variation in X_1 that is contaminated by its correlation with X_2. Consequently, the structural bias in our estimate is no longer driven by the interaction between X_1 and the error term through X_2; instead, the bias is isolated within the final term, $(X_1'M_{X_2}X_1)^{-1}(X_1'X_2)(X_2'X_2)^{-1}X_2'\varepsilon$. This residual bias highlights the remaining endogeneity where ε is correlated with X_2, thereby allowing us to clearly distinguish between the reduction of omitted variable bias via orthogonalization and the persistent challenge of regressor endogeneity.