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

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Abstract:

Two-sided platforms, such as Airbnb, capture multi-billion-dollar marketplaces online. Nonetheless, disintermediation, where participants bypass platforms to transact directly, has challenged the business model and dwindled the profits of these platforms. Despite those explicit and implicit strategies to mitigate disintermediation by Airbnb, such as withholding contact information before the completion of transactions, little is known regarding (i) the extent of disintermediation, largely due to the unobservability of such actions; and (ii) differential efficacy of various mitigation policies (Zhu and Iansiti 2019). We hence aim to fill these important voids in the literature by offering the empirical evidence of disintermediation on Airbnb, quantifying its magnitude, and evaluating the causal impacts of policies such as Instant Bookable on disintermediation mitigation.

We accomplish these by analyzing the occupancy data from Airbnb and a large-scale novel individual mobile location dataset, with a multitude of methodologies, including Geographic Information System (GIS), machine learning, and spatial-temporal statistical analysis. Specifically, we first develop a process to identify the daily occurrences of disintermediation by combining the population-scale yet individual-level mobile location data, which pinpoints the granular traffic to each Airbnb property, with the Airbnb booking calendar data. Our analyses, bolstered by a series of robustness studies, reveal a 5.4% rate of disintermediation in Austin, TX, in 2019. Next, we estimate the causal impacts of Instant Bookable on disintermediation reduction by deploying Difference-in-Differences (DiD) in conjunction with Propensity Score Matching and Look Ahead Matching to mitigate selection issues both on observables and unobservables. We discover that Instant Bookable, which allows guests to book without requesting hosts' approval, decreases disintermediation by 9%. Such effects of Instant Bookable on disintermediation mitigation are stronger among hosts without long-term lease preference, for properties with more repeated guests, and more experienced hosts. We also investigate the effects of alternative platform policies such as Airbnb Plus property certificate, which requires application fees for on-site property inspections and a higher quality standard than that of Superhost, and find that it reduces disintermediate by 6% based on daily observations. Superhost badge, which requires the host to have at least 10 trips or 3 reservations that total at least 100 nights on the platform, as well as information concealment, has no effect on disintermediation.

Our study provides quintessential managerial implications on disintermediation mitigation strategies such as direct deterrence (e.g. information concealment), lowering matching or transaction costs (e.g. Instant Bookable), and implementing quality certification (e.g. Superhost and Airbnb Plus) which may escalate hosts' commitment to on-platform transactions.

Keywords: disintermediation, two-sided platform, sharing economy, geo-spatial analysis, location big data, Difference-in-Differences

1. Introduction

In a multisided market such as Airbnb, Uber and DoorDash that facilitate on-demand connections across people, businesses and devices, disintermediation happens when end-users bypass platform to transact and threatens the value creation and capturing process of networked economies. ZBJ, a Chinese outsourcing platform for knowledge workers estimated that the disintermediation issues could lead to a loss of 90% of its business on platforms (Zhu et al. 2018). The actual income of service providers on ZBJ, according to their survey, are 10 times as higher as their reported platform income (Zhu and Iansiti 2019). Similar phenomenon exists on freelancers' platforms in the U.S. such as Upwork: it is not necessary for clients to transact through the platform after they matched and exchanged contact with suppliers. Both sides have incentives to take business offline, either because they would like to circumvent a marketplace fee charged by the platform, or because they have trusted each other after a few transactions (Gu and Zhu, 2021). In either case, online marketplaces do not exhibit comparative advantages over direct transactions offline, in terms of value creation, yet impose significant economic costs on participants due to the high commission fee.[1] Despite of its tremendous effects on platforms, disintermediation is unobservable to platform owners and therefore it is difficult to quantify and combat.

Multisided platforms create value by reducing transaction costs and facilitating business among participants. A solution to reduce significant transaction costs of online commerce proposed by Alibaba, is to invest in telecommunication tools with fast penetration of Internet in China in 1999, when communication and information are limited (Evans and Schmalensee, 2016). By enabling buyers and suppliers to communicate with instant messages and discussion forums, Alibaba has gradually established a thick two-sided marketplace with millions of users all around the world. Similarly, the introduction of language translation systems on eBay has reduced transaction costs between suppliers in U.S. and buyers in Latin America, resulting in a lift of 10.9% in overall exports (Brynjolfsson et al. 2019). However, an unexpected consequence brought by convenient communication tools is disintermediation especially among those participants who rely on the platforms to sorely exchange information with prospective service providers, which challenges value capturing of platforms (Gu and Zhu, 2022).

Despite these values offered by platforms, home-sharing platforms such as Airbnb are vulnerable to disintermediation, especially when the gains of disintermediation outweigh the costs of doing it. In contrast

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[1] For instance, ZBJ.com charged service providers 20% of transaction value as commission fees (Zhu et al. 2018). Upwork charged clients 20% service fee with earnings range from $0-$500, 10% service fee with earnings range from $500.1-$10,000, and 5% service fee for earnings from $10,000.01 and more. Most hosts of Airbnb pay a flat service fee of 3% of the booking subtotal, and guests typically pay a service fee of around 14% of the booking subtotal. And the marketplace fees of Uber, Lyft and DoorDash are as high as 30%.

to Airbnb, the market characteristics protect ride-hailing platforms (e.g. Uber) from disintermediation, because riders typically prefer the closest available driver and drivers do not substantially differ in quality. However, listings on Airbnb are horizontally differentiated, and guests who were satisfied with hosting experience and location may return for a second stay -- which put Airbnb under risk of disintermediation based on two factors. First of all, guests and hosts have to communicate at length before finalizing a complicated purchase, and therefore they have more opportunities to take the transaction off the platform. In addition, hosts and listings are heterogeneous and they vary greatly in quality. In this case, hosts and guests can exchange contacts after their first successful match, and form continuous transactions offline, with a long-term contract and a higher level of trust (Edelman and Hu, 2016). Even prior to the completion of transactions, anecdotal evidence shows that guests can bypass platforms' restrictions on sharing contact information via messaging and easily circumvent Airbnb's filtering algorithm. Some hosts even offer incoming guests with offline GPS navigation from the nearest public transportation stops or landmarks to the listings.[2]Instant Bookable is a feature to streamline the booking process to handle guests, who meet guest requirements, agree to house rules and do not ask for unique requests of stays. Instant Bookable feature reduces chances that guests initialized a request to exchange contact information before booking or bypass the platform through a lengthy conversation.

Based on a framework on value enhancement and cost reduction to hosts and guests, this paper causally identifies the effects of Instant Bookable on mitigating disintermediation on Airbnb. By analyzing occupancy data and a novel individual mobile geolocation dataset, our study provides the first large-scale empirical evidence to quantify the magnitude of disintermediation and evaluate the causal effects of mitigation policies. First of all, we develop a process to uncover daily occurrence of disintermediation based on granular individual traffic with occupancy data of each Airbnb property, and reveal a 5.4% disintermediation rate in Austin, Texas in 2019. Second, this research estimates the impacts of Instant Bookable by deploying Difference-in-Differences estimation (DID) in conjunction with Propensity Score Matching and Look Ahead Matching to mitigate selection issues both on observables and unobservables. Our results provide supportive evidence that enabling Instant Bookable, which bypasses lengthy communication between hosts and guests before finalizing transactions, reduces disintermediation by 9%. Third, we explore a number of heterogeneous treatment effects, including hosts' preference in long-term leases, intensity of repeated guests of each property, and experience of hosts. We find that stronger mitigation effects among hosts without long-term lease preference, properties with more repeated guests, and more experienced hosts. In the end, our results hold under a battery of robustness checks, including tests on geographic spillovers of disintermediation behavior and adoptions of instant bookable feature,

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[2] [Airbnb Community Website](#)

effects of multi-homing listings, as well as extensive placebo tests of treatment timing. Lastly, our study also examines alternative strategies for mitigating disintermediation, such as Airbnb Plus certificate, Superhost badge, and information concealment. Our investigation finds that the adoption of Airbnb Plus Certificate, which standardize both property and hosts' service quality, leads to a reduction of 6% in disintermediation. We do not find any significant effects from Superhost badge and information concealment.

Our study provides quintessential managerial implications on disintermediation mitigation strategies, such as direct deterrence (e.g. information concealment), lowering transaction costs (e.g. Instant Bookable), and implementing quality certification (e.g. Superhost badge and Airbnb Plus Certificate), which may escalate hosts' commitment to on-platform transactions. Our results suggest that lowering transaction costs through enabling Instant Bookable, reduces the risk of disintermediation. Airbnb Plus Certificate program, which requires application fees for on-site property inspections and a higher quality standard than that of Superhost, also mitigates disintermediation behaviors. We do not find significant effects on information concealment, which is the practice of Airbnb on preventing disintermediation, and Superhost badge, which is automatically assigned to qualified hosts. Our research speaks to the current heated debates on platform design and platform governance, in particular on how platforms sustain in network growth and value capturing process. Given that some explicit strategies to combat disintermediation are usually costly and sensitive to enforce,[3] our study helps platform owners understand which policies could implicitly help reduce disintermediation. For example, in order to discourage disintermediation, Upwork invested in advanced AI techniques for dispute resolution, and hence enhanced the value of transacting through their platform. Another example is Handy, which only allows communication between clients and freelancers to occur after a job is assigned. Given that platform owners may implement design features to fulfill other objectives such as increase demand, reduce attrition rate and so on, some strategies may work as an implicit deterrence strategy and reduce disintermediation at a much lower cost.

2. Theory and Literature Review
    2.1 Value and Cost of Mitigating Disintermediation

Our study develops a framework to predict effectiveness of combating disintermediation, based on value enhancement and cost reduction to hosts and guests, respectively. Consider a host or guest chooses to

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[3] From Gu and Zhu (2021), authors mentioned that the platform learns about disintermediation when users seek its help with disputes or payment enforcement for transactions off the platform. In other trials, the platform issued warning messages based on disintermediation scores of chat messages.

bypass the platform based on the surplus of taking their business on the platform, we compare the value and cost of mitigating strategies to hosts and guests (Table 1).

Table 1 Comparison of Strategies in Mitigating Disintermediation

Strategy	Intentional	Value to Hosts	Cost to Hosts	Value to Guests	Cost to Guests	Effects
Instant Bookable	No	↑	↑↑	↑	↔	↓9%
Airbnb Plus	No	↑	↑↑	↑	↔	↓6%
Superhost	No	↑	↑	↑	↔	↔
Information Concealment	Yes	↔	↔	↓	↑	↔

For the first three strategies which are originally not intended for mitigating disintermediation, we find a similar pattern of cost and benefit for hosts and guests, respectively. For example, all of these strategies increase both the value of the platform and cost of disintermediation to hosts, but only increase the value of platform to guests. The adoption of Instant Bookable feature and Airbnb Plus certificate imposes a higher cost. For instance, to be eligible for an Airbnb Plus property, a host has to pay additional application fees and money to maintain the property for quality and service inspection. For Instant Bookable, hosts may lose control on their calendar planning. Once getting caught, hosts with Instant Bookable and Airbnb Plus bear with a larger magnitude of loss. Therefore, we expect to find significant effects of disintermediation reduction after hosts adopted Instant Bookable.

The cost of disintermediation to hosts with Superhost badge is relatively lower, which may mainly include reputation cost because the Superhost badge is automatically granted to hosts. Regarding information concealment that is intentionally designed for mitigating disintermediation, we find that withholding information of the property or host does not affect value or cost from a host's perspective. Concealing information may lead to a lower value and higher cost of bypassing the platform when a guest intends to disintermediate at the first time. However, hosts still have the incentive to contact guests and take the business offline, as hosts are not discouraged by this strategy. Therefore, we do not find supported evidence of reducing disintermediation for information concealment.

2.2 Factors of Disintermediation

Extant literature shows that hosts tend to bypass home-sharing platforms with both monetary incentives and non-economic motivation. A case study by Wang and Heng (2017) implies that hosts consider long-term stay as a legitimate reason to bypass Airbnb, and they perceive that the commission is too high for a long-term lease from a guest's perspective. Hosts can evaluate bypassing guests based on profiles and reviews from Airbnb guest pages and cues they get from online messaging to mitigate adverse selection issues, and moreover, trust between hosts and guests reinforced after a long-term stay. Some hosts internalize Airbnb's functions, to reduce risk of disintermediation from guests. For instance, hosts may require bypassing guests to pay fees in advance or deposit money and negotiate their own refund policy to mitigate moral hazard issues from guests. In addition to disintermediation that occurs prior to transactions online, some hosts request bypassing guests to book through Airbnb for the first few days, but bypass the platform for the remaining days, which is consistent to results in 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' preference in long-term leases, as well as repeated transactions of same guests.

From a perspective of platform design, platforms that feature higher proportions of high-quality providers lower heterogeneity in service quality, and longer waiting time, are more resistant to disintermediation (He et al. 2020). In their analytical settings of customers with perfect information about service providers, platforms tend to be more vulnerable to off-platform transactions when customers have high waiting costs and where the provider pool size is small. 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: first is that platform can shorten customer waiting process; second is to invest in provider training to upskill providers. In a setting of 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. Despite providing empirical evidence for analytical results of reducing transaction costs and providing standardization certificates, 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 repeated 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 in both vertical differentiation (service quality) and horizontal differentiation (location preference), as mentioned in their future research part.

Classifying disintermediation in current transactions or subsequent transactions, Edelman and Hu (2016) associates certain features of marketplaces with risk of disintermediation. For instance, an Airbnb guest often has idiosyncratic question about a property, and therefore the guest and the host have to communicate at length before completing their current transaction. For those platforms with heterogeneous suppliers and fixed customer requirements, the risk of disintermediation is also higher. A taxonomy of drivers of disintermediation is discussed in Ladd (2021), including economic incentives, types of relationship between buyers and sellers, and types of services. Concerning economic incentives, Ladd (2021) mentions that high commission rate and higher price gap between services on platform and direct purchase from vendors are more likely to increase disintermediate. In terms of relationship between buyer and sellers, a platform that emphasizes monetary value and disconnects from social contexts, such as group norms and culture, may increase the risk of disintermediation (Granovetter, 2005). Hosts and guests from Airbnb may disregard the terms and agreements and bypass the platform, without many concerns on ethical principles. With respect to types of service, the author mentioned the threat of disintermediation from heterogeneous service quality from suppliers and complicated purchases.

On a freelancers' marketplace, Gu and Zhu (2021) finds 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. By leveraging an exogenous shock of blocking Skype, Gu and Zhu (2022) studies the impacts of restricting alternative communication tools on mitigating disintermediation of focal platforms. Their results provide supported evidence that improving communication technology in the environment lowers participants' communication costs of transacting outside the intermediary. The effects between disintermediation on focal platforms and restrictive alternative communication tools are moderated by job characteristics, such as communication intensiveness, and customers' characteristics, such as enterprise buyers versus personal buyers.

Waldfogel and Reimers (2015) and Peukert and Reimers (2018) attribute digital disintermediation of book publication market to availability of new technologies, such as Amazon's Kindle and tablets. Substantial growth of self-published books circumvents publishers to directly face with readers, and consequently enables books to be affordable, and with more available choices. Peukert and Reimers (2018) studies the diffusion of Amazon's Kindle across various product categories, and finds that digital disintermediation allows authors to obtain higher license fees with improved outside option.

2.3 Intermediary Roles and Mitigation Strategies

Intermediaries benefit participants by reducing transaction and coordination costs, and utilize network effects to grow and sustain. Bailey and Bakos (1997) presents emerging roles of electronic intermediaries facilitated by information technology and suggests that intermediaries do not necessarily become disintermediated. Four important roles of market intermediaries include: (i) aggregate buyer demand or seller products to achieve economies of scale and to reduce bargaining asymmetry; (ii) protect buyers and sellers from the opportunistic behaviors by becoming an agent of trust; (iii) facilitate the market by reducing operating costs; and (iv) match buyers with sellers. Enhancing these four roles of intermediaries connects with the mitigating strategies of disintermediation. In contrast to electronic commerce and freelancers' market, an efficient matching between suppliers and consumers on sharing economy platforms such as Airbnb, requires platforms to provide more functions in addition to reducing transaction costs and facilitating transactions. For instance, the coordination costs of renting are higher because the usage of listings is typically broken up into many small "chunks" of time. Compared with offline transactions, calendar and booking settings on Airbnb help hosts control their schedules. Second, some sharing economy platforms, such as Uber, determine the transaction price based on cost per mile, cost per minute, and a surging price to balance the supply of drivers and demand of riders (Filippas et al. 2021). It is less likely that individual suppliers can internalize these bring-to-market costs, such as depreciation of cars and price of gas, in a temporal manner without the help of computer algorithms provided by platforms. Third, a moral hazard could be a severe problem for some sharing economy platforms such as freelancer marketplaces and Airbnb, since both sides of participants have the tendency to form a repeated game with more transactions. Some platforms can deter moral hazard issues with on-time inspections, as discussed in Liu et al. (2021), whereas others rely on more effective certification programs for quality signaling (Dewan et al. 2019). Taken together, the availability of high-resolution GPS, mobile Internet and effective reputation systems tie these transactions closely to these sharing economy platforms, rather than direct offline transactions.

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.[4] 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.[5]

To discourage disintermediation, intermediaries can provide homogeneous services and remove incentives for both sides to bypass the platform (Edelman and Hu 2016). To more effectively compete against

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[4] https://www.airbnb.com/host/experiences

[5] Host liability insurance, a part of AirCover, provides Hosts with $1 million in coverage in the rare event a guest gets hurt or their belongings are damaged or stolen while they're staying at your place. People who help you host, like Co-Hosts and cleaners, are also included, so you can feel confident hosting on Airbnb.

standardization and relatively lower quality uncertainty offered by the hotel industry, Airbnb launched a self-certification program itself – Airbnb Plus certificate in 2018 (Dewan et al. 2019). Compared to a Superhost badge, an Airbnb Plus certificate requires higher standards covering both services of hosts and quality of properties. For example, a given property needs to have at least 4.8 out of 5 rating, and the host needs to have a response rate over 90%, at least 80% of 5-star host reviews, and no cancellation in the last year. Other than host service, properties have to undergo an inspection with a $149 fee paid to Airbnb, covering how well properties are designed, equipped and maintained. For those listings with an Airbnb Plus certificate, they are less likely to disintermediate, which is at a cost of incremental 7.6% booking rate if being suspended by Airbnb, compared to non-Plus listings. In addition, this certificate of standardization also discourages guests from initializing off-platform transactions, since guests tend to find interchangeable listings with lower uncertainty in quality. Our study joins this literature and evaluates the impacts of offering standardize services on mitigating disintermediation, by investigating the effects of Airbnb Plus certificates and Superhost badges.

Intermediaries can enhance value to transact online via reducing transaction costs. As discussed in Fradkin (2015), market frictions on Airbnb increase because about one third of guest requests are potentially rejected due to hosts' screening. And similar results are found on Upwork, such inefficiency can be reduced when buyers forgo screening and allow inexperienced workers to obtain their first jobs (Pallais 2014). Excessive usage of screening on Airbnb not only increases transaction costs to both sides of participants and decrease market inefficiency, it also leads to substantial discrimination issues over younger guests, tourist with disability, and guests with children (Ameri et al. 2017; Karlsson et al. 2017; Edelman et al. 2017; Cui et al. 2020). In addition to the effects of screening in discrimination, Mayya et al (2020) finds that enabling instant bookable also economically benefits hosts on Airbnb. Our study supplements this literature by evaluating the impacts of enabling instant bookable on mitigating disintermediation. Without lengthy communication to screen guests, the adoption of instant bookable may discourage guests from initializing off-platform transactions. 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 brought by forgoing screening also enhance the value of transacting on Airbnb, compared to the online transactions. Third, guests with potential discrimination from screening may have a better chance transacting on Airbnb other than go offline.

Literature also documents other strategies to mitigate disintermediation, including information concealing and changing revenue models. For instance, current practice of Airbnb is to withhold the precise physical address and contact information of hosts before the transactions are finalized on the platform. And as discussed in Zhu and Iansiti (2019), such strategies are not always effective since it increases transaction

costs of taking business online and becomes less attractive to a platform using streamlined designs. Our study extends this conversation by offering empirical evidence of information concealing on disintermediation. 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).

3. Identification of Disintermediation for Home-sharing Platforms

We develop a process based on individual mobile location traffic and match individual mobile locations to geocoordinates of each Airbnb property using geographic information systems and tempo-spatial analysis. First of all, we remove individuals with only a few records and preserve individuals with a complete record to identify geographic trajectories within each day. Second, we leverage flow-based network community detection algorithm to infer locations and stops for each individual using their mobile trajectories on a daily basis (Aslak and Alessandretti 2020). Third, after obtaining locations for each individual, we match geocoordinates of individual traffic to each geocoordinate of Airbnb's property listings with a precision of 4th decimal of longitude and latitude. The precision of matching individual mobile locations and Airbnb locations is between 10 meters and 100 meters. We refine our sample by excluding hosts' trajectories and find our results robust. Fourth, we search the daily calendar of each Airbnb property, and identify the booking status of property each day, which includes *available*, *reserved* and *blocked*. The status of *blocked* can be set by hosts, for preparation and cleaning for the next booking, or because hosts does not want to receive requests during that timeframe. We define a listing is disintermediated if a specific calendar date is blocked and we find individual traffic associated with this listing between 1-5AM on this date. To separate mobile trajectories of hosts from those of guests, we identify hosts using the mobile location between 1-5 AM along all observation periods. After filtering hosts' trajectories, we can determine guests' trajectories.

Based on a daily record, we quantify the rate of disintermediation between 4.9% and 5.4% based on various criteria to refine our sample.[6] The rate of disintermediation is defined as the No. of Disintermediation Days over the sum of Block Days and Reservation Days. To circumvent the data sparsity of disintermediation measurement in our panel data, we aggregate daily observations to a weekly-listing panel and focus on the Number of Disintermediation Days within a week as our dependent variable, throughout this research.

4. Data and Empirical Strategies

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[6] For instance, we can allow a higher tolerate value between distance of mobile location and property location, and match with more pairs with less confidence. We can also apply a stronger condition by requesting the host's location to occur next to the property every day within a month.

We report the descriptive statistics and correlation table of main variables in Table 2(a) and Table 2(b). As shown in Table 2(a), the mean weekly number of disintermediation days is about 0.3 out of 7 days per week. And the average ratios of properties with Instant Bookable feature and Airbnb Plus are 48% and 3%, respectively, and 16.5% of observations belong to listings with Superhost badge. In Table 2(b), we conduct a pair correlation of variables, and show that Instant Bookable and Airbnb Plus adopters are more likely to show lower number of disintermediation days. We supplement an exploratory analysis to investigate what types of properties are more likely to disintermediate (Table A-1). We find that properties with longer minimum stays and stricter cancellation policy are more likely to disintermediate. In addition, more experienced hosts, measured by a greater number of reviews, photos and a Superhost badge, are less likely to bypass the platform.

Table 2(a). Descriptive Statistics of Variables

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 Repeated Customers	117430	0.024	0.060	0	1

Table 2(b). Correlation Table of Main Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) No. Disintermediation	1.00					
(2) Airbnb Plus	-0.04***	1.00				
(3) Instant Bookable	-0.05***	0.03***	1.00			
(4) Superhost Badge	-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

Our research design relies on Difference-in-Differences (DID) estimate in conjunction with Propensity Score Matching (PSM) and Look Ahead Matching, with weekly observations of disintermediation from June 1, 2019 to August 31, 2019 for listings of Airbnb in Austin, Texas. We constructed a measure of disintermediation based on the block status on the calendar of Airbnb properties, and the granular guest trajectories inferred from mobile GPS data, as discussed in Section 3.

Next, we examine the impacts of Instant Bookable on the changes in disintermediation. We define treatment group as listings that enable Instant Bookable feature. We use property listings which did not turn on Instant Bookable as our control group, to conduct Difference-in-Differences analyses. Given that listings adopted Instant Bookable may suffer from selection issues, we utilize PSM to mitigate selection on observable covariates, and Look Ahead Matching on unobservable covariates. In terms of Look Ahead Matching, we select properties which did not turn on Instant Bookable between June 2019 and August 2019, but immediately became treated between September 2019 and November 2019 as a potential control group, and then we match these properties with treated properties based on observable covariates, including size of properties, type of properties, type of rooms, price and star rating of listings using PSM.

Using the matched treatment group and control group, we implement a DID model to estimate an average treatment effects on the treated (ATT), and evaluate the impacts of Instant Bookable on mitigating disintermediation. Our empirical strategy follows Equation (1) as below:

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

where y_{it} stands for Number of Disintermediation Days of listing i in week t and $treated_i \times post_t$ indicates observations in the treatment group and post the treatment period. x_{it} represents other time-varying control variables that may affect y_{it} such as price and star rating of a listing. μ_i, λ_t, and ε_{it} denote listing fixed effects, time fixed effects and independent and identically distributed random shocks, respectively. β_1 is the parameter of interest, which identifies the causal effects of enabling Instant Bookable on mitigating disintermediation.

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 time. The relative time model follows Equation (2) as below:

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

where $m = -4, -3, -2, -1$ denotes the time periods prior to treatment begins. Therefore, we expect none of β_{-4}, β_{-3} and β_{-2} to be statistically significant, which indicates that disintermediation between treatment

group and control group is statistically indifferent prior to treatment periods. 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 control group and treatment group prior to the treatment time, which support the validity of our DID estimation, whereas immediately after treatment, the coefficients of β_m drop substantially and gradually become significant.
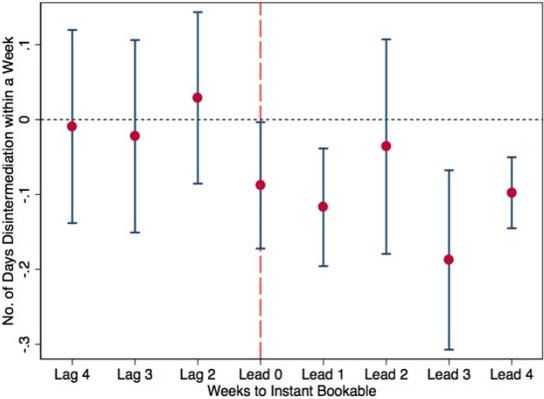

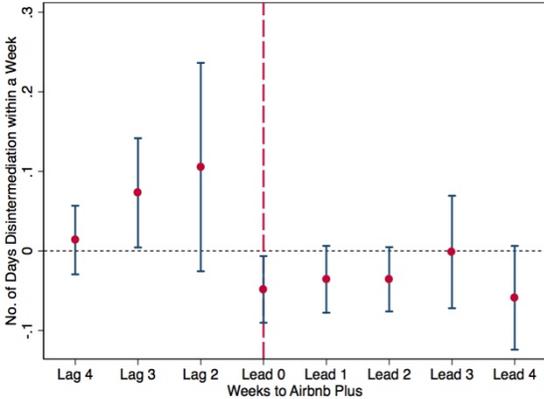Figure 1 Relative Time Model of Instant Bookable   Figure 2 Relative Time Model of Airbnb Plus

5.   Main Results

Following Equation (1), we present results of DID estimation in Table 3. From Column (1) to Column (3), we show enabling Instant Bookable mitigates weekly disintermediation by 0.10 days using the two-way fixed effects model aforementioned. The coefficient of Instant Bookable remains consistent in models with or without control variables. To address estimation issues of staggered treatment adoption and heterogeneous treatment effects in recent Difference-in-Difference literature, this study also implements a two-step GMM method proposed by Gardner (2021) to obtain a more interpretable treatment effect estimation. The intuition of a two-step GMM method is to identify an average treatment effects on the treated from a regression of outcomes on treatment status in the second step, after we remove individual and time fixed effects in the first step. Column (4) of Table 3 shows results of DID estimation with a two-step GMM method. We still find a consistent mitigation effect of Instant Bookable on disintermediation.

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

	(1) TWFE No. of Disintermediation Days	(2) TWFE No. of Disintermediation Days	(3) TWFE No. of Disintermediation Days	(4) Two-Step GMM No. of Disintermediation 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 (4)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note that the treatment of enabling Instant Bookable may suffer from endogeneity issues, because it is possible that properties that selectively enable Instant Bookable are different from those that do not. We utilize the Propensity Score Matching to mitigate selection issues on observables, including Superhost badge, types of properties, types of rooms, price, star rating, and number of bedrooms and bathrooms. We verify our PSM using t-test on these covariates across treatment and control group and find them balanced after the matching procedures (Table 5). We then used the matched sample and re-estimated our DID model. Another selection issue even after PSM is selection on unobservable covariates of each listings or unobserved market factors. We mitigate the selection on unobservable covariate by using Look Ahead Matching. By matching listings treated between June 2019 and August 2019, to listings that were not treated between June 2019 and August 2019 but immediately got treated between September 2019 to November 2019, we are able to cancel out the potential selection concerns caused by unobservable factors. Meanwhile, we also ensure that the observable covariates are balanced after the Look Ahead Matching. Before conducting PSM, we have 78 listings in treatment group and 5289 listings in the control group. A matched sample from PSM has 51 listings in treatment group and 117 listings in the control group. After the Look Ahead Matching, we have 50 listings in treatment group and 14 listings in the control group.

We report DID results for Instant Bookable based on PSM matched sample and Look Ahead Matching sample in Table 4 and Table 6, respectively. Shown in Table 4, the estimated impacts of enabling Instant Bookable feature on the number of weekly disintermediation days remain robust and consistent at -0.9, with a match sample on observable covariates. Concerning unobserved factors leading to selection bias, our DID estimation with matched sample based on Look Ahead Matching and PSM shows that enabling Instant Bookable reduces weekly disintermediation by 0.09 days. Together with the estimated effects found in Table 3, we provide supported evidence that Instant Bookable significantly mitigates the weekly number of disintermediation days.

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

	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days	(3) No. of Disintermediation Days
Instant Bookable	-0.0916**	-0.0845**	-0.0873**
	(0.0427)	(0.0423)	(0.0429)
Weekly Price Log		0.4900***	0.5029***
		(0.1618)	(0.1650)
Star Rating			0.2287**
			(0.0899)
Constant	0.2782***	-2.0290***	-3.2191***
	(0.0136)	(0.7597)	(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 5 Balance Check of Propensity Score Matching

	Mean Instant Bookable		t-test Instant Bookable		Mean Airbnb Plus		t-test Airbnb Plus	
Variable	Treated	Control	t-stat	p-value	Treated	Control	t-stat	p-value
Superhost	1.392	1.333	0.610	0.541	0.654	0.654	0.000	1.000
Apartment	0.078	0.059	0.390	0.699	0	0	--	--
Condo	0.098	0.098	0.000	1.000	0.385	0.385	0.000	1.000
House	0.569	0.549	0.200	0.844	0.577	0.705	-0.950	0.345
Otherhouse	0.157	0.183	-0.350	0.728	0.192	0.192	0.000	1.000
Types of Rooms	0.314	0.34	-0.280	0.781	0.077	0.077	0.000	1.000
Price	178.29	151.24	0.720	0.472	250.38	357.45	-0.980	0.332
Star Rating	4.941	4.948	-0.210	0.836	4.981	4.981	0.000	1.000
No. of Bedrooms	1.686	1.654	0.140	0.889	2.192	2.526	-0.760	0.453
No. of Bathrooms	1.422	1.507	-0.620	0.535	1.654	1.776	-0.440	0.659

Table 6 Main Results: Impacts of Instant Bookable on Number of Disintermediation Days
(Look Ahead Matching)

	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days	(3) No. of Disintermediation Days
Instant Bookable	-0.0911*	-0.0912*	-0.0910*
	(0.0503)	(0.0502)	(0.0504)
Weekly Price Log		0.1217	0.1215
		(0.1288)	(0.1292)
Star Rating			-0.0124
			(0.0530)
Constant	0.1728***	-0.4062	-0.3439
	(0.0237)	(0.6112)	(0.7514)
Observations	896	896	896
R-squared	0.6894	0.6897	0.6897
Time FE	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes

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

6. Robustness Checks and Extension

6.1 Poisson Regression

We further conduct a battery of robustness checks to provide empirical validity of the estimated effects found in Section 5. Given that our dependent variable No. of Disintermediation Days is a count variable, we switch to a Poisson regression with time and listing fixed effects. Poisson regression assumes that the dependent variable follows Poisson distribution and its logarithmic form can be modelled by a linear combination of independent variables. We estimated a Poisson Regression with time and listing fixed effects to assess the robustness based on model specification on count data. Another concern in our dependent variable is the occurrence of zeros, which may challenge the estimation precision. We resolve this concern by implementing a zero-inflated Poisson regression, which use another Probit model to control the zero-inflation process. The Voung test is used to select a preferred model between Zero-inflated Poisson and standard Poisson models.

We report results of both Poisson Fixed Effects model and zero-inflation Poisson model in Table 7 and Table 8, respectively. Our results of Instant Bookable on mitigating disintermediation still hold, under both model specifications.

Table 7 Robustness Check: Poisson Regression of Impacts of Instant Bookable on Disintermediation

	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days	(3) No. of Disintermediation Days
Instant Bookable	-0.4390***	-0.4374***	-0.4340**
	(0.1564)	(0.1564)	(0.2104)
Weekly Price Log		0.2622***	0.2302*
		(0.0963)	(0.1290)
Star Rating			0.6931*
			(0.3563)
Observations	31,794	31,794	17,757
Number of Listing	2,271	2,271	1,278
Time FE	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes

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

Table 8 Robustness Check: Zero Inflated Poisson Regression of Impacts of Instant Bookable on Disintermediation

	(1) No. of Disintermediation Days	(2) Zero Inflation (Logit)
Instant Bookable	-0.9846***	
	(0.2238)	
Weekly Price Log	-0.1179***	0.2591***
	(0.0145)	(0.0190)
Star Rating	0.1986***	0.1205*
	(0.0542)	(0.0716)
Constant	0.2479	-0.0256
	(0.2761)	(0.3575)
Observations	44,396	44,396

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Vuong test of Zero-Inflated Poisson vs. standard Poisson: z =41.34, Pr>z = 0.000

6.2 Placebo Test

To further strengthen our confidence in the estimated effects, we implement a placebo test as a falsification test. Our procedure is to preserve the same ratio treatment units over all units, and randomly assign the treatment status to these listings. Once we randomly select treated listings, we randomly select a time period to start the treatment for those treated listings. After obtaining one such sample, we estimate Equation (1) and save the estimated β_1 and its p-value. We repeat this procedure for 10,000 times and save those 10,000 replicas. We report the distribution of estimated β_1 and its p-value in Figure 3. The distribution of estimated

β_1 is centered at 0 and symmetric, which falsify our results if the treatment and outcomes are randomly matched. The red dashed line denotes the position of our real estimation coefficient, which indicates the statistical power of our estimated effects with a small probability of being random. The estimated β_1, -0.087, falls on the left tail of the distribution, indicating that the probability that -0.087 is randomly obtained is small as 0.06.
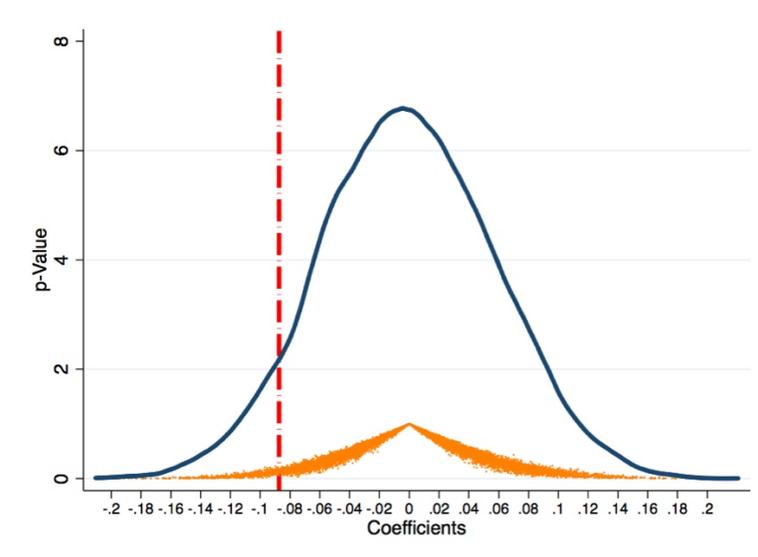

Figure 3 Placebo Test of DID model of Instant Bookable

6.3 Geographic Spillovers

As Airbnb property listings are geographically adjacent, a natural question is to investigate whether or not there is a spatial spillover across neighboring Airbnb properties. Our goals to include a DID estimation with spatial spillovers are threefold: First of all, if there exhibits a spatial spillover of disintermediation within a neighborhood, the threat of off-platform transactions would be contagious and more severe to platform owners in the absence of mitigation actions. Second, if there exhibits a spatial spillover of Instant Bookable adoption, it may violate the stable unit treatment value assumption (SUTVA) that implies no spillovers of treatment status. Third, we test the omitted variable bias on a spatial error model, to verify whether our standard DID model omits variables and exhibits spatial dependence in the error term. We extend these three aspects in a spatial Difference-in-Differences setting:

$$y_t = \beta_1 DD_t + \beta_2 W y_t + \beta_3 W DD_t + \delta_t + \mu + \epsilon_t \qquad (3)$$

$$\epsilon_t = \beta_4 W \epsilon_t + \varepsilon_t \qquad (4)$$

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 time and listing fixed effects. In Equation (3) and Equation (4), if β_3 and β_4 equals 0 and $\beta_2 \neq 0$, it reduces to DID in Spatial Auto-regressive model (SAR-DID). If β_4 equals 0 and β_2, $\beta_3 \neq 0$, it reduces to DID in Spatial Durbin model (SAR-DID). If β_3 equals 0 and β_2, $\beta_4 \neq 0$, it reduces to DID in Spatial autocorrelated error model (SAC-DID). And if β_2, β_3 equals 0 and $\beta_4 \neq 0$, it reduces to DID in Spatial error model (SAC-DID). We estimated these models using Quasi-Maximum Likelihood Estimation (Quasi-MLE).

We report all four model settings in Table 9. We do not find supported evidence for either spillovers in disintermediation or spillovers in the adoption of Instant Bookable, and therefore geographic spillovers would not contaminate our estimation using DID. In other words, the decisions to disintermediate and enable Instant Bookable are less likely to be affected by their neighboring properties. Our results still hold after the spatial correlation is taken into consideration.

Table 9 Robustness Check: DID in Spatial Panel Model with Geographic Spillovers

	(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*u	--	--	-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

6.4 Robustness to 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 fall into a sample selection issue because properties which cross-list on Vrbo are more likely to block their calendar on Airbnb or even withdraw from Airbnb. If multi-homing is common, we have to test whether it biases our estimation. In order to examine the robustness of our results and to address the sample bias, 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). Second, we re-run our main analysis with property listings which only single-home Airbnb platform.

In Table 10, we model both the outcome equation and selection equation, a.k.a. the probability for a listing to multi-home on both platforms. 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 inverse Mill's ratio in Lambda. Our results still hold even when we model the multihoming selection, and the coefficient of Lambda is not significant, indicating a low risk of sampling bias in our estimation.

In Table 11, we only include the property listings of single homing. We re-run our DID estimation and find that the results are consistent.

Table 10 Robustness Check: Disintermediation with Heckman Two-step Estimator

	(1) Disintermediation	(2) Multi-Homing	(3) Selection Hazard
Instant Bookable	-0.1203** (0.0477)		
Weekly Price Log	-0.0669** (0.0306)	0.4148*** (0.1379)	
Star Rating	0.2623** (0.1069)	-0.1570 (0.6991)	
Vrbo-Manager		6.6601*** (0.2372)	
Lambda			0.0217 (0.0216)
Constant	-0.8792** (0.4271)	-2.5156 (3.5686)	
Observations	2,348	2,348	2,348

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

Table 11 Robustness Check: Subsample Analysis of Airbnb Single-homing Listings

	(1) No. of Disintermediation Days (Airbnb Only)	(2) No. of Disintermediation Days (Airbnb and Vrbo)
Instant Bookable	-0.0995** (0.0465)	0.0382 (0.0867)
Weekly Price Log	0.5064*** (0.1802)	0.4422* (0.2445)
Star Rating	0.2537*** (0.0958)	-- --
Constant	-3.3086*** (1.2252)	-2.1996* (1.2480)

Observations	2,096	252
R-squared	0.6592	0.2362
Time FE	Yes	Yes
Listing FE	Yes	Yes

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

6.5 Robustness to 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 12, 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 locate, and booking rate, which are consistent with prior findings in the literature (Mayya et al. 2020).

Table 12 Robustness Check: Reverse Causality on Instant Bookable

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

Median Income (Thousand)	-0.0172***	-0.0171***	-0.0174***
	(0.0058)	(0.0058)	(0.0058)
Observations	39,692	36,641	33,587

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

7. Heterogeneous Effects

In this section, we examine heterogeneous treatment effects of Instant Bookable on mitigating disintermediation. Based on He et al. (2020) and Wang and Heng (2017), we investigate moderating roles of hosts' preference in long-term leases, intensity of online repeated users, market thickness of local suppliers, 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' preference in long-term leases. Hosts with preference in long-term leases are more likely to bear with 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). Therefore, even though some hosts enable Instant Bookable to reduce transaction costs online, those with preference in long-term leases still can block their calendar and reserve for long-term leases. Our strategy to identify hosts' preference in long-term leases is to search for keywords, such as "long term" and "discount", from 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 examine its moderating role in the impacts of Instant Bookable on disintermediation mitigation. We expect that properties with hosts' preference 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 repeated customers under complicated purchase (Edelman and Hu 2016). We believe that repeated customers are more likely to initialize off-platform transactions due to three reasons. First, both sides of Airbnb – hosts and guests, probably exchange their contact information, such as mobile phone or email, after their first-time transactions and aim for repeated transactions offline. Second, given that home-sharing services are experience goods with both horizontal differentiation and vertical differentiation, customers develop a more comprehensive view of a focal property, such as taste alignment and quality expectation, during their first stay, and are more likely to stick to one property for a second visit. Third, repeated 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 repeated users, we extract 327,011 reviews left by guests, and implemented a semi-supervised topic model to estimate the intensity of repeated customers. Anchored correlation explanation is a semi-supervised model that allows topics to be interpretable by effectively splitting apart a topic with mixed 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 repeated customers, to proxy the intensity of repeated users across properties. The topic of repeated 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 repeated customers. The anchored keywords and keywords output from NLP are reported in Table 13. Therefore, we expect that properties with higher proportions of repeated users will show stronger mitigation effects after hosts enable Instant Bookable.

Table 13 Anchored Topic Modelling on Repeated Online Customers

	Anchor words	topics
Location	'distance','neighborhood','street','walk'	('distance', 'walk', 'street', 'neighborhood', 'within', '6th', 'restaurant', 'rainey', 'bar', 'shop')
Amenities	'kitchen', 'bedroom', 'bedroom', 'bathroom'	('kitchen', 'bathroom', 'bedroom', 'great', 'place', 'but', 'living', 'location', 'towel', 'that')
Cleanliness	'clean','sanitize', 'comfortable', 'spacious'	('spacious', 'clean', 'comfortable', 'very', 'modern', 'sanitize', 'surprisingly', 'sparkle', 'anique', 'gen')
Value	'price','cheap', 'deal', 'value','worth', 'low', 'high', 'expensive', 'rate', 'good'	('value', 'good', 'price', 'worth', 'deal', 'cheap', 'low', 'rate', 'expensive', 'money')
Recommendation	'recommend','highly'	('highly', 'recommend', 'anyone', 'would', 'this', 'others', 'thanks', 'visit', 'austin', 'thank')
Check-in	'check','check-in', 'arrive'	('check', 'arrive', 'easy', 'out', 'process', 'breeze', 'early', 'in', 'smooth', 'late')
Communication	'question', 'respond', 'answer', 'quick', 'message', 'communicate'	('respond', 'question', 'quick', 'communicate', 'answer', 'message', 'any', 'quickly', 'response', 'promptly')

Repeated Online Customers	'second', 'second time', 'second stay', 'third time', 'back', 'come back', 'return', 'again'	('return', 'second', 'back', 'again', 'will', 'come', 'hope', 'definitely', 'soon', 'forward')

Other than hosts' preference and repeated guests, we explore the role of competition environment around a focal Airbnb property, in moderating the mitigating effects of Instant Bookable on disintermediation. An 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 compete with other properties nearby. For instance, after an Airbnb Plus badge is assigned to a focal property, it exerts an indirect effect to non-Plus listings by reducing their booking rate by 1.5% (Dewan et al. 2020). We take a similar strategy to identify the number of listings within a radius of 1 kilometer to a focal property listing. We term this new variable as nearby competitors, which proxies the intensity of competition in nearby neighborhood of a given property listing. We expect that a more intense competition 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 conduct a subsample analysis. Given that inexperienced hosts may be highly dependent on the platform, we expect this group of hosts are 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 repeated guests. Therefore, we expect that the impacts of Instant Bookable on mitigating disintermediation are stronger among experienced hosts.

Shown in Table 14, we provide supported evidence that the dampening effects on disintermediation brought by Instant Bookable are stronger among hosts with more repeated customers and with more experience. However, the mitigation effect on disintermediation may be attenuated for properties with hosts' preference in long-term leases and intense competition environment.

Table 14 Results of Heterogeneous Treatment Effects: Impacts of Instant Bookable on Number of Disintermediation Days

	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days	(3) No. of Disintermediation Days	(4) No. of Disintermediation Days (Below Median Tenure)	(5) No. of Disintermediation Days (Above Median Tenure)
Instant Bookable	-0.0982*** (0.0354)	-0.0616 (0.0443)	-0.1645** (0.0710)	-0.0667 (0.0695)	-0.1189*** (0.0300)

	(1)	(2)	(3)	(4)	(5)
Instant Bookable*Long-Term Preference	0.0900** (0.0444)				
Instant Bookable*Repeated Customers		-1.7627* (1.0592)			
Instant Bookable*Nearby Competitors			0.0002* (0.0001)		
Weekly Price Log	0.0530* (0.0309)	0.0309 (0.0474)	0.0531 (0.0476)	-0.0463 (0.0503)	0.1165*** (0.0393)
Star Rating	0.0696 (0.0932)	0.0603 (0.2347)	0.0672 (0.2011)	-0.3246*** (0.1061)	0.5893*** (0.1617)
Constant	-0.3170 (0.4782)	-0.1680 (1.1590)	-0.3059 (1.0045)	2.1288*** (0.5540)	-3.2236*** (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
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

8. Alternative Mitigation Strategies: Airbnb Plus, Superhost Badge and Information Concealment

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 are resulted from increased booking rate. Using the same framework in Table 1, we expect Airbnb Plus would enhance the value of the platform to hosts, and also significantly increase the costs of disintermediation, because in the case of being caught, hosts will forfeit this hard-earned reputation as well as associated economic benefits associated with it.

In Table 15 and Table 16, we present the DID estimation in conjunction with PSM and Look Ahead Matching, respectively. Note that we report balance check of PSM in Table 5. We provided evidence that obtaining an Airbnb Plus certificate reduces the number of weekly disintermediation days by 0.06 to 0.07, based on matched sample of two matching methods. We report the results of heterogeneous treatment effects of Airbnb Plus certificate in Table 17. Note that we have much fewer observations from the Airbnb Plus case. We are unable to estimate the heterogeneous treatment effects on preferences in long-term leases, because none of observations obtained both Airbnb Plus Certificate and disclose preferences in long-term leases at the same time. We do not find evidence of heterogeneous treatment effects on competition environment. In Column (1), we provide similar evidence that property listings with more repeated customers and Airbnb Plus certificates show stronger effects on mitigating disintermediation. And in Column (2) and Column (3) of Table 10, we compare the effects of obtaining Airbnb Plus certificate on disintermediation, among hosts with higher tenure and lower tenure. We find out that this standardization and quality signaling certificate reduces the weekly number of disintermediation days significantly among

hosts with lower than median tenure years. One explanation for this is that the Airbnb Plus certificate benefits inexperienced hosts and help them more on the platform.

Table 15 Alternative Strategy: Impacts of Airbnb Plus on Number of Disintermediation Days (PSM)

	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days	(3) No. of Disintermediation Days
Airbnb Plus	-0.0626*	-0.0638*	-0.0647*
	(0.0334)	(0.0340)	(0.0342)
Weekly Price Log		-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 16 Alternative Strategy: Impacts of Airbnb Plus on Number of Disintermediation Days

(Look Ahead Matching)

	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days	(3) No. of Disintermediation Days
Airbnb Plus	-0.0656*	-0.0670*	-0.0670*
	(0.0362)	(0.0366)	(0.0366)
Weekly Price Log		-0.0839	-0.0839
		(0.1265)	(0.1266)
Star Rating			-0.0054
			(0.0317)
Constant	0.1271***	0.5595	0.5863
	(0.0047)	(0.6524)	(0.7178)
Observations	1,181	1,181	1,181
R-squared	0.4721	0.4723	0.4723
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 17 Alternative Strategy: Results of Heterogeneous Treatment Effects: Impacts of Airbnb Plus on Number of Disintermediation Days

VARIABLES	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days (Below Median Tenure)	(3) No. of Disintermediation Days (Above Median Tenure)
Airbnb Plus	-0.0371	-0.1451**	-0.0113
	(0.0338)	(0.0603)	(0.0288)
Airbnb Plus*Repeated Customers	-0.0486*		
	(0.0272)		
Weekly Price Log	-0.0881	-0.1201	0.0223
	(0.1267)	(0.1840)	(0.0514)
Star Rating	0.0126	0.1150	--
	(0.0338)	(0.1607)	--
Constant	0.5179	0.1889	-0.0657
	(0.7109)	(1.2150)	(0.2643)
Observations	1,181	537	560
R-squared	0.4724	0.1751	0.1619
Time FE	Yes	Yes	Yes
Listing FE	Yes	Yes	Yes

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

Other than Airbnb Plus certificate, another well-known quality signaling badge launched by Airbnb is the Superhost program, which recognizes top-rated and most experienced hosts by check their performance.[7] According to the criteria of earning and keeping Superhost badge, a focal host needs to maintain an average overall rating of 4.8 or above in the past year, less than 1% cancellation rate, at least respond to 90% of new messages within 24 hours, and completed at least 10 stays in the past year. A Superhost badge will be awarded to hosts once they fulfilled those criteria, and Airbnb check these requirements every 3 months. Compared to Airbnb Plus certificate, which requires an extra $149 application fee and inspection on properties' design, maintenance, equipment and hosts' service quality, the Superhost badge is awarded to hosts automatically by the platform and does not require any applications initialized by the hosts. Overall, Superhost-awarded listings represent 19.4% of all property listings, whereas Airbnb Plus listings only

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[7] https://www.airbnb.com/d/superhost

represent 0.6% of the properties in the cities where the Plus program is available.[8] In our data of Austin, we observe 16.5% of Superhost badge and 3% of Airbnb Plus properties, among all listings in 2019. The ratios of both programs are consistent to the number reported from external data sources. We interpret the impacts of Airbnb Plus certificate as standardization of properties and host services, as well as quality signaling. However, the Superhost badge may more on the side of quality signaling.

To test whether a badge of high quality solely helps to mitigate disintermediation, we implement a DID estimation in conjunction to PSM, and report the results in Table 18. 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 properties characteristics, nor the Superhost badge brings a large enough value to transact online.

Table 18 Alternative Strategy: Results of Impacts of Superhost on Number of Disintermediation Days (PSM)

	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days	(3) 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

Another strategy to mitigate disintermediation is information concealing, such as Airbnb's withholding hosts' phone numbers and exact addresses prior to transactions finalization. As discussed in Zhu and Iansiti (2019), such strategies are not usually effective because they make a platform too cumbersome to lose its business to streamlined competitors. We empirically test the effectiveness of information concealment strategy on mitigating disintermediation on Airbnb. To detect changes of information concealment, we look

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for a keyword "Phone number hidden by Airbnb" from 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" shows in our sample, we can proxy the time of information concealment and estimate whether such strategy affect disintermediation.

Shown in Table 19, our empirical results show 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.

Table 19 Alternative Strategy: Results of Impacts of Information Concealment on Number of Disintermediation Days

	(1) No. of Disintermediation Days	(2) No. of Disintermediation Days	(3) 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
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

9. Conclusion and Discussion

This study proposes geolocation-based methods to quantify disintermediation of home-sharing platforms, and causally estimate the impacts of a variety of mitigation measures on disintermediation. With individual geolocation traffic and calendar booking records of Airbnb in 2019 in Austin, we leverage a Difference-in-Differences design in conjunction with Propensity Score Matching and Look Ahead Matching, to mitigate selection on observable and unobservable factors. We provide the first empirical evidence that enabling Instant Bookable feature reduces No. of Disintermediation Days by 0.09 and obtaining Airbnb Plus certificate decreases No. of Disintermediation Days by 0.06. Our study employs extant robustness checks and alternative specifications to mitigate concerns on selection and sampling biases and presents a set of

consistent and robust results. Other than Instant Bookable and Airbnb Plus certificate, we take a look on evaluating Superhost badge and information concealment and find no significant evidence.

In addition, we explore the heterogeneous treatment effects of enabling Instant Bookable, such as hosts' preferences in long-term leases, intensity of repeated customers, nearby competitors, and hosting tenure. We find out that the impacts of enabling Instant Bookable on mitigating disintermediation are stronger among listings without preferences in long-term leases, with more repeated customers, less nearby competitors, and longer hosting tenure. Regarding Airbnb Plus, we find out that the effects of Airbnb Plus on reducing disintermediation are stronger among listings with more repeated customers, and shorter hosting tenure.

In summary, as disintermediation increasingly plagues the multi-billion dollar sharing economy platforms, this research contributes to the literature and industry along a number of dimensions. First, by leveraging novel location big data and Geographic Information System (GIS) methods, this research offers the first region- and population-scale quantification of disintermediation, which has been conventionally challenging to observe and measure. Second, this research enlists DiD to causally gauge the impact of a variety of platform strategies to mitigate disintermediation; and uncover the differential efficacy of these policies, hence enriching the theory and practice of disintermediation mitigation. 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, suppliers, and consumers.

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