Concentration and Platform Growth in the Sharing Economy: A Resource Partitioning Perspective

Angela Lu
City University of Hong Kong, qinglilu@cityu.edu.hk

Abhay Mishra
Information Systems and Business Analytics, abhay@iastate.edu

Jintao Du
City University of Hong Kong, jintaodu@cityu.edu.hk

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Angela Lu
Department of Information Systems
City University of Hong Kong
Tat Chee Avenue, Kowloon Tong,
Hong Kong SAR
qinglilu@cityu.edu.hk

Abhay Mishra
Department of Information Systems
and Business Analytics
Ivy College of Business
Iowa State University
abhay@iastate.edu

Jintao Du
Department of Economic and Finance
City University of Hong Kong
Tat Chee Avenue, Kowloon Tong, Hong Kong SAR
jintaodu@cityu.edu.hk

Abstract

The emergence and growth of sharing economy platforms have engendered significant research interests recently. These platforms have witnessed increased entry of professional service providers, who have large amounts of excess assets and standardized business practices. Meanwhile, sharing economy platforms have witnessed an astounding growth, much of which is not attributed to professional service providers. This paper examines two seemingly contradictory phenomena – increased concentration among professional service providers and rapid growth of non-professionals on sharing economy platforms. Using the resource partitioning theory from the organizational literature, we explain how these two phenomena are inherently related. We further emphasize the role of income inequality that affects the resource partitioning process. The empirical analysis uses 1.4 million zip-code level Airbnb data, with Airbnb Plus policy as a natural experiment. Findings reveal that professional service provider concentration facilitates non-professional growth but reduces their performance, and the effects are significantly moderated by income inequality.

Keywords: Concentration, resource partitioning, sharing economy, platform growth, professional service provider

Introduction

The emergence and growth of platform-enabled sharing economy companies—spearheaded by Airbnb and Uber — disrupt traditional industries by giving rise to new market phenomena and have been dominant themes in recent research (Barron et al. 2021; Burtch et al. 2018; Filippas et al. 2020; Han et al. 2021; Li et al. 2022; Zervas et al. 2017). These platforms have seen increased professionalization due to participation of "professional service providers," who typically have large amounts of excess resources, employ seasoned and standardized business practices, and outperform non-professionals (Chen et al. 2022; Cui and Davis 2021; Li et al. 2016). The entry and growth of professional service providers, however, directly contrast with the original intent of the sharing economy as an equalizing digital force with low entry barrier in facilitating peer-to-peer sharing (Cohen and Sundararajan 2015). In recent years, many Airbnb apartments are from professional hosts that function like unregistered hotels, and car rental or taxi services are regularly available on Uber. As a result, these platforms have become increasingly concentrated, a trend similar to those traditional industries where a few firms play dominant roles in driving up market concentration.

Despite the upsurge in platform professionalization, two puzzling phenomena remain under-examined. First, the entry, growth and strong competitive performance of professional service providers tend to drive away non-professionals (Chen et al. 2022), which could result in increased market concentration and lower entry of non-professionals. Yet, contrasting evidence exists as the sharing economy platforms have witnessed an astounding growth, much of which is not attributed to professional service providers (Ke 2017; Yaraghi and Ravi 2017). Second, while local regulations enacted to both facilitate and curb the growth of the sharing economy platforms that have been studied (Edelman and Geradin 2016; Miller 2016), variation in the local resource distribution (e.g., income) that drives service providers' market participation has been ignored in the literature (Benjaafar et al. 2019; Huang et al. 2020). Further, no research has examined how the distribution of income affects the growth and performance of sharing economy service providers through its interaction with market concentration.

These two puzzles suggest significant research gaps in the sharing economy literature and motivate the current study. Our research questions are two-fold. *First, how does concentration among professional service providers affect the growth and performance of different types of service providers on sharing economy platforms? Second, how do local income inequality and professional service provider concentration jointly affect different service providers' growth and performance?* We examine these issues in the context of Airbnb, one of the largest sharing economy platforms, accounting for 20% of the market share in the hospitality industry globally.

Our study is founded on the theory of resource partitioning, a long standing organizational theory that highlights the joint trends of concentration among large generalist producers and the growth of small specialists based on partitioning of resource niches with different niche widths and customer appeals (Carroll 1985; Carroll and Swaminathan 2000; Dobrev et al. 2001; Dobrev et al. 2002). Considering the niche widths of professional and non-professional service providers based on excess resources, we recognize that professionals with wide resource niches parallel generalists, whereas non-professionals with narrow niches are specialists. We further recognize that the phenomenon of rising concentration among professional service providers and rapid growth of non-professionals – as evidenced by the proliferation of sharing economy services – echoes the key insight from the resource partitioning literature. Moreover, as the resource partitioning literature suggests that the distribution of local environmental resources can affect concentration and moderate its effect on business growth (Boone et al. 2002), we consider the role of income inequality, a key condition of environmental resource distribution, specifically through its interaction with concentration in driving the growth and performance of different sharing economy service providers. We find that higher income inequality decreases concentration in resource partitioning but also curbs the growth of non-professionals, while it positively moderates the effect of concentration on non-professional service providers' performance.

The empirical analysis uses 1.4 million Airbnb rental records at the zip-code level between October 2014 and December 2019 to examine the effect of professional host concentration on Airbnb host growth and performance across the United States. We leverage an Airbnb platform-wide policy shock, the entry of the Airbnb Plus program into cities, as a natural experiment. Our analysis reveals heterogenous effects of professional host concentration given local income inequality in driving platform growth and host performance, and the identified effects are largely consistent. The results suggest that: 1) Increased concentration of professional hosts increases the growth of non-professionals but decreases that of professionals overall; 2) Although there are more non-professional hosts joining the platform, their performance on average decreases with rising professional host concentration; and 3) The effects of professional host concentration on host growth and performance are moderated by local income inequality.

Our study makes four contributions to the literature on the sharing economy and resource partitioning. First, this study reveals novel insight into supply-side platform ecology by drawing upon resource partitioning theory to a technology platform context. Second, the study highlights that competition in resource partitioning is size- and location-based on sharing economy platforms, and it can be mediated by platform designs. Third, we extend the resource partitioning theory by integrating an inequality perspective, emphasizing that market concentration is moderated by environmental resource distribution such as income inequality. Finally, our findings suggest the interactive forces between income inequality and service provider concentration on platform growth and performance, providing key insight into market dynamics based on environmental resource heterogeneity.

Theory and Hypotheses

Sharing Economy: Related Work

The sharing economy arguably provides equitable economic opportunities, as these two-sided platforms can more efficiently match suppliers and demanders than traditional firms based on resource utilization in local market conditions (Benjaafar et al. 2019; Filippas et al. 2020), while lowering participation cost (Farronato and Fradkin 2018). Recently, the platforms have witnessed increased entry of "professional service providers" who have large amounts of excess resources which enable them to rent a multitude of properties across different locations that cater to varied market demands (Chen et al. 2022; Li et al. 2016). The higher resource endowments and scale-based advantage, such as lower production and marketing costs, leverage over suppliers, and pricing power, enhance the performance of professional service providers (Chen et al. 2022; Cui and Davis 2022; Li et al. 2016). They also rent out properties more frequently with standardized business practices to adjust to seasonal trends, resulting in higher occupancy rates and revenues (Li et al. 2016; Priporas et al. 2017; Gibbs et al. 2018). The scale-based competitive advantage and standardized business practices of professional service providers thus affect platform competitive dynamics and growth significantly.

The growth of sharing economy platforms is accompanied by socioeconomic inequality, however, rendering sustainable platform development a key concern. A stream of research has examined the relationship between sharing economy platforms and inequality along the social dimensions of race (Cui et al. 2020; Edelman et al. 2017), gender (Cook et al. 2021), and human capital (Schor 2017). Critically, local income inequality shapes market structure and segmentation (Chatterjee and Raychaudhuri 2004; Tan 2022), a key condition that affects the competitive advantage of different service providers. The competitive dynamics of market concentration is thus likely to be moderated by income inequality, an indicator of differential resource distribution and market heterogeneity that affect service provider performance. Yet, there is limited insight into how income inequality moderates platform concentration in affecting service provider growth and performance.

We posit that both concentration and supply-side income inequality jointly shape platform growth and supplier performance. We next provide a synthesis of the sharing economy literature and the theoretical lens of resource partitioning, explicating the roles of concentration and income inequality that jointly affect platform growth and service provider performance.

Resource Partitioning and Platform Growth

The resource partitioning theory addresses two contradictory phenomena found in many traditional industries: the rising concentration among late-stage generalist firms and the proliferation of small specialist producers. In the resource partitioning literature, generalist and specialist firms are defined by niche widths: generalists are firms with a variety of products in wide niches, and they utilize varied niche resources to pursue strategies that target broad market segments; in contrast, specialists have narrow niches with a limited range of products, but they can efficiently exploit the narrow niches and target customers who value those niches (Carroll 1985; Carroll and Swaminathan 2000; Hannan and Freeman 1977). The theory explains that the emergence and proliferation of specialist producers are fundamentally linked to generalists' failure to capture niche market segments, in which specialists can appeal to customers through differentiated forms or identity claims (Carroll 1985; Carroll et al. 2002; Carroll and Swaminathan 2000). The key assumption is therefore different competitive advantages of generalists and specialists, as the former is scale-based and the latter has unique appeal to niche markets. Increased concentration among large generalist firms is a direct result of scale-based competition for a variety of customer bases, during which small generalists perish and the surviving generalists become larger and more dominant. However, the exit of small generalists frees up resource space for the emergence of specialist firms, which appeal to the market segments that established generalists fail to capture. The market eventually becomes partitioned such that generalists and specialists do not directly compete as they are sustained by different niches (Carroll 1985; Carroll and Swaminathan 2000).

The theoretical logic of resource partitioning is apt to examine the joint trends of rising concentration among professional service providers and proliferation of small suppliers on sharing economy platforms. A consistent finding from resource partitioning is that the growth of specialist producers is interdependent on rising concentration among established generalists, whose consolidation in the market center frees up peripheral resources that facilitate the growth of specialists. Extending the theory to the sharing economy context, professional service providers are "generalists" with large amounts of excess assets, and non-professionals are "specialists" that operate in narrow niches. Professional and non-professional service providers may target at different customer segments. The market segmentation can happen along the dimensions of price, quality, culture, or unique needs of renters (Lutz and Newlands 2018), in addition to location preferences. For instance, non-professionals may specialize in catering to customers with unique tastes related to local culture, cuisine and entertainment options, while professionals may accommodate customers who use Airbnb as a substitute for hotels. If the mechanism of resource partitioning drives platform growth, we expect a positive relationship between professional service provider concentration and non-professionals' growth. Meanwhile, consolidation of large professional service providers decreases the growth of professionals overall as small professionals are outcompeted. Smaller professional hosts are unable to obtain the efficiencies and scale economies of large professional hosts, leading to a negative relationship between supplier concentration and professionals' growth. These considerations lead to the following hypotheses:

Hypothesis 1a. *Increased concentration among professional service providers increases the growth rate of non-professional service providers.*

Hypothesis 1b. *Increased concentration among professional service providers decreases the growth rate of professional service providers.*

Moderation of Income Inequality in Resource Partitioning

The process of resource partitioning also depends on local resource heterogeneity. Different from past research that studies the impact of sharing economy platforms on market inequality (Cook et al. 2021; Edelman and Luca 2014; Schor 2017), we emphasize that platform growth and competitive dynamics depend on local income distribution, a critical aspect of supply-side environmental heterogeneity that shapes market structure and customer segmentation.

Income inequality affects platform growth and resource partitioning in two notable ways. First, income distribution is a key factor that affects sharing economy service participation, which depends on individual financial incentives and local socioeconomic conditions. As the sharing economy provides flexible employment that alleviates financial distress, those who are unemployed or underemployed are more incentivized to participate, especially during economic downturns (Burtch et al. 2018; Huang et al. 2020; Kummer et al. 2020). Moreover, as excess resources are nonrandomly distributed, heterogeneity in supplier income and resources affects their ability to grow in different markets. For instance, participation as a host in the real estate market requires asset ownership that signifies one's socioeconomic status. Those in disadvantaged status, such as individuals in poor neighborhoods or without housing, would be difficult to join platforms as service providers. Conversely, those enjoying advantaged or privileged status, such as individuals in high-end neighborhoods or with multiple properties, can more readily join the platforms as service providers, and they can establish competitive market positioning based on socioeconomic advantages.

Second, income inequality affects the competitive dynamics in resource partitioning. A strand of resource partitioning literature argues that concentration increases with environmental resource homogeneity, but rising concentration in a homogenous market also leaves more peripheral resources, facilitating small supplier growth (Boone et al. 2002). Income inequality, a key dimension of environmental resource heterogeneity, would decrease concentration while customers have heterogeneous buying power and prefer different price ranges, and no single producer can monopolize demands and offer products that cater to all customers (Chatterjee and Raychaudhuri 2004; Määttänen and Terviö 2014; Tan 2022). High income inequality thus indicates more resource heterogeneity in the market, giving rise to market segmentation and decreasing non-professional growth. Platforms in markets with heterogeneous income distribution (i.e. high income inequality) would thus witness slower growth of non-professional service providers alongside lower concentration among professionals. These reasonings suggest significant interaction between income inequality and service provider concentration, leading to the following hypotheses:

Hypothesis 2a. *The effect of professional service provider concentration is significantly moderated by local income inequality, such that there is a negative interaction effect on non-professionals' growth rate.*

Hypothesis 2b. *The effect of professional service provider concentration is significantly moderated by local income inequality, such that there is a positive interaction effect on professionals' growth rate.*

Concentration, Income Inequality, and Service Provider Performance

In addition to growth, concentration in resource partitioning has significant implications for platform service providers' performance. In the context of Airbnb, service provider performance is defined as average listing revenue. While the proliferation of small suppliers is critical to platform expansion, the overall market share of non-professionals is decreasing due to market consolidation among large professionals. Professional service providers outcompete non-professional service providers due to size, uniform business practices, and economies of scale and scope. Recall that professional service providers are able to put forth a large number of rental properties, possibly with varied features, into different locations. Their scale economies and standardized business practices allow them to serve customer niches that are in the center of the market, such as renters who do not have unique local or cultural preferences, rather than those in the fringes. The resulting economies of scale and scope enjoyed by professional service providers thus enhances their revenue performance.

Non-professional service providers, in contrast, do not employ standardized business practices. They are also unable to obtain scale economies because they do not have a large number of properties to rent. While professional concentration facilitates non-professionals' growth, the performance of non-professionals may worsen over time, due to more peer growth alongside decreased market share such that each supplier has narrower resource space. An implication is that the rising concentration among large professionals decreases non-professionals' average performance but increases that of professionals. This leads to the following hypotheses:

Hypothesis 3a. *Increased concentration among professional service providers decreases the average performance of non-professional service providers.*

Hypothesis 3b. *Increased concentration among professional service providers increases the average performance of professional service providers.*

We next turn our attention to the role of income inequality and how it may impact the performance of professional and non-professional service providers in the sharing economy. Critically, income inequality in the market environment affects market segmentation with supply-side heterogeneity, which can moderate the effect of concentration on service provider performance. Service providers with differential resource endowments are likely to have different products and service quality in markets with higher income inequality. Their appeal to varied customer segments can lead to market fragmentation and slower growth of non-professionals.

As mentioned, generalist producers (i.e., professional service providers) have lower concentration in markets with higher income inequality due to customer segmentation. It follows that the performance advantage of professional service providers would be less pronounced in markets with large income dispersion and highly segmented demands. Specifically, as demands are less concentrated in a segmented market and customers have more choice uncertainty, professional service providers are less likely to consolidate market shares. This implies that professional service providers would have lower concentration in markets with higher income inequality, leading to their lower average performance. Meanwhile, non-professionals would have more free resource space to scale up performance, and they also have slower growth in markets with higher inequality due to professionals' difficulty in market consolidation. Therefore, the performance of non-professionals would be higher due to more free resources and slower entry of peer competitors. These arguments imply significant interactions between income inequality and supplier concentration on service provider performance, leading to the following hypothesis:

Hypothesis 4a. *There is a positive interaction between professional service provider concentration and local income inequality on non-professionals' average performance.*

Hypothesis 4b. *There is a negative interaction between professional service provider concentration and local income inequality on professionals' average performance.*

Data and Measures

The empirical analysis uses U.S. rental data from Airbnb, the world's largest sharing economy platform for short-term rentals. The data were acquired from the market intelligence firm AirDNA that specializes in Airbnb data collection. The sample includes 24,458 U.S. zip-code aggregates of Airbnb listing performance between October 2014 and December 2019 at monthly intervals, which is then combined with four additional data sources to construct the key variables. First, we acquired the entry dates of the Airbnb Plus program into different U.S. cities from AirDNA. The Plus entry dates vary by city and provide identification for the effects of professional host concentration, as the latter is an endogenous variable with local market conditions. Second, zip-code demographics and inequality data are collected from the American Community Survey (ACS), which provides zip-code demographics and the estimate of the Gini coefficient, a standard measure of income inequality. Third, we use the Census Zip Codes Business Patterns (ZBP) surveys to obtain the numbers of hotels and restaurants in zip codes that reflect local business and tourism demands. We linearly interpolated the annual estimates of ACS and ZBP while matching them to the monthly observations of the Airbnb sample. Fourth, we used the Zillow Home Value Index (ZHVI) to capture real estate prices, which provides the monthly median prices of housing stocks at the zip-code level. The combined panel data include 1,405,161 monthly zip-code observations. We next discuss variable construction.

Variables

The analysis focuses on two dependent variables. First, we measure host growth rates at the zip-code level, defined as the monthly change of host observations divided by last month's observations. We separate host growth by professional/non-professional host status, as we are interested in the effects of professional host concentration and inequality on different types of hosts. Following established research, professional hosts are operationalized as hosts with at least two entire properties (Chen et al. 2022; Cui and Davis 2021; Li et al. 2016). These hosts account for 15.1% of Airbnb hosts in the sample. We further check the robustness of the professional host definition with different property cut-offs. Second, we measure host performance by average monthly revenue, also by professional/non-professional status.

The key independent variable is professional host concentration, measured with a Herfindahl-Hirschman Index (henceforth HHI):

$$H_{z,t} = \sum_i \left(\frac{r_{i,z,t}}{\sum_j r_{j,z,t}} \right)^2$$

Where $\frac{r_{i,z,t}}{\sum_j r_{j,z,t}}$ is professional host i's revenue share among all professional hosts in zip code z at time t. Because professional host concentration is an endogenous variable confounded with local Airbnb demands and socioeconomic conditions, we use a platform-wide policy shock, Airbnb Plus entry, as a natural experiment to identify its causal effects.

To examine the interaction between professional host concentration and inequality, we measure income inequality with the Gini coefficient at the zip-code level and construct a multiplicative interaction between professional host concentration and Gini to examine their joint effects.

We additionally control for local Airbnb business conditions and demographics that potentially confound with the effects of professional host concentration and inequality. Because professional host concentration can be related to local conditions that affect host growth and performance, we control for the overall revenue concentration in a zip code (i.e., local HHI). We also control for the total number of Airbnb hosts in a zip code and local price variance. Controls of local demographics include logarithmic population, employment rate, percentages of Whites and college graduates, which may affect platform growth and performance. Local Airbnb businesses could be correlated with other rental and market conditions, and thus we control for the Zillow Home Value Index (ZHVI) that captures median house prices in zip codes. In addition, we control for the numbers of restaurants and hotels to measure local tourism and business demands. Table 1 provides the summary statistics of the variables and their correlation coefficients.

Descriptive Patterns: Host Growth

Figure 1 illustrates the trends of Airbnb host growth across the United States. The left panel shows the distribution of hosts in different zip code locations in January 2015. The right panel shows host distribution in January 2019. At the beginning of 2015, there are only 126,668 hosts across the United States, most of whom reside in a few states, such as California, New York, Florida, Texas, and Colorado. By January 2019, however, the number of Airbnb hosts increased more than three-fold to 413,056, showing rapid growth and diffusion of sharing economy services across all geographical locations in the U.S. Although 85% of hosts are non-professionals with single properties, 47% of properties belong to professional hosts, some of whom have an extremely large number of properties. For instance, one professional host has 2,398 properties across 288 cities. Growth of professional hosts and their concentration pattern thus have important implications for platform growth and competitive dynamics.

	Variable	Ave	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Host growth	0.32	0.52													
2	Host revenue	1148	2287	-0.26												
3	Prohost HHI	0.23	0.37	-0.29	0.22											
4	Local HHI	0.31	0.37	-0.36	0.14	0.19										
5	Gini coefficient	0.42	0.06	-0.11	0.09	0.07	-0.05									
6	Total hosts	0.02	1.04	-0.15	0.28	-0.01	-0.15	0.21								
7	Price variance	0.00	1.05	0.00	0.12	0.00	0.00	0.00	0.00							
8	Home value	0.00	1.00	-0.19	0.22	0.09	-0.06	0.16	0.32	0.00						
9	N restaurants	0.04	1.02	-0.22	0.12	0.11	-0.10	0.27	0.49	0.00	0.30					
10	N hotels	0.02	1.03	-0.12	0.14	0.06	-0.07	0.19	0.36	0.00	0.10	0.58				
11	Ln(population)	8.65	1.53	-0.23	0.03	0.14	-0.02	0.27	0.22	0.00	0.17	0.63	0.34			
12	Employment %	0.61	0.10	-0.06	0.01	0.00	-0.02	-0.17	0.11	0.00	0.18	0.25	0.10	0.30		
13	White %	0.83	0.19	0.10	-0.01	-0.07	0.05	-0.23	-0.13	0.00	-0.10	-0.31	-0.16	-0.40	-0.04	
14	College %	0.19	0.12	-0.22	0.19	0.12	-0.03	0.14	0.29	0.00	0.62	0.34	0.14	0.15	0.29	0.03

Table 1. Descriptive Statistics and Correlation Coefficients of Variables

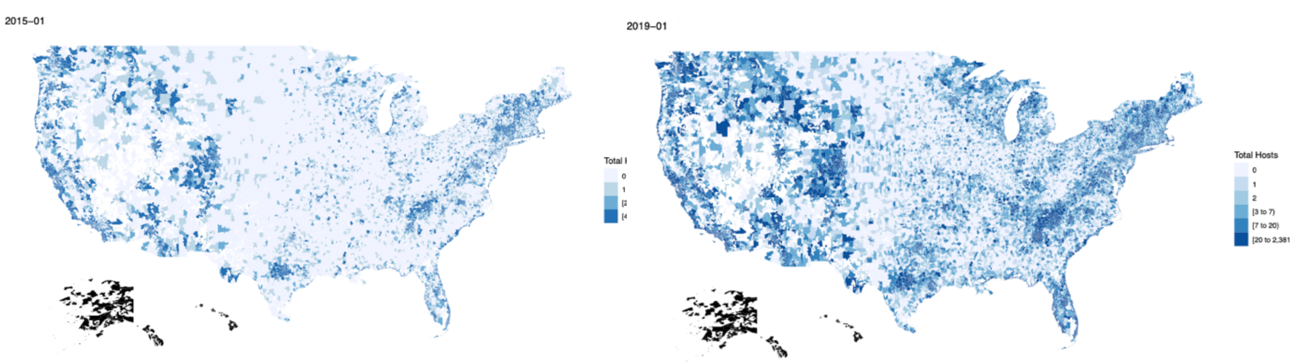

Figure 1. Airbnb Host Presence in the United States, 2015 to 2019

Methodology

The baseline regression applies a fixed-effects model to estimate the impacts of professional host concentration and income inequality on host growth and performance. The regression starts with the following specification:

$$Y_{i,t} = \beta_0 + \beta_1 Prohost\_HHI_{i,t} + \beta_2 Gini_{i,t} + \beta_3 Prohost\_HHI_{i,t} Gini_{i,t}$$
$$+ X_{i,t}\Gamma + \alpha_i + \gamma_t + \theta_c \gamma_t + \epsilon_{i,t}$$

Where the dependent variable, $Y_{i,t}$, is the growth rates of non-professional/professional hosts, or their average revenue in zip code i at time t. $Prohost\_HHI_{i,t}$ is the revenue concentration of professional hosts in zip code i at time t. $Gini_{i,t}$ is the Gini coefficient in zip code i at t. The interaction effect between professional host concentration and Gini is given by β_3 which estimates the effect of professional host concentration in areas with average income inequality. In addition, $X_{i,t}$ is a vector of time-varying zip-code controls. A full set of zip-code dummies, α_i, absorbs any fixed differences in the dependent variables such that the coefficients of interest, β_1 and β_3, are estimated using within-zip-code changes to ensure that location-specific characteristics will not drive empirical findings. In addition, we include month fixed effects, γ_t, and an interaction between county and month fixed effects, $\theta_c\gamma_t$, to absorb any county-specific time trends that may change over time. The county fixed effect, θ_c, is absorbed by zip-code fixed effects α_i, because zip codes are nested within counties.

Platform Policy Shock as a Natural Experiment

We use a platform-wide policy shock, the entry of Airbnb Plus program into cities, to identify the causal effects of professional host concentration using exogenously induced variations in host concentration before and afterwards. In February 2018, Airbnb launched a new program named Airbnb Plus. This program has high qualification standards to vet listings, including high rating and acceptance rate in the past year, zero cancellation rate, and vetted in-person by a third-party inspector.[1] As a result, the qualified listings can receive more marketing exposure. Notably, the policy has increased the market share of professional hosts, as areas with the Plus entry have witnessed a jump in professional host market share. Although only 3.3% of professional hosts participated in the Plus program in those areas, the median market share of professional hosts increased from 38.9% before Plus launch to 84.5% afterwards.

We apply a difference-in-differences design with coarsened exact matching (CEM) (Iacus et al. 2012), using Airbnb Plus entry into zip codes as a natural experiment. The treatment group includes zip codes with the Plus program entry, whose dates start from March 2018 until December 2019. The controls include zip codes with no Plus entry but similar demographic and business conditions based on the matching criteria, including total number of Airbnb hosts, housing value, number of restaurants, log population, employment rate, percentages of Whites and college graduates. The matched sample includes 1,269 treated zip codes and 6,174 controls, contributing to 439,518 zip-code-month records.

The following DID specification tests the causal relationship between professional host concentration and host growth/performance, using Plus entry for identification of the treatment effect:

$$Y_{i,t} = \beta_0 + \beta_1 Plus_{i,t} Treat_i + X_{i,t}\Gamma + \alpha_i + \gamma_t + \theta_c\gamma_t + \epsilon_{i,t}$$

Where $Plus_{i,t}$ is an indicator for time after Airbnb Plus entry into a zip code i, and $Treat_i$ is an indicator for the treatment group in which the Plus program is launched. The treatment effect, given by β_1, identifies the causal effect of professional host concentration increase on the dependent outcomes based on exogenously induced changes by Plus entry. Note that the main effect of $Treat_i$ is absorbed by zip-code fixed effects, and the main effect of $Plus_{i,t}$ is absorbed by month fixed effects. Findings from the analytical strategies are reported next.

Results

We start with the baseline fixed-effects estimates of professional host concentration on non-professional and professional host growth, moderated by income inequality as measured by the Gini coefficient. Three model specifications are reported in Table 2. Model 1 reports the estimates of professional host concentration, local HHI and Gini when controlling for zip-code, month, and county-month fixed effects. Model 2 reports the estimates with local business and demographic controls. Model 3 adds an interaction between professional host concentration and Gini. We observe the effect of professional host concentration is positive and highly significant on non-professional host growth (H1a), and its effect is negative on professional host growth (H1b). When including the moderator of income inequality (Gini), the interaction between professional host concentration and inequality has a negative effect on non-professional host growth (H2a) but positive on professional host growth (H2b). Based on model 3, in zip codes with income inequality in the bottom quintile (Gini = 0.35), increasing professional host concentration by 0.1 increases non-professional growth by 0.49% but decreases professional host growth by 5.17%. In contrast, in zip codes

[1] https://www.airbnb.com/help/article/2195/airbnb-plus-program-terms-and-conditions

with income inequality in the top quintile (Gini = 0.50), increasing professional host concentration by 0.1 increases non-professional growth by 0.05% and decreases professional host growth by 4.6%.

	Non-Professional Host Growth			Professional Host Growth		
	(1)	(2)	(3)	(1)	(2)	(3)
Prohost HHI	0.02***	0.02***	0.15***	-0.48***	-0.49***	-0.65***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Prohost HHI × Gini			-0.29***			0.38***
			(0.02)			(0.02)
Gini	0.01	0.02	0.08***	0.01	0.01	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Local HHI	-0.30***	-0.30***	-0.30***	0.05***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total hosts		0.02***	0.02***		-0.03***	-0.02***
		(0.00)	(0.00)		(0.00)	(0.00)
Price variance		0.00	0.00		-0.00	-0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Controls		✓	✓		✓	✓
Zip code, month, county-month FE	✓	✓	✓	✓	✓	✓
Constant	0.43***	0.44***	0.41***	0.69***	0.71***	0.74***
	(0.01)	(0.05)	(0.05)	(0.00)	(0.04)	(0.04)
R-squared	0.52	0.52	0.52	0.63	0.63	0.63

Table 2. Effect of Professional Host Concentration on Host Growth

Number of observations = 1,405,161. *** p<0.001, ** p<0.01, * p<0.05
Note: Robust standard errors in parentheses. Demographic controls are included. Price variance, total host, home value, number of restaurants and hostels are standardized

Table 3 reports the estimates on average host revenue by non-professional and professional hosts. Although concentration among professional hosts increases growth of non-professionals, we find that the effect is negative and significant on non-professionals' average revenue (H3a). The interaction between professional host concentration and income inequality is positive, however, showing that non-professionals tend to have higher performance in markets with higher income inequality (H4a). In contrast, the effect of professional host concentration on professional host performance is positive and significant (H3b), while its interaction with Gini is negative (H4b). Based on model 3, in zip codes with income inequality in the bottom quintile (Gini = 0.35), increasing professional host concentration by 0.1 decreases the average monthly revenue of non-professionals by $10.4 but increases that of professionals by $208. In contrast, in zip codes with income inequality in the top quintile (Gini = 0.50), increasing professional host concentration by 0.1 decreases the average revenue of non-professionals by $2 and increases that of professionals by $186. The results suggest significant interaction between income inequality and professional host concentration on host performance.

	Average Non-Professional Host Revenue			Average Professional Host Revenue		
	(1)	(2)	(3)	(1)	(2)	(3)
Prohost HHI	-77.83***	-60.27***	-301.34***	1,802.17***	1,967.91***	2,590.90***
	(3.25)	(3.18)	(26.09)	(10.33)	(10.27)	(92.42)
Prohost HHI × Gini			565.07***			-1,460.29***
			(60.34)			(216.12)
Gini	-13.04	-22.67	-138.08***	-293.32*	-187.00	111.26
	(40.07)	(40.06)	(40.62)	(139.22)	(142.67)	(130.08)
Local HHI	494.81***	503.35***	504.73***	-202.97***	-108.33***	-111.91***
	(4.00)	(3.64)	(3.64)	(7.20)	(7.22)	(7.21)
Total hosts		152.18***	152.86***		1,620.62***	1,618.87***
		(3.60)	(3.62)		(30.41)	(30.40)
Price variance		267.82***	267.82***		1.51*	1.50*
		(0.26)	(0.26)		(0.69)	(0.69)
Controls		✓	✓		✓	✓
Zip code, month, county-month FE	✓	✓	✓	✓	✓	✓
Constant	692.50***	348.38**	404.41**	1,228.64***	38.33	-106.48
	(17.02)	(128.70)	(128.85)	(59.21)	(517.03)	(520.85)
R-squared	0.51	0.55	0.55	0.57	0.59	0.59

Table 3. Effect of Professional Host Concentration on Host Performance

Number of observations = 1,405,161. *** p<0.001, ** p<0.01, * p<0.05
Note: Robust standard errors in parentheses. Demographic controls are included. Price variance, total host, home value, number of restaurants and hostels are standardized

To check the robustness of our findings, we use an alternative measure that defines professional hosts as hosts with at least 3 entire properties. Professional host concentration is then measured as the revenue concentration among hosts with at least 3 properties. Table 4 reports the estimates from the alternative professional host measure, and the model specification follows model 3 in Tables 2 and 3. We observe consistent effects of the key variables in terms of significance levels and effect directions. The results show that professional host concentration has a positive effect on non-professional hosts' growth (H1a), and the effect is negatively moderated by income inequality (H2a). Furthermore, professional host concentration has a negative effect on non-professional hosts' performance (H3a), and the effect is positively moderated by income inequality (H4a). In addition, professional host concentration reduces the growth of professionals (H1b) but increases their performance (H3b), and the effects are significantly moderated by income inequality (H2b and H4b). Overall, the results suggest the presence of resource partition in the sharing economy such that concentration and inequality play significant roles in service provider growth and performance. Competing explanations, such as network effect, would predict a positive effect of professional host concentration on host growth regardless of professional status, since higher performance by any host would attract more hosts joining the platform. The opposite effects of professional host concentration on host growth by professional status, however, shows a distinct process of resource partitioning in producing outcomes different from the expectations of competing mechanisms.

	Host Growth		**Host Revenue**	
	Non-pro	Pro	Non-pro	Pro
Prohost HHI	0.07***	-0.57***	-64.83*	2,510.48***
	(0.01)	(0.01)	(26.75)	(94.25)
Prohost HHI × Gini	-0.16***	0.53***	270.76***	-2,926.27***
	(0.02)	(0.02)	(61.26)	(217.63)
Gini	0.05***	-0.11***	-72.84	441.64**
	(0.01)	(0.01)	(40.31)	(134.62)
Local HHI	-0.29***	-0.01***	498.23***	110.98***
	(0.00)	(0.00)	(3.59)	(7.81)
Total hosts	0.02***	-0.01***	159.11***	1,552.93***
	(0.00)	(0.00)	(3.72)	(29.40)
Price dispersion	0.00	0.00	267.82***	1.02
	(0.00)	(0.00)	(0.26)	(0.69)
Controls	✓	✓	✓	✓
Zip code, month, county-month FE	✓	✓	✓	✓
Constant	0.43***	0.78***	334.98**	-277.02
	(0.05)	(0.04)	(129.06)	(522.57)
R-squared	0.52	0.59	0.55	0.58

Table 4. Estimates from Alternative Professional Host Measure

Number of observations = 1,405,161. *** p<0.001, ** p<0.01, * p<0.05
Note: Robust standard errors in parentheses. Demographic controls are included. Price variance, total host, home value, number of restaurants and hostels are standardized

Airbnb Plus Entry as a Natural Experiment

We leverage the Airbnb Plus program entry into cities as a natural experiment to identify the causal effects of professional host concentration on host growth, exit, and performance. As a platform-wide policy change, Airbnb Plus entry exogenously alters local professional concentration, as 80.5% of properties with "Plus" badges belong to professional hosts. We expect that 1) zip codes with the Plus program launch would see higher growth compared to those without the program; and 2) non-professional hosts' revenue may decrease after the program launch, since most of the "Plus" properties belong to professionals that increase their market share.

Figure 2 tests the parallel trends assumption of DID with a relative-time model, interacting time to Plus entry with the treatment group and using -1 period (1 month before Plus entry) as the reference group. The figure shows a twelve-month range before and after the program launch since March 2018. We observe indistinguishable trends between the treatment and the control groups in terms of non-professional host growth rates (the left panel), as well as average revenue before the initial entry of the Plus program (the right panel), after which non-professional hosts in the treatment group have significantly higher growth in the month of the program launch. However, non-professional hosts' revenue declines after the program launch within a twelve-month period, showing that the Plus program may not enhance their performance.

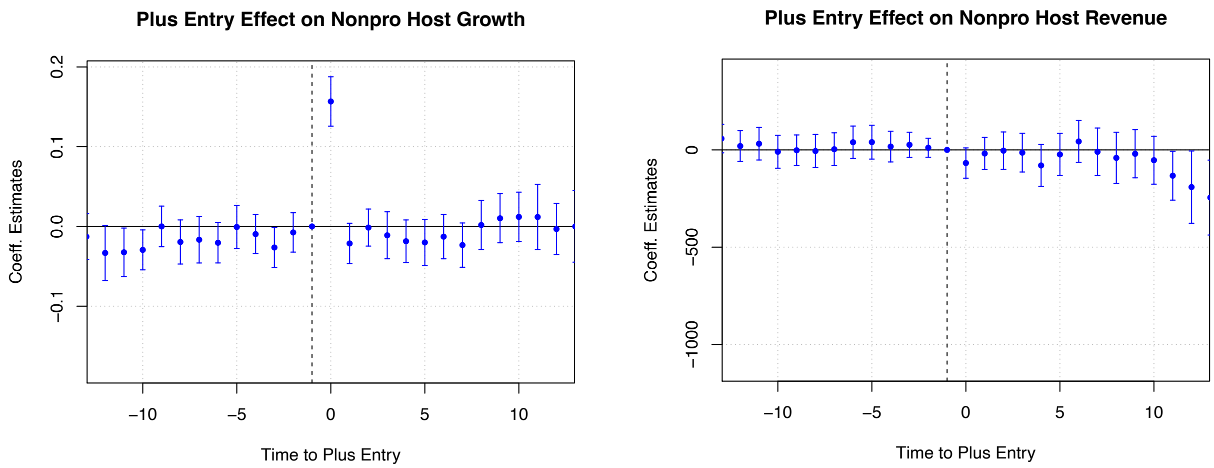

Figure 2. Plus Entry Estimates from Relative Time Models

Table 5 reports the fixed-effects estimates of Plus entry on host growth and average revenue by non-professional and professional hosts. The model includes the treatment effect of Plus entry, the main effects of professional host concentration and Gini, as well as all controls and fixed effects. The estimates show that Plus entry increases the growth rates of non-professional by 8% but has no effect on professional hosts (column 1). Also as expected, the Plus program launch decreases revenue for non-professionals, and it has no significant effect on professional hosts' revenue (column 2). The treatment effect of Plus entry decreases average non-professional host revenue by $231.25 in the treated zip codes relative to controls, which is statistically significant at 0.001 level and economically significant, given that the reduction is 30% of a non-professional host's average monthly revenue ($782).

	Host Growth		**Host Revenue**	
	Non-pro	Pro	Non-pro	Pro
Plus entry	0.08***	-0.01	-231.25***	-89.00
	(0.02)	(0.01)	(56.87)	(146.20)
Prohost HHI	0.04***	-0.57***	-50.65	2,066.77***
	(0.01)	(0.01)	(31.98)	(55.36)
Gini	0.07	-0.09	-478.17	1,280.19**
	(0.15)	(0.07)	(336.00)	(464.01)
Local HHI	-0.35***	0.02***	636.01***	-254.75***
	(0.01)	(0.00)	(34.04)	(26.07)
Total hosts	-0.10	-0.35***	1,304.53***	4,317.85***
	(0.06)	(0.05)	(251.31)	(385.45)
Price dispersion	2.03*	-1.76	113,237.83*	448,503.47***
	(1.02)	(1.55)	(53,990.97)	(88,328.87)
Controls	✓	✓	✓	✓
Zip code, month, county-month FE	✓	✓	✓	✓
Constant	-0.14	0.89**	178.03	-116.29
	(0.37)	(0.33)	(2,721.83)	(3,344.70)
R-squared	0.62	0.72	0.59	0.66

Table 5. Effects of Airbnb Plus Entry on Host Growth and Performance

Number of observations = 439,518. *** p<0.001, ** p<0.01, * p<0.05
Note: CEM weights are applied in fixed-effects regressions. Standard errors clustered at the matching subclass level.

Results from Table 5 show that the platform policy contributes to host growth but does not enhance host performance given selective platform exposure. It is likely that the performance gap between professionals and non-professionals are enlarging following the Plus program entry, and as a result, the platform policy would induce differential growth rates and performance of hosts in markets with varying concentration and inequality. In Table 6, we interact the treatment effect of Plus entry with professional host concentration and income inequality. The first model includes an interaction between the treatment effect of Plus entry and professional host concentration, and the second model includes an interaction between Plus entry and local income inequality. We break down the estimates by host type, showing the effects on host growth and performance by non-professional and professional hosts respectively.

	Non-Pro Growth		**Non-Pro Revenue**		**Pro Growth**		**Pro Revenue**	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Plus entry	0.12***	-0.16*	-433.73***	779.67**	-0.01	-0.25***	-610.08***	1,383.30*
	(0.02)	(0.07)	(96.09)	(285.36)	(0.02)	(0.07)	(178.57)	(687.33)
Plus × prohost HHI	-0.12***		571.90***		0.00		1,471.78***	
	(0.03)		(142.06)		(0.03)		(280.80)	
Plus × Gini		0.54**		-2,332.07**		0.57***		-3,396.42*
		(0.18)		(729.12)		(0.17)		(1,622.20)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Zip code, month, county-month FE	✓	✓	✓	✓	✓	✓	✓	✓
Constant	-0.14	-0.14	186.69	176.10	0.89**	0.89**	-94.01	-119.11
	(0.37)	(0.37)	(2,720.95)	(2,721.35)	(0.33)	(0.33)	(3,338.62)	(3,344.89)
R-squared	0.62	0.62	0.59	0.59	0.72	0.72	0.66	0.66

Table 6. Interaction Effects of Airbnb Plus Entry on Host Growth and Performance

Number of observations = 439,518. *** $p<0.001$, ** $p<0.01$, * $p<0.05$
Note: CEM weights are applied in fixed-effects regressions. Standard errors clustered at the matching subclass level. The main effects of professional host concentration, local HHI, Gini, total hosts, price variance, and demographic controls are included

Column 1 of Table 6 shows the treatment effect of Plus entry; its interactions with professional host concentration and income inequality on non-professionals' growth. We find that the Plus program mainly facilitates non-professional host growth in areas with lower professional concentration. While Plus entry has a positive effect on non-professionals' growth, its interaction with professional concentration is negative and significant. The interaction between Plus entry and Gini is positive, however, while the main effect of Plus entry becomes negative. This is because the Plus program is launched in cities with higher income inequality where its positive effect on host growth is likely to occur. Given that the average income inequality in the treatment group is 0.43, the overall treatment effect of Plus entry on host growth is still positive, as Plus entry has increased non-professional host growth by 7.2% on average.

Column 2 shows the effect of Plus entry and its interactions on non-professional hosts' revenue, which overall has a negative effect. In zip codes with professional host concentration of 0.3, Plus entry decreases non-professional hosts' revenue by $262 in the treated zip codes relative to controls. Whereas the main effect of Plus entry is positive when including an interaction term with Gini, the overall effect is still negative on average. In zip codes with the average Gini coefficient of 0.43, Plus entry decreases non-professionals' revenue by $223 in the treated zip codes relative to controls.

Column 3 shows the treatment effect of Plus entry and its interaction effects on professional hosts' growth. Different from the effects on non-professionals' growth, Plus entry has an overall negative effect on professional hosts, particularly in areas with lower income inequality. The estimates show that Plus entry decreases professional hosts' growth by 0.5% in treated zip codes with average income inequality (Gini = 0.43).

Column 4 shows that the Plus program launch decreases professional hosts' average revenue, especially in markets with higher income inequality. Based on the main effect and the interaction with Gini, in treated zip codes with average income inequality (Gini = 0.43), Plus entry decreases professional hosts' revenue by $77 on average relative to controls. The estimates of the treatment effects and its interactions combined are consistent with the effect magnitudes observed from Table 4.

Overall, the results suggest that the Plus program has increased host growth but reduced host performance, and the effects are moderated by income inequality and professional host concentration. Despite market growth, both non-professional and professional hosts receive no particular gain from the program launch while concentration among local professional hosts rises. This might be due to the small portion of professional hosts who participated in the program, and as they receive more platform exposure and increase concentration, other hosts' performance does not improve. The policy that selectively increases platform exposure of certain hosts may thus disproportionately benefit these service providers, while others simply join the platform without actual gain or even witness declining performance. Another possibility is that the decreased host performance is due to more competitive pressure for limited market share, which is concentrated among a small number of players while more hosts are joining the platform. Notably, the treatment effect on differential host performance is moderated by income inequality, which increases market heterogeneity and growth but decreases performance. Effects from the identification strategy is consistent with those from the baseline regressions, and the interactions with income inequality produces additional insight into the impact of platform policy on competitive dynamics in heterogeneous markets.

Discussion

Our study advances an understanding of digital platform economy through the theoretical lens of resource partitioning. The theory explains two contradictory yet inherently related phenomena found in many traditional industries of rising concentration among large generalists and the proliferation of specialists. Consistent with the theory's prediction, we find that concentration among professional hosts on Airbnb facilitates the growth of non-professionals but curbs the growth of professionals. We further develop an argument that emphasizes the role of environmental resource heterogeneity, highlighting that income inequality significantly moderates the effect of professional host concentration on growth due to environmental resource distribution. The identification strategy that utilizes Airbnb Plus entry as a natural experiment yields consistent results, showing that heterogeneous platform exposure to the policy has varied implications for hosts with differential resources.

Implications for Research

Our study makes four substantive contributions to the literature on the sharing economy, resource partitioning, and digital inequality. First, our study contributes to a burgeoning literature on the sharing economy in recent years through the theoretical lens of resources partitioning, highlighting the importance of concentration and income inequality to platform growth and competition. These issues are important but less examined, as existing research largely studies the disruptive impacts of the sharing economy on established industries or social welfare (Barron et al. 2021; Burtch et al. 2018; Greenwood and Wattal 2017; Han et al. 2021). Supply-side user dynamics in the sharing economy are also less studied with a few exceptions (Burtch et al. 2018). Our study shows that sharing economy platform growth is influenced by consolidation among professional service providers, who play a paradoxical role that on the one hand facilitates growth, but on the other hand enlarges the inequality gap among users with differential resources. The platforms essentially function as "crowd-based capitalism" instead of an equalizing digital force (Sundararajan 2016), with increasing consolidation among large suppliers over time, similar to the concentration trends observed in traditional industries.

Second, our study shows that resource partitioning occurs in not only traditional industries where generalist producers are established and market niches are well-defined, but also emerging technology markets such as the sharing economy, in which platforms have expanded rapidly with rising demands for digital services. Different from traditional markets where generalist and specialist producers do not directly compete based on established niche boundaries (Hannan et al. 2007), the sharing economy platforms are emerging and market niches are shifting with changing customer preferences, environmental conditions, or rapid technological development. Our results indicate that competition on platforms is not simply scale- or location-based as service providers are targeting at different customer niches.

Third, our study extends the resource partitioning theory by emphasizing the role of income inequality as a key aspect of environmental heterogeneity that moderates concentration. This angle differs from the extant studies on the main effects of niche width and identity in resource partitioning (Carroll and Swaminathan 2000; Dobrev et al. 2001), highlighting that ex ante resource distribution in the market environment shapes market structure and changes the effect of concentration on competitive outcomes. Also different from previous research that studies environmental resource distributions along demographic dimensions (Boone et al. 2002), our study pinpoints income inequality, a universal and critical dimension of inequality that is rising over time (Piketty 2014). By emphasizing this fundamental aspect of environmental heterogeneity, we bring an inequality perspective into the resource partitioning literature.

Fourth, the study expands the literature on digital inequality by explicating the role of supply-side income inequality in platform growth and resource partitioning. Digital inequality is a long-standing theme that highlights how technological advancement enlarges the socioeconomic inequality among market actors with disparate accesses to physical and human capital (Acemoglu 2002; Acemoglu and Restrepo 2018; Krueger 1993; Piketty 2014). Existing research has found that demographic inequality extends to the digital context with heterogeneous trends (Chan et al. 2016; Greenwood and Agarwal 2016). Yet, the impacts of inequality on platform competition and growth remain significant and understudied issues, specifically how inequality in environmental resource distribution affects the growth and performance of service providers. Different from extant studies that examine varied market aspects that affect platform development, such as market thickness (Li and Netessine 2020) and supplier density (Li et al. 2018), the current research suggests that income inequality may drive platform development through distribution of supplier resources. This line of inquiry expands the literature on digital inequality by emphasizing that inequality is not only an unintended consequence of platform development, but also a key driver that interacts with platform competitive dynamics in shaping user growth and performance.

Implications for the Practice

This study also has practical implications for policymakers and practitioners who are interested in striking a balance between platform growth and sustainable development. While sharing economy platforms have the potential to generate significant economic impacts, the social implications of these platforms have been debated vigorously. For policymakers, how to design policies for sustainable business and equal opportunities is a key concern, as the platforms bring both positive and negative externalities to local market players and residents (Barron et al. 2021; Burtch et al. 2018; Greenwood and Wattal 2017). Our research suggests that platform policymakers should consider income inequality in designing policies for equitable distribution of opportunities and platform growth, as participation in programs that increases platform exposure may benefit the traditionally disadvantaged or underrepresented users who have more economic needs.

This research also has design implications for digital platforms in the sharing economy. Platform operators should realize that certain service providers are relatively disadvantaged compared to professional service providers. In response, platforms could implement IT designs to reduce the consequences of inequality, such as by increasing the marketing exposure of products by non-professional service providers or providing incentives for them to participate in new policies. For platform service providers, it is also important to recognize how local market conditions or policies could affect their performance. Considering the differential performance impact on different service providers from platform policies, platform designers may consider providing online guidance to these service providers on how to participate and benefit from new policies. Non-professional service providers are recommended to seek policy guidance from sharing economy platforms for enhanced marketing exposure and performance.

Airbnb is a leading sharing economy platform that consumers, policymakers, and researchers watch closely. We believe that insights from this platform can provide significant implications for other sharing economy platforms as well as digital platforms that display similar concentration and growth trends. The concepts of generalists and specialists are also generalizable to other sharing and digital platforms because the key aspect that distinguishes these service providers is their differential accesses to excess resources. As service providers on other platforms may also have differential resources, which they can leverage to target different customer segments, the competitive dynamics may also follow the resource partitioning process as we have currently identified.

Limitations and Future Directions

Our study is subject to a number of limitations that provide opportunities for future research. First, our study focuses on the role of income inequality in platform development, but inequality also varies by user demographics that constitute key sources of environmental heterogeneity. For instance, existing studies find that race and gender discrimination is rampant in the sharing economy on both supply and demand sides (Cook et al. 2021; Cui et al. 2020; Edelman and Luca 2014; Edelman et al. 2017). While the issues of race and gender are beyond the current scope of investigation, how user demographics affect ex ante resource distribution and drive differential growth and performance on both sides of sharing platforms remains an open question. Moreover, an integration between the literature on inequality and resource partitioning can benefit from the study of demographic inequality in resource partitioning, a potential extension of this line of inquiry. Future work is necessary to explore the relationship between local demographic inequality and platform competitive dynamics.

Second, while our analysis leverages platform policy for identification of causal effects, such policies may yield additional theoretical insights on the role of platform algorithms, which selectively expose certain users for greater visibility and economic gain. This feature is unique to IT-enabled platforms on which user performance are influenced by digital technologies and platform design. An extension of the current research can provide an IT-focused analysis on platform mediation when investigating the effects of differential service provider exposure and platform competitive dynamics.

Third, the current research may also benefit from considering alternative explanations of the concentration effect, such as that of platform complementors. Platform service providers may shift governance strategy as they become more dominant, leading to increased concentration and decreased performance of complementors (Rietveld et al. 2020). A future investigation of competing explanations from the platform complementor perspective is encouraged.

Fourth, although the rapid growth of the sharing economy in the last decade has produced significant social and economic values, how these platforms provide digital resilience during economic downturns is still an under-examined issue. Notably, these digital platforms have emerged during the depths of the last financial recession (Schor 2017), and a crisis of even higher magnitude has unfolded over the last two year and is still ongoing. The current economic crisis brought by the COVID-19 pandemic has severely impacted the profitability of sharing platforms due to travel restrictions and shrinking market demand on a global scale. Meanwhile, other digital innovations, such as remote working and online retailing have proliferated. Local markets may display heterogeneous trends of post-pandemic recovery with the help of digital innovation that rebuilds community resilience and social trust. While the extensive impact of the COVID-19 pandemic on the sharing economy in the long run is yet to be established, the unexpected event provides a critical test for global digital resilience post crisis.

Conclusion

Findings from this study echo a long-standing literature on the relationship between inequality and market growth. Contrary to the expectation that sharing economy platforms could produce more equitable opportunities and resource utilization, the competitive dynamics on platforms are dominated by both supplier consolidation and rapid growth. Notably, the relationship between professional service provider concentration and market growth parallels the recent trends in the literature on rising capital concentration and declining labor share (Dorn et al. 2017; Volscho and Kelly 2012) driven by superstar firms in information technology that expands the market (Autor et al. 2020). While established theories suggest that inequality spurs short-term growth but has negative long-term consequences (Banerjee and Duflo 2003; Forbes 2000), sharing economy platforms that are driven by and enlarge socioeconomic inequality may become unsustainable if society and platform designers do not address these issues effectively. The long-run implications of inequality in platform development is a significant issue that is yet to be understood. The current research offers an initial step towards unpacking this issue through the perspective of resource partitioning, which affects sharing economy growth and user performance with implications for platform sustainability based on market inequality conditions.

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