Disintermediation and Its Mitigation in Online Two-sided Platforms: Evidence from Airbnb

Jinan Lin
University of California, Irvine, jinanl1@exchange.uci.edu

Tingting Nian
UC Irvine, tnian@uci.edu

Natasha Z. Foutz
University of Virginia, nfoutz@virginia.edu

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Jinan Lin
University of California, Irvine
4291 Pereira Dr, Irvine, CA, 92697, USA
jinan.lin@uci.edu

Tingting Nian
University of California, Irvine
4291 Pereira Dr, Irvine, CA, 92697, USA
tnian@uci.edu

Natasha Zhang Foutz
University of Virginia
140 Hospital Dr, Charlottesville, VA, 22904, USA
nfoutz@virginia.edu

Abstract

Disintermediation, where providers and customers transact bypassing an intermediary, has challenged the business model and dwindled profits of the multi-billion-dollar platform economy. Despite the platforms' efforts to mitigate disintermediation, little is known regarding the extent of disintermediation or efficacy of the mitigation policies, largely due to unobservability of disintermediation. We tackle these challenges by designing a geo-analytic methodology to identify and quantify disintermediation by matching online Airbnb booking and offline granular mobile location data. We further leverage DID with matching samples to causally examine the efficacy of four Airbnb policies; and finally propose a cost-and-benefit conceptual framework to interpret the findings and guide platform designs of mitigation policies. We find, for instance, a 5.4% of disintermediation in Austin, TX over Summer 2019; and Instant Bookable reduces disintermediation by 9%, with a stronger effect among the hosts without preference for long-term lease, with more repeated guests, and more hosting experience.

Keywords: disintermediation, two-sided platform, sharing economy, location big data

Introduction

In a multi-sided market that facilitates on-demand connections across people, businesses, and devices, such as Airbnb, disintermediation commonly occurs, where the providers (supply-side, such as Airbnb hosts or other service providers) and customers (demand-side) bypass the intermediary (platform) to transact. Disintermediation undermines the value chain of the two-sided sharing economy and results in profit loss (e.g. 90% in the case of ZBJ – a knowledge outsourcing platform) (Zhu et al. 2018; Zhu and Iansiti 2019). Disintermediation may arise due to a variety of reasons, such as repeated interactions.

Providers engage in disintermediation if the benefits of disintermediation outweigh the costs. For instance, an Airbnb provider may transact directly with a customer satisfied with the prior stay and returning for a second, hence bypassing the potential communication cost with another new customer. Platforms, such as Airbnb, have implemented a variety of policies, some of which are designed explicitly to mitigate disintermediation, such as information concealment, whereas others, such as Airbnb Superhost, are not albeit may impact disintermediation.

Despite the prevalence and substantial profit impact of disintermediation on platforms, two types of challenges confront the academic research and the multi-billion-dollar industry: (a) the challenge of quantifying its prevalence, largely due to a lack of observability, which further leads to (b) the challenge of assessing the efficacy of mitigation policies. We aim to tackle these critical challenges in the context of Airbnb by addressing the following key research questions:
(1) How to quantify the magnitude of disintermediation?
(2) How effective are various mitigation strategies of disintermediation?
(2) How do heterogeneous providers and customers respond to mitigation differently?

To accomplish this, we combine the online booking data and offline location big data, and further leverage a variety of policies implemented on Airbnb as natural experiments. Specifically, we causally examine the efficacy of four policies on disintermediation: Instant Bookable (allowing guests to book immediately without needing to send a request to hosts for approval), Superhost (awarded to only top-rated and most experienced hosts with 4.8+ average customer rating, <1% cancellation rate, response to 90%+ new messages within 24 hours, and completion of 10+ stays over the past year), Airbnb Plus (granted to those who satisfy all Superhost criteria and boast the highest quality with great attention to details verified through Airbnb's in-person quality inspection), and Information Concealment (withholding hosts' exact locations and phone numbers until guests have made payments). While some of these strategies decrease the value of disintermediation to hosts, others increase the cost of disintermediation to hosts, as we will discuss further in the next section of Theory and Literature Review.

Leveraging the TB-sized online booking data and offline location data, and DiD methods with Propensity Score Matching and Look Ahead Matching, we empirically estimate the rate of disintermediation and the significant effects of Instant Bookable (0.09 days per week) and Airbnb Plus (0.06 days per week) on reducing disintermediation. A series of robustness checks address a variety of selection and sampling biases and yield consistent findings. Analyses of the heterogeneous treatment effects of Instant Bookable show that the mitigation effect of Instant Bookable is stronger among the hosts without preference for long-term leases, with more repeat customers, less nearby competition, and longer hosting tenure.

In summary, this research contributes to the theories and practices along multiple directions. First, by leveraging the novel location big data and geo-analytic methods, this research offers the first region- and population-scale quantification of disintermediation. Second, this research assesses the effectiveness of a variety of mitigation strategies of disintermediation; and uncovers differential efficacies, hence enriching the theories on mitigation of disintermediation (detailed in the full paper available upon request). Finally, our study offers valuable guidance to platforms on the design and selection of mitigation strategies. We hope this study will serve as a valuable stepping stone to attracting fruitful future research on many intriguing aspects of disintermediation, creating win-win-win scenarios for platforms, service providers, and customers.

Theory and Literature Review

Our study develops a framework to predict the effectiveness of strategies combating disintermediation, based on a benefit-and-cost calculus. As customers bear the majority of the platform service fees (14% of the nightly subtotal, compared to 3% for providers), they hold stronger incentives to disintermediate, although the final decisions rest with providers. We hence take a provider's perspective and propose a conceptual framework of a provider's utility calculus (benefit-cost) to synthesize the drivers of disintermediation and potential mitigations. By taking the transaction off the platform, they forego the value brought by the platform, which includes various services and tools provided by the platform to simplify and facilitate transactions between suppliers and consumers. In the meantime, they also need to bear some costs, such as the transaction costs of taking the transaction offline, including time and effort spent in the lengthy communication between parties. Potential costs also include the loss of market access if such disintermediation behavior is caught, because platforms typically ban users who violate platform policies for a certain period. On the other hand, both hosts and guests can save a significant amount of platform fees. Considering a host who chooses to bypass the platform based on the surplus of taking his/her business off the platform, we compare the value and cost of mitigating strategies to hosts (Table 1).

Drivers of Disintermediation	Mitigation Strategies	Why Strategies Work?
Commission Fees (Wang and Heng, 2017; Ladd 2021)	Complementary services (Edelman and Hu 2016); **Information Concealment** (Edelman and Hu 2016; Zhu and Iansiti 2019)	Increase disintermediate cost to hosts;
Information Asymmetry (He et al. 2020; Gu and Zhu, 2021)	**Superhost; Airbnb Plus (Dewan et al. 2019);**	Increase disintermediate cost to providers; Increase platform value to hosts;
Transaction Time and Communication (Gu and Zhu 2022; He et al. 2020)	**Instant Bookable (Mayya et al. 2020);**	Increase disintermediate cost to providers; Increase platform value to hosts;
Repeated Transactions (Wang and Heng 2017; Gu and Zhu 2021)	Charge up-front fees; Complementary services (Edelman and Hu 2016);	Increase platform value to hosts;

Table 1. Theory Framework of Disintermediation Mitigation

Drivers of Disintermediation

Extant literature shows that hosts tend to bypass home-sharing platforms to evade high commission fees. Some hosts consider long-term stay as a legitimate reason to bypass Airbnb, and view commissions as too high for long-term guests (Wang and Heng 2017). Some hosts also internalize Airbnb's functions while bypassing the platforms, such as by requiring fees or deposits in advance, or setting their own refund policies. Some hosts request booking the first few days on Airbnb but bypassing the platform for the remaining days (Gu and Zhu 2021). With repeated interactions offline, moral hazard issues between hosts and guests can be reduced (Dellarocas 2005). Our study extends this literature by examining the moderating effects of hosts' preferences in long-term leases, as well as repeated transactions of the same guests.

The second driver of disintermediation comes from the heterogeneity of services and information asymmetry. From a perspective of platform design, platforms that feature higher proportions of high-quality providers and lower heterogeneity in service quality are more resistant to disintermediation (He et al. 2020). When customers have imperfect information about providers' quality, platforms are more susceptible to disintermediation when the degree of heterogeneity in providers' quality is high. Their results suggest two managerial levers to curb leakage: (1) platforms can shorten the customer waiting process; (2) platforms can invest in provider training to upskill providers. In a setting with perfect information, a large size of providers reduces disintermediation; whereas in a setting with imperfect information,

standardization to reduce heterogeneity in service quality can mitigate platform leakage. Our differentiations from He et al. (2020) are threefold: (i) We highlight the role of repeated transactions to reduce moral hazard issues and examine the impacts of reducing transaction costs under repeated transactions. Our results extend the one-time decision-making process in He et al. (2020), given that repeat customers and providers are more likely to take transactions offline (Wang and Heng 2017; Gu and Zhu 2021). (ii) Our study provides robust results for multi-homing providers who optimize their schedules on and off the platforms, which He et al. (2020) does not include in their model settings. (iii) We supplement He et al. (2020) by focusing on home-sharing platforms with products with both vertical differentiation (service quality) and horizontal differentiation (location preference), as mentioned in their future research part. In a freelancers' marketplace, Gu and Zhu (2021) find that the provision of accurate reputation scores of service providers may lead to a higher degree of disintermediation, due to enhanced trust between clients and freelancers with high satisfaction scores. Their results suggest that geographic proximity of clients and freelancers, higher job divisibility, and longer expected duration would increase the likelihood of disintermediation.

Transaction costs and lengthy communication also play roles in disintermediation. Platforms that feature shorter waiting time are less vulnerable to disintermediation. He et al. (2020) propose in their analytical models that customers with high waiting costs are more likely to disintermediate in a setting with perfect information about service providers. By leveraging an exogenous shock, the ban of Skype in China, Gu and Zhu (2022) study the impacts of restricting alternative communication tools on mitigating disintermediation. Their results provide supportive evidence that improving communication technology in the environment lowers participants' communication costs of transacting outside the intermediary. The effects between disintermediation and the restrictive usage of alternative communication tools are moderated by job characteristics, such as communication intensiveness, and customers' characteristics, such as enterprise buyers versus personal buyers.

Mitigation of Disintermediation

To discourage disintermediation, intermediaries can provide homogenous services and remove incentives for both sides to bypass the platform (Edelman and Hu 2016). To more effectively compete against standardization and relatively lower quality uncertainty offered by the hotel industry, Airbnb launched a self-certification program itself – the Airbnb Plus certificate in 2018 (Dewan et al. 2019). Compared to a Superhost badge, an Airbnb Plus certificate requires higher standards covering both the services of hosts and quality of properties. For example, a given property needs to have at least a 4.8 out of 5 rating, and the host needs to have a response rate of over 90%, at least 80% of 5-star host reviews, and no cancellations in the last year. Other than host service, properties have to pay a $149 application fee and undergo an inspection covering how well properties are designed, equipped, and maintained. For those listings with an Airbnb Plus certificate, they are less likely to disintermediate due to a greater cost if suspended by Airbnb, which is the incremental 7.6% booking rate compared to non-Plus listings (Dewan et al. 2019). In addition, this certificate of quality also discourages hosts from initializing off-platform transactions, since hosts perceive an increased value of the platform as well as an increased cost of bypassing the platform. Thus, we expect the disintermediation rate to decline for properties that have received the Airbnb Plus certification.

Similar to Airbnb Plus certification, Superhost is another quality signaling device that recognizes top-rated and most experienced hosts by checking their performance. According to the criteria for earning and maintaining the Superhost badge, a focal host needs to maintain an average overall rating of 4.8 or above in the past year, have less than 1% cancellation rate, respond to at least 90% of new messages within 24 hours, and complete at least 10 stays in the past year. A Superhost badge will be awarded to hosts once they fulfill those criteria, and Airbnb will check these requirements every 3 months. However, the Superhost badge is typically automatically granted to top-rated hosts who have maintained excellent ratings, high response rates, and low cancellation rates. The cost of disintermediation for hosts with Superhost badge is relatively lower, compared with that for hosts with Airbnb Plus certification. The potential costs of disintermediation to hosts will likely increase after they receive the Superhost badge, whereas consumers' disintermediation costs are not likely to be affected. Thus, we expect to see a reduction in disintermediation for properties whose hosts recently received the Superhost badge.

Another important strategy to mitigate disintermediation is to reduce transaction time and lengthy communication. In order to circumvent the excessive screening that increases transaction costs, Airbnb launched the Instant Bookable feature. Instant Bookable allows guests to book the property without the hosts' approval. This streamlined booking process greatly enhances the value of the platform to both guests and hosts. It has been reported that enabling Instant Bookable also economically benefits hosts on Airbnb (Mayya et al., 2020). However, the downside is that hosts may lose most of their control of the properties' booking calendar. If they were to disintermediate, the chance that they could find a suitable time slot outside of the booked dates is much lower. On the consumer side, without the lengthy communication process prior to booking, the adoption of Instant Bookable may discourage guests from initializing off-platform transactions as well. First of all, the time to communicate with hosts and propose to bypass Airbnb has been reduced, after the introduction of Instant Bookable feature. Second, the reduced transaction cost resulting from forgoing screening also enhances the value of transacting on Airbnb, compared to transacting offline. Third, guests with potential discrimination risks from screening may have a better chance transacting on Airbnb than going offline. Taken together, the Instant Bookable feature imposes a higher cost on hosts who are inclined to disintermediate, significantly increasing the value of transacting on the platform to consumers. Therefore, we expect to find significant decreases in disintermediation rates after hosts adopt Instant Bookable.

Information concealment is also implemented to mitigate disintermediation by withholding external contact and location information from Airbnb. As opposed to these three strategies discussed above, information concealment is intentionally designed to mitigate disintermediation. The current practice of Airbnb is to withhold the precise physical address and contact information of hosts before the transactions are finalized on the platform. As discussed in Zhu and Iansiti (2019), such strategies are not always effective since they increase the transaction costs of taking business online and make it less attractive to a platform using streamlined designs. We conjecture that withholding information of the property or host does not affect the value of the platform, but may increase the cost of disintermediation. Both hosts and guests may still have the incentive to take the business offline, despite that the platform has hidden the contact information. To bypass the platform, the guest or the host would have to spend significant time and effort to figure out alternative ways, such as communicating the contact information via chat tools, leading to an increased cost of disintermediation. Therefore, we expect to see a decrease in disintermediation due to information concealment.

Other mitigation strategies include proper design of revenue models, which essentially try to reduce the benefits of transacting offline. Some platforms, including Thumbtack, ZBJ, Taobao, and Monster.com, also change the revenue models of transaction-based commissions to combat disintermediation. Alternative revenue models may include charging up-front fees before providing access to their platform, charging for lead generation, and charging for advertising (Edelman and Hu 2016; Zhu and Iansiti 2019). Intermediaries can deter platform leakage by offering complementary and ancillary services to facilitate transactions (Edelman and Hu 2016; Zhu and Iansiti 2019; Ladd 2021). For instance, Airbnb offers experiences that are independent of home-sharing but for a fee. In addition to ancillary services, Airbnb provides escrow services, dispute resolution, and insurance for hosts and guests, which enhance the value of transacting through Airbnb.

Data

We integrate the online Airbnb booking data with offline mobile location data. The Airbnb data includes 1.83 million daily records of 19,826 properties in Austin, Texas from June to August of 2019. For each property, the data includes the geo-coordinates (longitude, latitude), photos, rules, facilities, star rating, customer reviews, features enabled by host (such as Instant Bookable), daily listing price, and daily status (available, reserved by customers, or blocked by hosts).

The mobile location data are provided by a leading U.S. data aggregator, who aggregates data across 400+ commonly used mobile apps, such as weather and maps, from one-quarter of the U.S. population, in compliance with privacy regulations such as GDPR and CCPA. The data is representative of the U.S. population given the company's detailed research. The sample under analysis covers Austin, TX over the same 3 months. Each individual's location is recorded every 5-15 minutes or when geo-coordinates change

substantially to reduce device battery drainage during tracking. And each record contains an anonymized individual ID, a timestamp, longitude, latitude, speed, and dwell time at the location visited.

Identification of Disintermediation

We propose a geo-analytic method to detect occurrences of disintermediation by matching individuals' stays at each Airbnb property with the property's booking calendar. Specifically, analyzing the location data, we (1) remove individuals with less than 40 daily records; (2) leverage a state-of-the-art stop detection algorithm to determine each remaining individual's stops (i.e., stays/dwells at a location for more than 5 minutes) (Aslak and Alessandretti 2020); (3) identify stops at Airbnb properties; (4) identify hosts, defined rather strictly/conservatively as those with stops at the respective properties for 10+ nights (1-5AM) per month (we later test relaxed criteria of 7+, 5+, or 3+ nights per month for robustness); and (5) identify occurrences of disintermediation if non-host stays are detected 1-5AM at a property on a blocked date .

We define each property's rate of disintermediation over the 3-month period as the number of disintermediated days divided by the total number of blocked and reserved days. Our estimated disintermediation rate is 5.4%, which is a lower bound estimate since location data does not cover the entire population. For the remaining analyses on the efficacy of the mitigation policies, we form a weekly panel of data and use the weekly number of disintermediation days for each property as our dependent variable.

Table 2(a) displays the descriptive statistics and correlations among the key variables in the subsequent analyses. The average weekly number of disintermediation days is 0.3. 48% (3%) of the properties have Instant Bookable (Airbnb Plus). 16.5% are Superhosts. Table 2(b) exhibits the pairwise correlations: Instant Bookable, Airbnb Plus adopters, and Superhosts are associated with lower numbers of disintermediation days. Our additional exploratory analysis (not reported here due to page limit) also reveals that the properties with longer minimum stays and stricter cancellation policies, more experienced hosts (measured by number of reviews), with photos, and Superhost, are less likely to disintermediate.

Variable	Obs	Mean	Std. Dev.	Min	Max
Week Disintermediation	263405	.298	.994	0	7
Airbnb Plus	176451	.03	.169	0	1
Instant Bookable	164116	.485	.5	0	1
Superhost	292304	.165	.372	0	1
Price	263237	257.849	550.558	1	24998.99
Rating	102686	4.877	.26	2.5	5
No. Reviews	290041	28.482	60.32	0	951
No. Photos	289575	16.662	12.993	0	506
No. Bedrooms	170167	1.793	1.269	0	23
Hotel Room	292213	.002	.046	0	1
Entire Home or Apartment	292213	.704	.457	0	1
Private Room	292213	.269	.443	0	1
Flexible Cancellation	292213	.217	.412	0	1
Moderate Cancellation	292213	.17	.376	0	1
Strict Cancellation	292213	.25	.433	0	1
Violent Crime	280494	38.952	13.434	13.3	61.2
Property Crime	280494	62.781	9.958	25.3	75.3
Median Household Income (K)	280441	54.279	24.674	12.786	130.199
Average Commuting Minutes	280494	22.023	3.206	16.6	35.6
Cleaning Fee/Price	136454	.499	.427	0	6.811
Security Deposit/Price	121243	1.834	4.495	0	180.945
No. of Competitors within 1 KM	263408	410.897	345.516	0	1223
Preference of Long-term Leases	263405	0.005	0.073	0	1
Intensity of Repeat Customers	117430	0.024	0.060	0	1

Table 2(a). Descriptive Statistics of Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) # Disintermediation	1.00					
(2) Airbnb Plus	-0.04***	1.00				
(3) Instant Bookable	-0.05***	0.03***	1.00			
(4) Superhost	-0.05***	0.16***	0.01**	1.00		
(5) Log Price	-0.02***	0.00*	0.01**	-0.04***	1.00	
(6) Rating	0.00	0.10***	-0.13***	0.22***	0.03***	1.00

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2(b). Correlation Table of Main Variables

Evaluation of Mitigation Efficacy

To evaluate the efficacy of the mitigation policies (Instant Bookable as our focal illustration here and later other policies), we leverage the Difference-in-Differences (DiD) statistical method with Propensity Score Matching (PSM) and Look Ahead Matching (LAM). That is, we measure the differential shifts in disintermediation in the control versus treatment groups before and after adopting the policy. The treatment group comprises the listings that have enabled Instant Bookable from June to August 2019, whereas the control group that has not by the end of this period. To address endogenous self-selection into adopting the policy, we deploy PSM and LAM to account for both observable and unobservable covariates that might influence the self-selection. Specifically, in LAM, we select the properties that did not turn on Instant Bookable June-August but turned it on within September-November of 2019, as a potential control group and then use PSM to match them with the treated properties based on a list of observable covariates, such as the size, type of the property, type of rooms, price, and star rating.

Using the matched treatment and control groups, we implement a DiD model to estimate the average treatment effect on the treated (ATT) and gauge the impact of Instant Bookable on mitigating disintermediation:

$$y_{it} = \beta_1 treated_i \times post_t + \beta_2 x_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where y_{it} stands for the number of disintermediation days of listing (or property) i in week t. β_1 is the parameter of key interest, measuring the impact of Instant Bookable on the change of disintermediation. x_{it} captures other time-varying control variables that may affect y_{it}, such as the price and star rating of a listing. μ_i, λ_t, and ε_{it} respectively denote the listing fixed effect, time fixed effect, and independent and identically distributed random shocks.

To verify the parallel trend assumption of DiD estimators, we further implement a relative time model to test whether the movement in dependent variables of the treatment group and control group follow parallel trends prior to treatment. The relative time model is specified as:

$$y_{it} = \sum_{m=-4}^{+4} \beta_m treated_i \times I_t(m) + \beta_2 x_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

where $m = -4, -3, -2, -1$ denotes the time periods before the treatment begins. Therefore, we expect none of β_{-4}, β_{-3} and β_{-2} to be statistically significant, which indicates that disintermediation between the treatment group and control group is statistically indifferent prior to treatment. We verify this key assumption and report coefficients of β_m in Figure 1 and Figure 2. We do not find any systematic differences between the control and treatment groups before treatment, supporting the validity of the DiD estimation, whereas immediately after treatment, β_m drop substantially and gradually become significant.
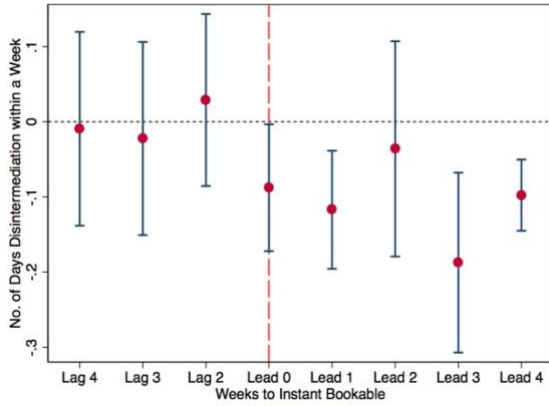
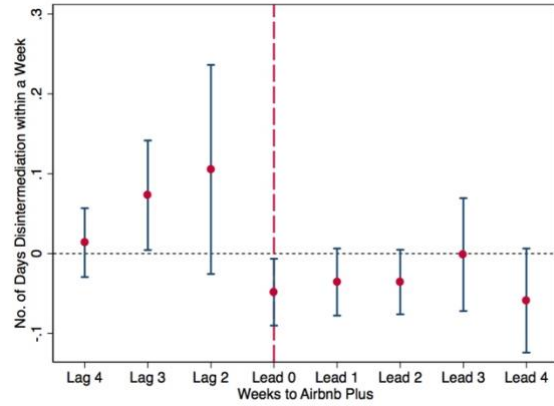**Figure 1. Relative Time Model of Instant Bookable**

Figure 2. Relative Time Model of Airbnb Plus

Main Findings

We present the DiD results in Equation (1) in Table 3. Columns (1) to (3) show that enabling Instant Bookable mitigates the weekly disintermediation by 0.10 days. The effect remains consistent across the models with or without the control variables. To address estimation issues related to the staggered treatment adoption and heterogeneous treatment effects, we further implement a state-of-the-art two-step GMM method proposed by Gardner (2021) to obtain a more interpretable estimation of the treatment effect. The intuition behind the method is to identify an average treatment effect on the treated from a regression of the outcome on the treatment status in the second step, after removing the individual and time fixed effects from the first step. Column (4) shows the results of the DiD estimation with this two-step GMM method. The mitigation effect of Instant Bookable remains consistent.

	(1) TWFE	(2) TWFE	(3) TWFE	(4) Two-Step GMM
	# Disinterm. Days	# Disinterm. Days	# Disinterm. Days	# Disinterm. Days
Instant Bookable	-0.1029**	-0.1019**	-0.0966***	-0.0923**
	(0.0449)	(0.0451)	(0.0375)	(0.0393)
Weekly Price Log		0.0775	0.0530	
		(0.0571)	(0.0476)	
Star Rating			0.0696	
			(0.2010)	
Constant	0.3136***	-0.0763	-0.3170	
	(0.0003)	(0.2871)	(1.0041)	
Observations	75,138	75,138	44,396	75,138
R-squared	0.6496	0.6496	0.6269	0.00016
Time FE	Yes	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, using bootstrap for 250 times in Column (4). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3. Main Results: Impacts of Instant Bookable on Number of Disintermediation Days

To address endogenous self-selection, i.e., properties enabling Instant Bookable might be different from those not enabling it, we utilize PSM of the observables, including Superhost badge, type of property, type of rooms, price, star rating, and number of bedrooms and bathrooms. We verify using the *t*-test that PSM

has balanced these covariates across the treatment and control groups (omitted due to page limit). We then re-estimate the DiD model on the PSM matched samples (Table 4).

We further use LAM to address selection on the unobservable covariates of each listing or unobservable market factors not addressed by PSM alone. By matching the listings treated from June to August 2019 to those not treated from June to August but immediately treated from September to November 2019, we cancel out the potential selection concerns caused by unobservable factors. Meanwhile, we also ensure that the observable covariates are balanced after LAM.

Before matching, there were 78 listings in treatment group and 5289 listings in the control group. PSM results in 51 and 117 units; and LAM produces 51 and 39 units, respectively. We re-estimate the DiD model on the PSM and LAM matched sample (omitted due to page limit), and the results are consistent. Table 4 reveals that the impact of Instant Bookable on the weekly disintermediation remains robust and consistent at 0.9 days based on the PSM matched sample; and the effect is 0.09 days based on the PSM and LAM matched samples. Together with the estimated effects displayed in Table 3, we offer coherent evidence that Instant Bookable significantly mitigates disintermediation.

	(1) # Disinterm. Days	(2) # Disinterm. Days	(3) # Disinterm. Days
Instant Bookable	-0.0916** (0.0427)	-0.0845** (0.0423)	-0.0873** (0.0429)
Weekly Price Log		0.4900*** (0.1618)	0.5029*** (0.1650)
Star Rating			0.2287** (0.0899)
Constant	0.2782*** (0.0136)	-2.0290*** (0.7597)	-3.2191*** (1.1377)
Observations	2,352	2,352	2,348
R-squared	0.6489	0.6518	0.6519
Time FE	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4. Main Results: Impacts of Instant Bookable on Disintermediation Days (PSM)

Robustness Checks

Geographic Spillovers. As Airbnb property listings are geographically adjacent, a natural next step is to investigate whether or not there is a spatial spillover across neighboring Airbnb properties. We include a DiD estimation with spatial spillovers because: (a) if there exhibits a spatial spillover of disintermediation within a neighborhood, then the threat of disintermediation would be contagious and more severe among the platforms in the absence of mitigation; (b) if there is a spatial spillover of the Instant Bookable adoption, it may violate the stable unit treatment value assumption (SUTVA), which implies no spillovers of the treatment status; and (c) test the omitted variable bias on a spatial error model to verify whether our standard DiD model omits any variables and exhibits spatial dependence in the error term. We accomplish the above three aspects via a spatial DiD:

$$y_t = \beta_1 DD_t + \beta_2 W y_t + \beta_3 W DD_t + \delta_t + \mu_i + \epsilon_t \tag{3}$$

$$\epsilon_t = \beta_4 W \epsilon_t + \varepsilon_t \tag{4}$$

where y_t denotes a $n \times 1$ column vector of No. of Disintermediation Days, DD_t represents a $n \times 1$ column vector of enabling Instant Bookable, and W stands for a $n \times n$ matrix of spatial weight with each entry $w_{ij} \in W$ denotes an inverse distance between property listing i and property listing j. δ_t and μ denote the time and listing fixed effects. In Equation (3) and Equation (4), if β_3 and $\beta_4 = 0$ and $\beta_2 \neq 0$, it reduces to a DiD in Spatial Auto-regressive model (SAR-DiD). If $\beta_4 = 0$ and $\beta_2, \beta_3 \neq 0$, it reduces to a DiD in Spatial Durbin model (SAR-DiD). If $\beta_3 = 0$ and $\beta_2, \beta_4 \neq 0$, it reduces to a DiD in Spatial autocorrelated error model (SAC-

DiD). And if $\beta_2, \beta_3 = 0$ and $\beta_4 \neq 0$, it reduces to a DiD in Spatial error model (SAC-DiD). We estimated all these models using Quasi-Maximum Likelihood Estimation (Quasi-MLE) (Table 5).

We do not find supportive evidence for either spillovers in disintermediation or spillovers in adoptions of Instant Bookable. Therefore, geographic spillovers would not contaminate our DiD estimates. In other words, the decisions to disintermediate or enable Instant Bookable is less likely affected by the neighboring properties; and our findings still hold even after the spatial correlation is taken into consideration.

	(1) SAR-DiD	(2) SDM-DiD	(3) SAC-DiD	(4) SEM-DiD
Main: Instant Bookable	-0.0915*	-0.0890*	-0.0916*	-0.0917*
	(0.0502)	(0.0506)	(0.0501)	(0.0500)
Spatial: W*y	-0.1204	-0.1220	-0.0660	--
	(0.0754)	(0.0755)	(0.1442)	--
Spatial: W*Instant Bookable	--	-0.0909	--	--
	--	(0.2251)	--	--
Spatial: W*ϵ	--	--	-0.0634	-0.1204
	--	--	(0.1436)	(0.0752)
Observations	2,352	2,352	2,352	2,352
R-squared	0.0068	0.0058	0.0067	0.0067
Time FE	Yes	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes	Yes

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

Table 5. Robustness Check: DiD in Spatial Panel Model with Geographic Spillovers

Multi-homing Properties. Some hosts cross-list their properties on multiple platforms, and the blocked status on Airbnb could be a result of bookings on other platforms such as Vrbo. Due to such multi-homing behavior, our main results may suffer from a sample selection issue, i.e., the properties that cross-list are more likely to block the calendars on Airbnb or even withdraw from Airbnb. To address this, we take two approaches: first, we estimate a Heckman Two-step model to test whether the sample bias is significant and whether our results hold after modelling the multi-homing probability (Heckman 1979); and second, we re-run the main analysis with the properties only listed on a single platform, Airbnb.

In Table 6, we model both the outcome equation and the selection equation (i.e., the probability for a listing to multi-home on both Airbnb and Vrbo). Given that a naturally exclusive variable is required, we use the adoption of Vrbo Managers as the natural exclusion that affects only the selection probability. We also report the selection hazard with a coefficient in the inverse Mill's ratio in Lambda. Our results still hold even when we take multi-homing into account, and the coefficient of Lambda is insignificant, indicating a low risk of the sampling bias in our estimation.

	(1) Disintermediation	(2) Multi-Homing	(3) Selection Hazard
Instant Bookable	-0.1203**		
	(0.0477)		
Weekly Price Log	-0.0669**	0.4148***	
	(0.0306)	(0.1379)	
Star Rating	0.2623**	-0.1570	
	(0.1069)	(0.6991)	
Vrbo-Manager		6.6601***	
		(0.2372)	
Lambda			0.0217
			(0.0216)
Constant	-0.8792**	-2.5156	
	(0.4271)	(3.5686)	

Observations	2,348	2,348	2,348

Robust standard errors in parentheses *** p<0.01, ** p<0.05, *p<0.1

Table 6. Robustness Check: Disintermediation with Heckman Two-step Estimator

Reverse Causality. Note that enabling Instant Bookable is entirely a host's decision, and another threat to our identification lies in reverse causality, especially when the past experience of disintermediation plays a role in enabling Instant Bookable in the future. We rule out this concern by conducting a survival analysis on the likelihood of enabling Instant Bookable, using Lag-1-Week, Lag-2-Week and Lag-3-Week terms of the disintermediation measure, a.k.a. No. of Disintermediation Days. If any of those terms is significantly positive/negative, our estimation suffers from reverse causality issues that hosts may strategically turn on Instant Bookable if they conducted more/less disintermediation in the past.

We report the results in Table 7. By adding lagging terms of No. of Disintermediation Days into survival models, we do not find any evidence of reverse causality. Other factors that may accelerate the decision on enabling Instant Bookable include median household income where the focal properties are located, and the booking rate, which are consistent with prior findings in the literature (Mayya et al. 2020).

	(1) Instant Bookable	(2) Instant Bookable	(3) Instant Bookable
Lag-1-Week Disintermediation	-0.0981 (0.1907)	-0.0814 (0.1308)	-0.0803 (0.1000)
Lag-2-Week Disintermediation		-0.0066 (0.1135)	0.0519 (0.0868)
Lag-3-Week Disintermediation			-0.0911 (0.1032)
Weekly Price Log	-0.0139 (0.1860)	-0.0156 (0.1882)	-0.0158 (0.1892)
Rating	0.6509 (0.7180)	0.6246 (0.7150)	0.5892 (0.7126)
Occupancy Rate	0.4883* (0.2962)	0.4957 (0.3028)	0.5032 (0.3069)
Superhost	0.2677 (0.2793)	0.2632 (0.2799)	0.2620 (0.2800)
Strict Cancellation	-0.1943 (0.3011)	-0.1952 (0.3007)	-0.2007 (0.3005)
Flexible Cancellation	-0.0046 (0.3632)	-0.0233 (0.3652)	-0.0145 (0.3631)
No. Bedrooms	0.0025 (0.1266)	0.0068 (0.1265)	0.0076 (0.1269)
Median Income (Thousand)	-0.0172*** (0.0058)	-0.0171*** (0.0058)	-0.0174*** (0.0058)
Observations	39,692	36,641	33,587

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7. Robustness Check: Reverse Causality on Instant Bookable

Heterogeneous Treatment Effects

In this section, we examine the heterogeneous treatment effects of Instant Bookable on mitigating disintermediation. Based on He et al. (2020) and Wang and Heng (2017), we investigate the moderating roles of hosts' preferences in long-term leases, the intensity of online repeated users, the market thickness of local providers, as well as hosts' tenure on the platform.

Given that some goods are more amenable to rental with usage in large chunks of time and with less time without usage in between (Filippas et al. 2020), we infer the coordination cost of home-sharing based on the disclosure of hosts' preferences in long-term leases. Hosts with a preference for long-term leases are more likely to bear the higher coordination costs in the management of home-rental activities. Their

coordination costs are probably too high that they usually offer discount for long-term guests, or even bypass the platform to transact directly (Wang and Heng 2017). As a result, even if some hosts enable Instant Bookable to lower transaction costs online, those who prefer long-term leases can still block their calendar and reserve for long-term leases. Our strategy to identify hosts' preferences in long-term leases is to search for keywords such as "long term" and "discount" in the description of each property. For instance, we observe that some hosts will disclose that discounts are available for repeated and long-term guests, and they are willing to negotiate. We therefore created a dummy variable to indicate hosts' preference in long-term leases and examined its moderating role in the impacts of Instant Bookable on disintermediation mitigation. We expect that properties with hosts' preferences in long-term leases are less likely to go offline, thereby attenuating the mitigating effects of Instant Bookable on disintermediation.

The extent of disintermediation can be amplified by the fraction of repeat customers under complicated purchase (Edelman and Hu 2016). We believe that repeat customers are more likely to initialize off-platform transactions for three reasons. First, both sides of Airbnb – hosts and guests, probably exchange their contact information, such as mobile phone or email, after their first transaction and aim for repeat transactions offline. Second, given that home-sharing services are experience goods with both horizontal and vertical differentiation, customers develop a more comprehensive view of a focal property, such as taste alignment and quality expectations, during their first stay, and are more likely to stick to one property for a second visit. Third, repeat customers are more likely to cooperate and go offline with enhanced trust formed between hosts and guests in their past transactions, especially in the presence of adverse selection and moral hazard issues in the online reputation systems (Dellarocas, 2005).

To test the moderating effects of repeat users, we extracted 327,011 reviews left by guests and implemented a semi-supervised topic model to estimate the intensity of repeat customers. Anchored correlation explanation is a semi-supervised model that allows topics to be interpretable by effectively splitting apart a topic with multiple themes embedded into distinct sets of topics. This model also allows word-level domain knowledge to be incorporated through anchor words, and it therefore allows topic separability and representation to be promoted with minimal human intervention (Gallagher et al. 2017). According to sub-category ratings on Airbnb, we start with six topics of reviews on location, amenities, cleanliness, value, recommendation, check-in, and communication to capture information left in each review. In addition, we supplement an extra topic called repeat customers, to proxy the intensity of repeated users across properties. The topic of repeat customers is the key topic of interest. We propose some anchor words to form this topic, such as "second stay", "back" and "return", and the anchored correlation explanation model supplements other keywords such as "definitely", "come", "hope" and "soon" to this topic. We aggregate weights of each topic from each review to a property level and form a continuous variable called repeat customers. The anchored keywords and keywords output from NLP are reported in Table 13 (omitted for page limit). Therefore, we expect that properties with higher proportions of repeat users will show stronger mitigation effects after hosts enable Instant Bookable.

Other than hosts' preference and repeat guests, we explore the role of the competitive environment around a focal Airbnb property, in moderating the mitigating effects of Instant Bookable on disintermediation. Intense competition among Airbnb properties nearby can encourage some of them to go offline and look for potential guests. Given that properties on home-sharing platforms are geographically dispersed, each property competes with other properties nearby. For instance, after an Airbnb Plus badge is assigned to a focal property, it exerts an indirect effect on non-Plus listings by reducing their booking rate by 1.5% (Dewan et al. 2020). We use a similar strategy to identify the number of listings within a radius of 1 kilometer of a focal property listing. We term this new variable as nearby competitors, which proxies the intensity of competition in the nearby neighborhood of a given property listing. We expect that a more intense competitive environment may offset the dampening effects brought by Instant Bookable, given that the intense competition in local markets tends to encourage them to seek customers in alternative ways.

We further investigate the moderating effects of host tenure. We split our sample based on the median number of host tenure, which is about 4.9 years, and conducted a subsample analysis. Given that inexperienced hosts may be highly dependent on the platform, we expect this group of hosts to be less likely to take their business offline. However, more experienced hosts are familiar with providing services to guests, and also have more chances to develop trust with their repeat guests. Therefore, we expect that the impact of Instant Bookable on mitigating disintermediation is stronger among experienced hosts.

As shown in Table 8, we provide supported evidence that the dampening effects on disintermediation brought by Instant Bookable are stronger among hosts with more repeat customers and with more experience. However, the mitigation effect on disintermediation may be attenuated for properties whose hosts prefer long-term leases and properties with intense competitive environment.

	(1)	(2)	(3)	(4)	(5)
	#Disinterm. Days	#Disinterm. Days	#Disinterm. Days	#Disinterm. Days (Below Median Tenure)	#Disinterm. Days (Above Median Tenure)
Instant Bookable (IB)	-0.0982***	-0.0616	-0.1645**	-0.0667	-0.1189***
	(0.0354)	(0.0443)	(0.0710)	(0.0695)	(0.0300)
IB*Long-Term Preference	0.0900**				
	(0.0444)				
IB*Repeat Customers		-1.7627*			
		(1.0592)			
IB*Nearby Competitors			0.0002*		
			(0.0001)		
Weekly Price Log	0.0530*	0.0309	0.0531	-0.0463	0.1165***
	(0.0309)	(0.0474)	(0.0476)	(0.0503)	(0.0393)
Star Rating	0.0696	0.0603	0.0672	-0.3246***	0.5893***
	(0.0932)	(0.2347)	(0.2011)	(0.1061)	(0.1617)
Constant	-0.3170	-0.1680	-0.3059	2.1288***	-3.2236***
	(0.4782)	(1.1590)	(1.0045)	(0.5540)	(0.8261)
Observations	44,396	40,413	44,396	21,177	23,219
R-squared	0.6269	0.6270	0.6269	0.6662	0.5782
Time FE	Yes	Yes	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8. Results of Heterogeneous Treatment Effects: Impacts of Instant Bookable on No. of Disintermediation Days

Alternative Mitigation Strategies

There are other policies implemented by Airbnb either intentionally or unintentionally, to combat disintermediation. Airbnb Plus is a quality certification program in which hosts need to pay an application fee, undergo a thorough in-person inspection by Airbnb and meet a collection of criteria that set the bar for well-designed spaces and exceptional hosts. According to Dewan et al. (2020), receiving Airbnb Plus certification will bring sizable returns to the property, which result from an increased booking rate. Using the same framework in Table 2, we expect Airbnb Plus would enhance the value of the platform to the hosts, and also significantly increase the cost of disintermediation, because, in the event of being caught, the hosts will forfeit this hard-earned reputation as well as the associated economic benefits.

In Table 9, we present the DiD estimation in conjunction with PSM. Note that we report the balance check of PSM. Obtaining an Airbnb Plus certificate reduces the number of weekly disintermediation days by 0.06 to 0.07, based on the PSM and LAM matched sample.

	(1)	(2)	(3)
	No. of Disintermediation Days	No. of Disintermediation Days	No. of Disintermediation Days
Airbnb Plus	-0.0626*	-0.0638*	-0.0647*
	(0.0334)	(0.0340)	(0.0342)
Weekly Price		-0.0889	-0.0887
		(0.1122)	(0.1122)
Star Rating			0.0633
			(0.0768)
Constant	0.0772***	0.5445	0.2279
	(0.0047)	(0.5911)	(0.6784)
Observations	1,097	1,097	1,097
R-squared	0.1555	0.1561	0.1562
Time FE	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9. Alternative Strategy: Impacts of Airbnb Plus on No. of Disintermediation Days (PSM)

Other than the Airbnb Plus certificate, another well-known quality signaling badge launched by Airbnb is the Superhost program, which recognizes the top-rated and most experienced hosts. According to the criteria for earning and maintaining the Superhost badge, a focal host needs to maintain an average rating of 4.8+ over the past year, a <1% cancellation rate, a response to 90%+ new messages within 24 hours, and a completion of 10+ stays over the past year. A Superhost badge will be awarded to a host once they fulfill the above criteria, and Airbnb will re-evaluate these requirements every 3 months. Compared to the Airbnb Plus certificate, which requires an extra $149 application fee and inspection of the properties' designs, maintenance, equipment, and hosts' service quality, the Superhost badge is awarded to the hosts automatically and does not require any applications to be initialized by the hosts. Overall, Superhost-awarded listings represent 19.4% of all property listings, whereas Airbnb Plus listings only represent 0.6% of the properties in the cities where the Plus program is available. Our Austin sample includes 16.5% of Superhost properties and 3% of Airbnb Plus properties. These statistics are consistent with those reported from external data sources and also indicate that the Airbnb Plus certificate serves as not only a standardization of properties and host services, but also a quality signal. However, the Superhost badge may only signal the hosts' quality.

To test whether a badge of high quality solely helps to mitigate disintermediation, we implemented a DiD estimation in conjunction with PSM, and report the results in Table 10. Compared to those listings without Superhost badges, the treatment of awarding a focal property a Superhost badge does not significantly affect its weekly number of intermediation days. This insignificant effect may occur because neither the Superhost badge significantly standardizes host services and property characteristics, nor does the Superhost badge bring a large enough value to transact online.

	(1)	(2)	(3)
	No. of Disintermediation Days	No. of Disintermediation Days	No. of Disintermediation Days
Superhost	-0.0123	-0.0138	-0.0131
	(0.0216)	(0.0216)	(0.0218)
Weekly Price Log		0.1206***	0.1245***
		(0.0370)	(0.0383)
Star Rating			-0.0476
			(0.1318)
Constant	0.2237***	-0.3600**	-0.1444
	(0.0053)	(0.1795)	(0.6867)
Observations	19,376	19,376	19,366
R-squared	0.6050	0.6053	0.6053
Time FE	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10. Alternative Strategy: Results of Impacts of Superhost on Number of Disintermediation Days (PSM)

Another strategy to mitigate disintermediation is information concealment, such as Airbnb's withholding of hosts' phone numbers and exact addresses prior to transaction finalization. As discussed in Zhu and Iansiti (2019), such strategies are not usually effective because they make a platform cumbersome and lose business to streamlined competitors. We empirically test the effectiveness of the information concealment strategy in mitigating disintermediation on Airbnb. To detect changes in information concealment, we look for a keyword "Phone number hidden by Airbnb" in the description of each Airbnb listing. For instance, we found one description: "Perfect ACL spot...Don't hesitate to contact us at (Phone number hidden by Airbnb) Yvette Giraud (Phone number hidden by Airbnb) Olivier Giraud)." By identifying when the keyword "Phone number hidden by Airbnb" appears in our sample, we can proxy the time of information concealment and estimate whether such a strategy affects disintermediation.

Table 11 shows that information concealment, such as hiding phone numbers of hosts from description, may not have an impact on mitigating disintermediation. Hosts and guests can exchange contact information immediately after their first on-platform transactions, or at the moment when they screen each other using Airbnb's message tool.

	(1)	(2)	(3)
	No. of Disintermediation Days	No. of Disintermediation Days	No. of Disintermediation Days
Hidden by Airbnb	-0.0547	-0.0559	-0.0447
	(0.0609)	(0.0610)	(0.1025)
Weekly Price Log		0.0408***	0.0401***
		(0.0094)	(0.0155)
Star Rating			0.0661
			(0.0684)
Constant	0.2652***	0.0609	-0.2895
	(0.0016)	(0.0470)	(0.3398)
Observations	138,740	138,740	87,903
R-squared	0.6381	0.6381	0.6087
Time FE	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11. Alternative Strategy: Results of Impacts of Information Concealment on Number of Disintermediation Days

Conclusion and Discussion

This study addresses two key challenges confronting the academic literature and the multi-billion-dollar two-sided sharing economy: the quantification of disintermediation and the efficacy of mitigation policies. We developed a geo-analytic methodology to gauge the extent of disintermediation on one of the largest platforms in the world, Airbnb, and causally determine the impacts of four mitigation strategies on disintermediation. Leveraging TB-sized online booking data and offline location data, and the DiD method with Propensity Score Matching and Look Ahead Matching, we offer the first population- and platform-scale empirical evidence of the disintermediation rate, as well as the significant effect of Instant Bookable (0.09 days per week) and Airbnb Plus (0.06 days per week) on reducing disintermediation, whereas Superhost badge and information concealment exhibit no significant impact. A series of robustness checks address a variety of selection and sampling biases and provide consistent findings. Analyses of the heterogeneous treatment effects pertaining to Instant Bookable show that the mitigation effect of Instant Bookable is stronger among the hosts without preferences for long-term leases, with more repeat customers, fewer nearby competitors, and longer host tenure.

In summary, as disintermediation increasingly plagues the multi-billion-dollar sharing economy platforms, this research contributes to the theories and practices along a number of dimensions. First, this study provides the first region- and population-scale quantification of disintermediation by leveraging novel location big data and geo-analytic methods. Second, this study evaluates the effectiveness of various disintermediation mitigation strategies and reveals differential efficacies, thus enriching theories on disintermediation mitigation (details in the full paper available upon request). Finally, our study offers valuable guidance to platforms on the design and selection of mitigation strategies. We hope this study will serve as a valuable stepping stone to attract fruitful future research on many intriguing aspects of disintermediation and its mitigation, creating win-win-win scenarios for platforms, service providers, and customers.

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