A Trade-Off Between Negative Externalities and Performance in the Sharing Economy

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***Abstract**. By enabling the transaction of private resources among strangers, the sharing economy has increased consumer welfare, but it has also created negative externalities for society. This study investigates the tradeoff between negative externalities and platform performance in the short-term rental market. The goal is to identify the economic incentives for sharing economy platforms to self-regulate. Using data from Airbnb and parking fines data, this study finds that heterogeneous complementors contribute differently to this tradeoff, providing an opportunity for platform governance.*

***Keywords.** trade-off, externalities, sharing-economy*

1 Introduction

Sharing economy platforms have been able to decrease the transaction costs for exchanging resources among peers (Sundararajan, 2016) that were previously used only privately (Munger, 2018). These platforms have been able to reduce transaction costs by implementing a rating system that effectively creates trust in the digital market space (Hui, Saeedi, Shen, & Sundaresan, 2016) and by exploiting the increased efficiency of information communication technologies (Sundararajan, 2016). On the other hand, the fast growth and the unregulated entry of sharing economy platforms have created negative externalities for society. Negative externalities are additional costs that individuals not directly involved in the sharing economy have to pay as a consequence of transactions completed within any sharing economy platform by its users (Hippel & Krogh, 2016; Zervas, Proserpio, & Byers, 2017). Examples of negative externalities associated with Airbnb tenants include guests being lost and asking for directions, consuming rivalrous public resources (e.g., parking spaces), and failing to care for shared resources (Edelman & Geradin, 2015; Zervas et al., 2017). Similarly, Uber's entry has led to an increase in traffic congestion (Edelman & Geradin, 2015; Ricart, Snihur, Carrasco-farré, & Berrone, 2020). When not properly addressed by the platform, these problems have led to the banning of sharing economy firms, and they may eventually cause the failure of the sharing economy (Chasin, von Hoffen, Hoffmeister, & Becker, 2018) if it does not satisfactorily address these negative externalities.

Numerous studies are emerging to document the existence of heterogeneity among digital platform complementors who differently affect the platform performance (Binken & Stremersch, 2009; Gretz & Basuroy, 2013; Hogendorn & Yuen, 2009; Kim, Prince, & Qiu, 2014), who produce different types and levels of network externalities (Corts & Lederman, 2009; Landsman & Stremersch, 2011), and who react differently to the platform's governance tools (Koo & Eesley, 2020; Rietveld, Seamans, & Meggiorin, 2021). This study looks at competitive strategies of sharing economy complementors to investigate the extent to which heterogeneous complementors are equipped and motivated to address the negative externalities produced by the sharing economy platform Airbnb. In particular, this study asks: *Is there a tradeoff between positive and negative externalities affecting a sharing economy platform's performance? If so, to what extent do heterogeneous complementors contribute to this tradeoff*?

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2 Theory

In this section, we will explore the theoretical framework that underlies the trade-off between negative externalities and platform performance in the sharing economy. We will examine the impact of complementors' portfolio size on transactions and negative externalities produced, and the potential curvilinear relationship between them. Understanding these relationships is crucial for identifying economic incentives for sharing economy platforms to self-regulate and for effective platform governance.

2.1 Portfolio size effect on transactions

Because of the nature of the products transacted in the sharing economy, where complementors and consumers share physical spaces (e.g., a car, a house) while being complete strangers, trust is a necessary condition for the transaction to take place, yet very hard to build (Fradkin, Grewal, & Holtz, 2021; Sundararajan, 2016; Uzunca, Rigtering, & Ozcan, 2018). Regardless of how the complementor is able to successfully signal its quality and trustworthiness to consumers, the more products the complementor provides on the platform, the more products will likely enjoy the higher likelihood of future transaction rates. The combination of trust-building tools on a platform and perception of quality spillovers across products managed by the same complementor then suggests that a complementor's portfolio size and the transactions fulfilled by each product in the portfolio may be curvilinear, not strictly monotonic. Specifically, this study argues that the more products a complementor manages on a digital platform, the higher the frequency of transactions per each of those products. However, in the exchange of experiential goods, there exists a natural limit to the number of transactions that can be fulfilled at any given time. For example, any Airbnb property can only be rented to one (party of) customer every day, as co-habitation by multiple customers is unacceptable on the platform. Even in Uber and Lyft, co-sharing of the same experience by multiple customers (i.e., carpooling) is limited by the number of seats available in a car. The self-reinforcing loop between products in the same portfolio predicts a curvilinear relationship of inverted U-shaped form between the number of products managed by a complementor and the number of transactions fulfilled by each product.

H1: The relationship between a complementor's portfolio size and the number of transactions fulfilled by each portfolio product is curvilinear (inverted U-shape).

2.2 Portfolio size effect on negative externalities produced

One dimension that differentiates complementors and is likely to lead to differences in the way they can control the quality of their transactions and, thus, the level of short-term negative externalities they produce is the complementor's portfolio size. The portfolio size reduces the span of attention that a complementor can dedicate to each of its products (Hsu, Hannan, & Kocak, 2009). Especially with service goods (like those in the sharing economy), it is difficult for a complementor to fully control and, hence, perfectly replicate a successful experience. The main challenge might derive from the unpredictability of human interactions, specifically how to react to new challenges or problems brought by the demand side positively and consistently. For example, heterogeneous Airbnb guests might bring up different problems and unexpected requests to the host. The complementor's ability to promptly act and solve any possible problem between, for example, the Airbnb guest and the neighbor depends on the complementor's number of similar situations that it must contemporaneously deal with. In other words, the more products a complementor provides in the sharing economy platform, the less attention it is able to allocate to any problem arising from any of these products, including problems creating negative externalities for society. Therefore, this study expects that the larger the size of a complementor's portfolio, the more short-term negative externalities it will produce.

H2: The larger a complementor's portfolio size, the higher the level of negative externalities produced (linear relationship).

3 Methods

This study uses AirDNA data about Airbnb activity in Los Angeles to test both hypotheses. Daily data was collected about all Airbnb providers active in the city of Los Angeles between November 2014 and February 2020. These data include the geolocation of each listing and performance measures like reservations and price. In addition to the Airbnb data, the study used public data about parking fines in the city of Los Angeles, also recorded on a daily basis and with precise geolocation data associated with each fine. The daily and geolocation features of both data sources enable the merge of the two datasets, hence the testing of this study's hypotheses.

3.1 Dependent variables

The two dependent variables of this study are *Number of transactions* fulfilled and *Level of negative externalities* produced at the product level. Both variables are measured at the listing and month level.

In line with previous studies in the platform literature, *Number of transactions* is measured as the number of nights booked by consumers on the Airbnb platform, per each listing in every month of data collection (Hagiu, 2011; Rietveld, 2018). The variable ranges from 0 to 31, which is the maximum number of nights any listing can be booked in a month (of 31 days).

The *Level of negative externalities* is measured by counting the number of parking tickets assigned any given month within a few meters from the target listing. For the measurement of this variable, only parking tickets related to overnight infractions or infractions that can be linked to Airbnb guests' stay have been considered (i.e., blocking the driveway, overnight parking, private property, parked in parkway (including "pkd in/on parkway")) For any given day, if the target listing was booked, the number of parking tickets assigned within a 250 meters (820 feet) radius was recorded. If the listing wasn't booked for that day, then a value of zero would be assigned to the listing.[1] The number of fines per day was then aggregated at the monthly level by counting the number of parking fines matched to the listing during the entire month. The variable ranges from 0 to 372.

3.2 Independent variables

The main independent variable of both hypotheses is the portfolio size of each complementor. This measure is recorded at the listing and month level. It is a count of the number of listings managed (in Los Angeles) by an Airbnb host at any month in time. It is a time-variant variable.

3.3. Controls

All the models include controls for time-variant features of the listing. They control for the month's average nightly price to book the listing (i.e., price), the number of months the listing has been active on the platform (i.e., tenure), and the number of nights made available for booking by the host at the listing level (i.e., nights for booking). In order to account for unobservable features of the listing that might affect either of the two dependent variables of the study, the study adds listing fixed effects to the main model. Similarly, the models include time fixed effects at the month level to control for time variant effects that might affect the results. Finally, there may be features of the geographical area that predict the likelihood of a listing being booked (e.g., trustiness of the neighborhood) or of the car being fined (e.g., patrol intensity by the police in the area). The study uses zip code fixed effects to control for these unobservable.

[1] This study assumes that Airbnb guests are not the only people committing parking infractions. Thus, to reduce the noise on the coding of the variable, the parking ticket was assigned to the listing only if a guest was present to be the potential target of the ticket.

4 Results

The results section presents the main findings of the study on the tradeoff between negative externalities and platform performance in the sharing economy. The section is divided into two subsections, each focusing on one hypothesis of the study.

4.1 Effect on the number of transactions

Table 1 reports the main results of the analysis pertaining to the effect of the complementor's portfolio size on the number of transactions fulfilled by each product. Model 1 in Table 1 reports the results of a simple OLS regression, Model 2 adds fixed effects at the listing level, Model 3 includes only monthly fixed effects, Model 4 includes only zip code fixed effects, Model 5 includes both listing and month fixed effects, while Model 6 includes all fixed effects (i.e., listing, month, and zip code). The results remain consistent across the different specifications of the model. Specifically, we see that portfolio size has a positive and significant effect on the number of transactions ($\beta = 0.0462$, $p < 0.001$, in Model 6). Moreover, we observe the presence of a significant curvilinear effect in that the coefficient of portfolio size square is also significant and negative ($\beta = -0.0004$, $p < 0.001$, in Model 6). This indicates the presence of an inverted U-shaped relationship between portfolio size and the number of transactions.

Table 1. Main results for Number of transactions fulfilled at the listing level (Source: Author's work)

	Dependent variable: Number of transactions at the listing level					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Complementor's portfolio size	0.117***	0.052***	0.102***	0.127***	0.046***	0.046***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)
Complementor's portfolio size square	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price (USD)	-0.000***	-0.001***	-0.000***	-0.000***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure (months)	0.023***	-0.087***	0.011***	0.019***		
	(0.001)	(0.001)	(0.001)	(0.001)		
No. of nights made available for booking	0.207***	0.344***	0.209***	0.214***	0.347***	0.347***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Listing FE	No	Yes	No	No	Yes	Yes
Month FE	No	No	Yes	No	Yes	Yes
Zip code FE	No	No	No	Yes	No	Yes
Constant	1.741***	0.171***	1.939***	1.573***	-1.099***	-1.098***
	(0.035)	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)
Observations	1,153,448	1,148,461	1,153,448	1,153,432	1,148,461	1,148,445
R-squared	0.032	0.587	0.047	0.050	0.599	0.599

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: "Tenure (months)" omitted because of collinearity in Models 5 and 6

4.2 Effect on negative externalities level

Table 2 reports the main results of the analysis pertaining to the effect of the complementor's portfolio size on the level of negative externalities produced. Model 1 in Table 1 reports the results of a simple OLS regression, Model 2 adds fixed effects at the listing level, Model 3 includes only monthly fixed effects, Model 4 includes only zip code fixed effects, Model 5 includes both listing and month fixed effects, while Model 6 includes all fixed effects (i.e., listing, month and zip code). The results remain consistent across the different specifications of the model. Specifically, the complementor's portfolio size is always positive and significant ($\beta = 0.0035$, $p < 0.001$, in Model 6). These results support the second hypothesis of this study.

Table 2. Main results for the Level of negative externalities at the listing level (Source: Author's work)

	Dependent variable: Level of negative externalities					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Complementor's portfolio size	0.014***	0.001*	0.010***	0.006***	0.004***	0.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Price (USD)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure (months)	0.002***	0.014***	-0.006***	0.004***		
	(0.000)	(0.000)	(0.000)	(0.000)		
No. of nights made available for booking	0.002***	-0.000	0.001***	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Listing FE	No	Yes	No	No	Yes	Yes
Month FE	No	No	Yes	No	Yes	Yes
Zip code FE	No	No	No	Yes	No	Yes
Constant	1.444***	1.429***	1.613***	1.518***	1.595***	1.595***
Observations	1,153,448	1,148,461	1,153,448	1,153,432	1,148,461	1,148,445
R-squared	0.003	0.442	0.037	0.105	0.464	0.464

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: "Tenure (months)" omitted because of collinearity in models 5 and 6.

5 Discussion and Conclusions

The paper delves into the dynamics of digital platform ecosystems, specifically exploring how various complementors contribute to both positive and negative externalities. It discovers that complementors with larger portfolios tend to increase transaction volumes yet concurrently elevate negative externalities. This finding enriches our comprehension of how different types of platform users impact the broader ecosystem (Binken & Stremersch, 2009; Koo & Eesley, 2020; Rietveld et al., 2021). Moreover, the study sheds light on the strategic potential for digital platforms to self-regulate, illustrating how they might navigate tradeoffs between positive and negative externalities throughout their life cycle (Cusumano, Gawer, & Yoffie, 2021; Parker, Petropoulos, & Van Alstyne, 2021; Tucker, 2019). By uncovering a nuanced relationship between complementor portfolio size and transaction fulfillment, the research suggests opportunities for value creation through ecosystem orchestration, thereby extending prior discussions on the influence of certification within platform settings (Hui et al., 2016; Rietveld et al., 2021).

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