Dog Eat Dog: Measuring Network Effects Using a Digital Platform Merger*

Chiara Farronato† Jessica Fong‡ Andrey Fradkin§

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Abstract

A monopolistic platform may increase consumer welfare if network effects are large enough to offset pricing power and reduction in platform variety. We use a difference-in-differences approach to study the net effect of this trade-off in the context of a merger between the two largest pet-sitting platforms. We find that platform prices did not change, users of the acquiring platform benefited from the merger because of network effects, and users of the acquired platform were harmed because their platform was shut down. These effects offset each other so that user outcomes are similar, on average, before and after the merger.

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†Harvard Business School and NBER, cfarronato@hbs.edu

‡University of Michigan, jyfong@umich.edu

§Boston University, fradkin@bu.edu

1 Introduction

Economists and policy-makers are increasingly worried about market power and the potential for its abuse by digital platforms. Of the 10 most valuable companies, at least 7 are platform companies.[1] From a consumer welfare perspective, the typical justification for large dominant platforms has been the assumption that they enjoy strong network effects. In platform businesses more so than in other businesses, the argument goes, the value per user increases with the number of other users on the platform. A monopolistic platform may thus be efficient because it maximizes total surplus. Less attention has been placed on the role of horizontal differentiation across platforms for welfare. In particular, users may vary in their preferences for platform attributes, even when platforms intermediate very similar services.

We study the relative importance of network effects and platform differentiation in a market for local services, in which the largest platform acquired its largest competitor. We find that, on average, users are not significantly better off with a single platform compared to two competitors. This is true despite significant network benefits experienced by the acquiring platform and no changes in platform prices. At the market level, we find that heterogeneity in user preferences across platforms and user attrition post-acquisition counterbalance platform-level network effects.

A large theoretical literature has made the presence of network effects an integral part of the definition of digital platforms (Rochet and Tirole (2003) and Cusumano et al. (2019) among many others). In the specific context of online marketplaces, network effects may increase the level or quality of platform-intermediated exchanges following an increase in the number of users. But network effects are difficult to quantify because platform growth is typically endogenous. For example, an improvement in the design of the platform may affect both the number of users and the types of interactions they experience on the platform, but this is not evidence of network effects. The ideal variation to measure network effects would be to randomly add or subtract users to a platform, which would allow the econometrician

[1] The ranking includes, from top to bottom: Amazon, Apple, Google, Microsoft, Visa, Facebook, Alibaba, Tencent, McDonald's, and AT&T.
`https://www.cnbc.com/2019/06/11/amazon-beats-apple-and-google-to-become-the-worlds-most-valuable-brand.html`.

to evaluate how interactions and thus user value change with market scale. This exogenous manipulation of the number of users would need to be repeated multiple times, unless the platform can be broken down into isolated clusters that do not interact with each other.

We have the unique opportunity to measure network effects from the combination of two online marketplaces for pet-sitting services, in which 1) a unique platform emerged from the acquisition by the largest platform of its closest substitute and biggest competitor 2) we observe data from *both* platforms before and after the acquisition, and 3) we are able to identify the same users across the two platforms.

This acquisition provides an excellent natural experiment for 1) testing for the presence of network effects, and 2) evaluating whether network effects are large enough to justify a single platform over two competitors. First, the local nature of services exchanged means that interactions in one city do not affect interactions in another city, so we can treat each geography as a separate market (Cullen and Farronato (Forthcoming)). Second, the two platforms were as similar as they can be, at least as to the services exchanged and the way in which buyers search for service providers. These similarities imply that the potential for network effects to arise is high and the risk of reducing product variety is low, as the two platforms are close substitutes. Third, prior to the acquisition, the two platforms varied in their market shares across cities, which means that some cities experienced bigger increases in the number of users interacting with one another compared to other cities. Finally, the acquiring platform did not increase its nominal or actual commission fees, a main antitrust worry that may offset the benefits of the acquisition to platform users. The features of our setting allow us to quantify local network effects, i.e., benefits arising to users living in the same geography from aggregating local interactions on a single platform.

The presence and size of network effects generated by combining the two platforms depends on the level of competition before the acquisition. We show that the two platforms are comparable in size and they are active in the same geographies. We also show that multi-homing is limited, thus reducing pre-merger interactions of buyers on one platform with sellers on the other. Finally, we find evidence that providers charge similar prices when selling on both platforms, suggesting that the two platforms are indeed similar in the eyes of some users. These preliminary analyses show that combining the two platforms does affect the number of people with whom each user can interact, implying that there is scope for network effects to arise.

There are several ways in which the presence and behavior of one user can affect the utility of other users in platforms like ours, which are essentially online marketplaces where many buyers and sellers exchange goods or services. First, more buyers can increase the profits of sellers through increased demand, and more sellers can improve the outcomes of buyers by providing better matches and prices.[2] These spillovers imply that the number of buyers *relative* to sellers affects the surplus created by the platform and how it is distributed across users. Second, and the specific focus of this paper, a change in the *absolute* number of buyers and sellers holding constant their relative shares may make buyers and sellers better off due to network effects. This may occur, for example, if greater variety on both the demand and the supply side results in more and higher quality matches.

Our first question is whether network effects even exist in platforms like ours. To answer this question, we study the *effect of the merger on the acquiring platform*, exploiting variation in pre-merger market shares that are at least in part explained by differences in the growth strategies of the two platforms. With network effects, one would expect the acquiring platform to benefit more in geographies receiving a bigger influx of users from the acquired platform.

Our second question is whether network effects are large enough to justify a single platform over two competitors. To answer this question we study the *effects of the merger on the market*, aggregating data from both platforms. If network effects are large enough, combining the two platforms would lead to larger benefits in geographies where each platform had 50% of the market before the merger compared to geographies where one platform was already dominant before the merger.

We use a difference-in-differences strategy to measure the effect of merging the two platforms, comparing outcomes before and after the acquisition, and across geographies with different market shares. We explicitly address selection into market shares and spillovers between geographies, which may result in bias if left unaddressed. Specifically, we match

[2]Some of these effects, namely changes in price as a function of aggregate demand and supply, are purely competitive effects, but other externalities across buyers and sellers are often called cross-side or indirect network effects.

geographies where Rover, the acquiring platform, was not dominant before the acquisition — our "treated" units — to geographies where Rover had more than 80% market share. We match these geographies based on their pre-acquisition number of active sellers across the two platforms. To address spillovers across geographies, in robustness checks presented in the Appendix, we use market definitions that are coarser than zip codes and are based on users' search behavior.

We find evidence of network effects at the *platform* level. In particular, we find that existing users on Rover increased their usage of the platform post-merger. They were more likely to submit requests, which resulted in more transactions given that request match rates for those existing users stayed relatively constant. However, even if existing DogVacay users benefited from network size, they decreased their platform usage after the merger *relative to* existing Rover users. In fact, DogVacay users were more likely to exit the market post-merger. Many of these users chose not to migrate their profile to Rover, and those who migrated transacted less frequently and matched at lower rates than comparable Rover users. The attrition almost perfectly offsets the increased usage of Rover users so that at the market-level we find no evidence that the combined platform substantially improves market outcomes more than the sum of the two separate platforms: not on the extensive margins such as user adoption, retention or total transactions, nor on the intensive margins, such as match rates or ratings. This implies that, at least in the short-run, users (both existing and new) are on average indifferent between two competing platforms or a single dominant platform.

Our results imply that even if network effects are strong in online platforms, preference heterogeneity can offset the benefits of a single platform compared to multiple competing platforms. This result is true across different types of geographies: geographies with a small versus large baseline number of users, and geographies where users have lower versus higher propensity to multi-home.

By revealed preference, DogVacay users prefer the DogVacay platform to the Rover platform. This may be due to one of a variety of factors, including the interface, algorithms, and selection on DogVacay. We find that repeat transactions help explain DogVacay user attrition. In particular, DogVacay users who have multiple transactions with the same trading partner prior to the merger are more likely to leave the market relative to similar Rover users. This effect is even larger when the prior transaction partner does not switch from DogVacay to Rover. These results point to two related mechanisms. The first is disintermediation, where users transact off the platform. The second is a coordination failure, where users can't find each other on the new platform.

The attrition results inform the generalizability of our main finding, that platform differentiation offsets network effects. Both disintermediation and coordination failure are more likely to be present post-merger in platforms where repeat interactions are relatively important, such as child or elderly care, as opposed to platforms where matches are unlikely to occur with the same trading partner, such as ride-sharing.

The rest of the paper is structured as follows. In Section 2, we present the relevant literature. Section 3 describes the data and the natural experiment. Section 4 presents a stylized model motivating our empirical specification and identification strategy, which are described in Section 5. Empirical results are in Section 6. In Section 7, we conclude by discussing implications for platform competition and antitrust regulation.

2 Literature Review

In this section, we present the mostly theoretical literature on platforms and network effects, and describe how the setting in this paper is ideal for studying network effects empirically.

Early theoretical work focuses on competition in the presence of network externalities and product compatibility (Katz et al. (1985) and Farrell and Saloner (1985)), but the pioneering models of multi-sided platforms came with Rochet and Tirole (2003), Caillaud and Jullien (2003), Parker and Van Alstyne (2005), and Armstrong (2006), which were later generalized by Weyl (2010). In their models, two characteristics define platform businesses. The first characteristic is that platforms attract multiple user groups and enable interactions between them – e.g. buyers and sellers, or advertisers and social media users. The second characteristic is the presence of positive network effects, which imply that surplus per user is an increasing function of the number of participating users. These models typically focus on cross-side network effects, where each user (e.g. buyer) is directly affected by the number of users in other groups (e.g. sellers). The focus of these early models was to study platform pricing strategies to attract multiple user groups. Other strategic choices, such as entry, vertical integration, and degree of openness have been studied by Zhu and Iansiti (2012), Hagiu and Wright (2014), and Boudreau (2010), among others. A crucial implication of this theoretical literature is that because of network effects, the value per user increases in the number of platform users. Two other theoretical papers, Tan and Zhou (2020) and Nikzad (2020), study how network effects, product variety, and prices lead to competition among platforms having ambiguous effects on consumer surplus. Our work adds an empirical focus to this literature, by estimating whether user outcomes improve with the number of other participating users on a platform and whether these network benefits more than offset increased market power and reduced product differentiation. Our results on the lack of market-level improvements emphasize the importance of product variety in counterbalancing network benefits.

Another related stream of theoretical literature on platforms focuses on multi-homing, i.e. the propensity of users to join and use multiple substitute platforms. A couple of papers look at multi-homing users on both sides of the interaction (Caillaud and Jullien (2003) and Bakos and Halaburda (2019)), while most papers either assume single-homing or allow for multi-homing by only one side of users. When multi-homing is limited to at most one side, the strategic interdependence between the two sides implies that a platform may maximize profits by subsidizing one side to charge the other (Weyl (2010)). We contribute to this literature by providing empirical evidence on the extent of multi-homing in practice, finding that multi-homing, albeit somewhat limited, is predominantly concentrated on the seller side.

The empirical literature on network effects dates back to Greenstein (1993), Gandal (1994), and Saloner and Shepard (1995), who show early evidence that network effects are present in federal computer procurement, in the adoption of computer spreadsheet programs, and in banks' adoption of ATMs, respectively. One of the first to empirically study cross-side network externalities is Rysman (2004). In the market for Yellow Pages, the paper finds that more advertising leads to more consumer usage which in turn leads to more advertising. Despite the existence of network effects, Rysman (2004) finds that platform competition is better for user surplus due to lower market power, although Chandra and Collard-Wexler (2009) find that concentration in the Canadian newspaper industry did not lead to higher prices for either newspaper subscribers or advertisers. Similar findings of positive cross-side network effects are confirmed on Taobao by Chu and Manchanda (2016). Other work includes Gowrisankaran and Stavins (2004), who study banks' adoption of automated clearinghouse (ACH) electronic payment systems, Berry and Waldfogel (1999) and Jeziorski (2014a,b), who study radio stations, and Tucker (2008) who study the adoption of a video-messaging technology in a bank. Dubé et al. (2010) study market tipping and find that network effects can lead to a strong increase in concentration in the market for video game consoles. More recently Kawaguchi et al. (2020) conduct simulated merger analysis of mobile apps. In part because of data limitations, these papers often focus on the extensive margins of user participation. In contrast, our ability to track individual users and their behavior on each platform allows us to measure the intensive margin and to isolate mechanisms through which network effects may materialize.

Data on how users interact with each other on platforms have allowed recent studies to estimate a particular manifestation of network effects, i.e. how the number of matches between the two sides of users changes as a function of aggregate user participation. In the market for domestic tasks and errands, Cullen and Farronato (Forthcoming) do not find evidence of increasing returns to scale in matching. Analogous findings were confirmed in home sharing by Fradkin (2018) and Li and Netessine (Forthcoming), and in online dating by Fong (2019). Kabra et al. (2017), on the other hand, find positive returns to scale in ride-sharing. Reshef (2019) studies how new sellers on a platform affect established sellers using data from the Yelp delivery platform and Grubhub. Another set of related papers focus on search frictions in online marketplaces. As marketplaces grow and user heterogeneity increases, search frictions can also go up. Even if more options are available, and thus a match is more likely, finding that match may become harder with increases in market size. Arnosti et al. (2018) study congestion in matching markets from a theoretical perspective, and Fradkin (2018) and Horton (2019) find that consumer's inability to discern who is available and who is unavailable reduces match rates in home-sharing and online labor platforms.

Our context is distinct from the existing literature for three reasons. First, similar to Li and Netessine (Forthcoming), we exploit the merger of two platforms resulting from an acquisition as an exogenous change in user participation on the combined platform. Unlike Li and Netessine (Forthcoming), we are able to measure user behavior on the acquired platform prior to the acquisition. This allows us to characterize the effects of merging two platforms not only at the platform level, but also at the market level, accounting for differences in how users search and transact on competing platforms. Second, our data allows us to understand the role of multi-homing, which to our knowledge has never been possible before in the digital setting.[3] Third, we can measure network effects on multiple dimensions, from the extensive margins – i.e. number of transactions – to the intensive margins – i.e. match rates and match quality.

3 Setting and Data

We have proprietary data from "A Place for Rover, Inc." (Rover). As of 2018, Rover, founded in Seattle in 2011, was the largest online platform for pet care services in the US, with a valuation of $970 million.[4] At the time, Rover processed roughly one million bookings per month. DogVacay was a nearly identical platform. Founded in 2012 in Santa Monica, DogVacay spent five years building a business to help dog owners find sitters, until it was acquired by Rover in 2017.

The pet industry market is large and growing. According to the American Pet Products Association,[5] in 2019 pet owners in the US spent $95.7 billion on their pets, including $10.7 billion in services like boarding, grooming, training, pet sitting, and walking. That constitutes a 5.5% increase over the previous year. In the US, 84.9 million households, or 68% of all households, own a pet. Of them, 75% own a dog.

Dog owners (buyers) use Rover – and DogVacay before the acquisition – to find pet care services from sitters (sellers).[6] The services range from dog walking to in-home pet

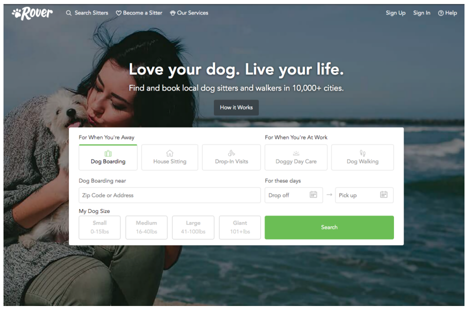
[3] The exception is the known consumer and merchant behavior over credit card use, where consumers own and merchants accept multiple credit cards. See Bakos and Halaburda (2019) for survey evidence.

[4] `https://www.wsj.com/articles/rover-raises-125-million-as-dog-sitting-war-heats-up-1527166801` (accessed July 2019).

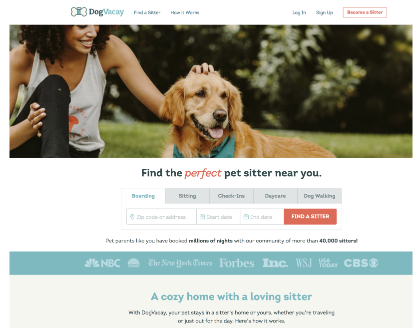
[5] `https://www.americanpetproducts.org/pr` (accessed April 2020).

[6] It is fairly easy to join the platform as a pet sitter. One of us signed up on Rover by creating a sitter

Figure 1: Rover's and DogVacay's Landing Pages



(a) Rover.com, March 2017.



(b) Dogvacay.com, March 2017.

The figures show the landing page of Rover and DogVacay before the acquisition. The screenshots are accessible on Wayback Machine (`https://web.archive.org/web/20170307101746/https://www.rover.com/` and `https://web.archive.org/web/20170228165616/https://dogvacay.com/`)

grooming, but their largest category is dog boarding. Before the acquisition, Rover and DogVacay were the largest players in the online dog boarding market. At the time, the next largest competitor was Wag Labs (Wag). Wag, which mainly offered dog-walking services, started offering overnight boarding only in 2016,[7] although it never grew to become their largest service category. In 2017, Rover earned five times higher revenues than Wag.[8] Offline competitors include more traditional businesses like kennels and dog hotels, and more informal alternatives such as friends and family.

Before the acquisition, Rover and DogVacay were as similar as they could be. A comparison of Figure 1a and Figure 1b highlights the high degree of similarity between the two platforms. Rover still works in a similar way today. When a buyer needs pet care services, they initiate a search for sellers available in the preferred category,[9] for a given location, and for the dates needed. As is typical in online platforms for local services, buyers then see a list of search results for available providers ranked by the companies' proprietary algorithms. Importantly, the algorithms prioritize sitters with frequent high ratings and repeat

profile. Platform approval was quickly granted after a general background check. Additional background checks can be performed at the sitter's will (`https://www.rover.com/background-checks/`, accessed July 2020).

[7] `https://www.vox.com/the-goods/2018/9/12/17831948/rover-wag-dog-walking-app`, accessed December 2020.

[8] `https://secondmeasure.com/datapoints/wag-rover-dog-walking-sales/`, accessed December 2020. Note that this figure includes total sales, not just from dog boarding.

[9] The service categories include pet overnight-boarding, sitting, drop-ins, daycare, and walking.

stays with the same customers when determining sitters' ranks in search results.[10] For each provider displayed in search results, buyers see their name, picture, location, online ratings, and nightly price. Buyers can then choose to contact sellers to discuss their needs and confirm availability. An exchange is not finalized until both users accept the transaction. After matching, Rover offers a series of services during and after the dog stay to ensure that users find it in their best interest to transact on the platform. These services include the Rover Guarantee,[11] reservation protection, trust and safety support, and a secure payment system. Except for the introduction of additional services over time, the way buyers search for sellers has remained virtually unchanged since the platforms' beginnings.

Just before the acquisition both Rover and DogVacay took about 20% of gross transaction volume in commission fees, up from 15% when they first started. Sellers would set the prices for their services. At the time of our study, the only price suggestion available was Rover's "holiday rate" feature, which suggested sellers to increase their prices during holidays. Currently on Rover, fees are divided into a provider (seller) fee and a owner (buyer) fee. The provider fee is 15% for sitters who joined before March 2016, and 20% for sitters who joined after March 2016. The owner fee is zero if the owner joined before September 2015, while it varies but is never more than $50 per booking for owners who joined after September 2015.[12] DogVacay had a very similar fee structure and its commissions closely tracked those of Rover throughout the period between 2012 and 2017 (see Figure 3 in Section 3.2 below).

3.1 The Acquisition

On March 29, 2017, Rover announced it would buy DogVacay.[13] Rover decided that it would shut down DogVacay and transfer all the business to the Rover platform rather than maintaining both websites independently. While the acquisition did shut down the acquired

[10]Details on how the current search algorithm works on Rover can be found at `https://www.rover.com/blog/sitter-resources/how-rover-search-works/` (accessed October 2020).

[11]`https://www.rover.com/rover-guarantee/` (accessed October 2020).

[12]Before July 2019, the maximum owner fee was $25 per booking, according to screenshots on Wayback Machine. These screenshots can be accessed at `https://web.archive.org/web/20190705174452/https:/support.rover.com/hc/en-us/articles/205385304-What-are-the-service-fees-`. Information on current policies is available at `https://support.rover.com/hc/en-us/articles/205385304-What-are-the-service-fees-` (accessed December 2020).

[13]`https://techcrunch.com/2017/03/29/rover-dogvacay-merge/` (accessed July 2019).

company, it was not a *killer acquisition*[14] because DogVacay was unlikely to be working on an innovative alternative, it was already large, and it was already competing with Rover by offering very similar services. Rather, DogVacay was reportedly struggling to keep up with the recent cash injections that Rover had received from venture capitalists.[15]

Rover acquired DogVacay in an all-stock deal.[16] Additional terms were not disclosed, so we do not know whether the deal was subject to merger review by the Federal Trade Commission or the Department of Justice. However, neither the Federal Trade Commission nor the Department of Justice have a publicly available case involving Rover.[17]

In addition to the many similarities between the two platforms, three features create a unique opportunity to study network effects from this acquisition: the acquisition led to a single aggregate platform; users migrated to the post-acquisition platform within 3 months; and we can identify the same users across the two platforms. We describe the three characteristics in order.

First, it is rare for the acquired platform to merge with the acquiring platform. For example, even though Zillow acquired Trulia in 2015, the two platforms are still both active. The same is true for Google Maps and Waze, and for many online travel booking sites, such as Booking.com, Kayak, and Priceline, which are jointly owned by Booking Holdings. As Aaron Easterly, the CEO of Rover, confirms in a public interview,[18] the decision to fully absorb DogVacay into the Rover brand was a consequence of the rapid growth that Rover was experiencing during the acquisition. At the time, Rover chose not to slow its growth to navigate the internal lobbying arising from two separate brands nor to integrate the back-ends while keeping two separate front-ends.

Second, the transfer of DogVacay's users to Rover happened quickly. In February 2017, Rover agreed to buy DogVacay. The acquisition was announced at the end of March. In

[14]Cunningham et al. (2019) define killer acquisitions as those when an incumbent firm acquires an innovative target and terminate development of the target's innovations to preempt future competition.

[15]`https://www.latimes.com/business/technology/la-fi-tn-dogvacay-rover-20170329-story.html` (accessed June 2020).

[16]`https://techcrunch.com/2017/03/29/rover-dogvacay-merge/` (accessed April 2020).

[17]`https://www.ftc.gov/news-events/media-resources/mergers-and-competition/merger-review` and `https://www.justice.gov/atr/merger-enforcement` (accessed April 2020).

[18]`https://soundcloud.com/acquiredfm/season-2-episode-10-the-rover` and `https://www.geekwire.com/2018/inside-rovers-dogvacay-deal-former-rivals-went-one-brand-not-two-acquisition/` (accessed April 2020).

early May, Rover announced that DogVacay would be shut down.[19] By early July, DogVacay ceased operations. If a buyer landed on DogVacay's landing page in July 2017, they were immediately redirected to book on Rover.[20]

Third, when Rover announced that DogVacay would be shut down, Rover also started allowing DogVacay users to migrate their accounts to Rover. This meant that a user could link their DogVacay account to their Rover account if they had been active on both platforms before the acquisition, or to a new Rover account otherwise. The account migration meant that a user would keep all their transaction and online rating history on the Rover platform, regardless of where those transactions or ratings originated from. Among those users who did not actively migrate their accounts, multi-homing users could still be identified from their email address. While matching users on email addresses can sometimes be inaccurate, we are confident that the similarity of services exchanged on the two platforms likely incentivizes people who are serious about using both platforms to link the two separate accounts to the same email address.[21]

3.2 Data

We have proprietary data from Rover, which retained pre-acquisition data from DogVacay. This allows us to have visibility into all service requests, buyer-seller booking inquiries, matches, and reviews from both platforms before and after the acquisition. A *request* refers to a buyer's need for a sitter (e.g. dog boarding in Seattle from August 16^{th} until August 18^{th}) and is created when a buyer initiates a search or contacts a sitter directly. Contacts for the same request with different sellers are recorded as separate *booking inquiries*. Note that a search only leads to a recorded request only if a buyer sends at least one booking inquiry to a sitter. If a booking inquiry leads to a transaction, it is matched to a *stay*. Both DogVacay and Rover have multiple service categories, but we restrict attention to dog

[19] Based on the publish date of this website: `https://www.rover.com/joining-forces/`

[20] Appendix Figure D.1 displays Rover's and DogVacay's landing pages after the merger.

[21] Survey evidence suggests that on average people have just less than two email accounts, and 2.5 when including a work account. Of those two accounts, one email address is often considered primary, and evidence suggests that there is huge inertia to changing the primary address. Finally, consumers are willing to share their primary address with businesses they trust. See `https://www.zettasphere.com/how-many-email-addresses-people-typically-use/`, which discusses results from the Data and Marketing Association (accessed April 2021).

overnight-boarding, which constitutes 70% of gross transaction volume on Rover and 91% on DogVacay before the acquisition.

We consider all buyer-seller booking inquiries initiated between June 2011 and January 2018 for requests between January 2012 and January 2018 included. Out of all booking inquiries, we remove those whose duration – i.e. number of nights requested – is recorded as negative or greater than 1 month (0.6% of requests), those with lead times – i.e. time between start date and request date – recorded as negative or greater than one year (1.1%), price outliers in terms of total price or commission fee percentage (2.3%). In particular, we remove prices lower than $1 or higher than $200 per night, and commission fees greater than 30%. In total, we exclude 4.2% of total requests, and 3.8% of successful transactions – i.e. transactions that were recorded as "completed" or "pending reviews."

We can use the pre-acquisition data to better understand whether merging the two platforms is likely to generate network effects. The potential for these effects depends on the nature of competition between the two platforms. In particular, if one platform is much smaller than the other, or if one platform is active in geographies where the other is not, then merging the two platforms is unlikely to affect the number of buyers and sellers who interact with one another. Similarly, if users are active on both platforms at once, then there is less scope for network effects to be generated by the merger.

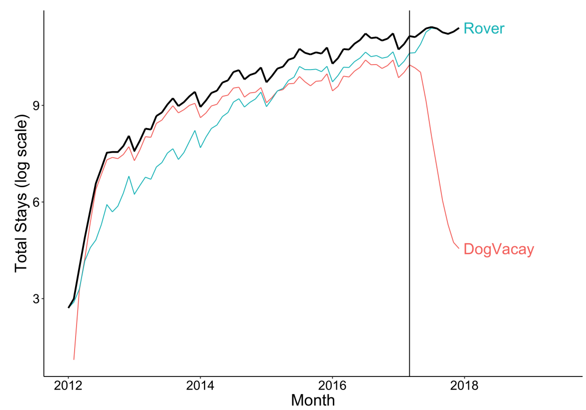
We first show that the two platforms were of approximately the same size before the acquisition. Figure 2 plots the number of monthly stays on DogVacay since January 2012, in log scale. DogVacay was founded in March 2012, after Rover, but immediately outgrew Rover in overnight boarding services, before being surpassed again around March 2015. Despite this, the two platforms were of similar size in the dog overnight boarding category before the acquisition, with Rover transacting at a 25% higher volume compared to DogVacay in the quarter before the acquisition.[22]

The local nature of the services exchanged implies that buyers are typically interested in transacting with sellers within the same city. Indeed, 79% of booking inquiries, and 81% of stays occur within a buyer's CBSA.[23]

[22] Across all service categories, Rover was 62% larger than DogVacay.

[23] CBSA stands for Core-Based Statistical Area, which roughly coincides with metropolitan and micropolitan areas.

Figure 2: Growth of Rover and DogVacay



The figure plots the number of monthly overnight-boarding stays on DogVacay and Rover in log scale. The black line is the sum of matches on both platforms. The vertical line corresponds to March 2017, when the acquisition between the two platforms was announced. The number of transactions does not completely fall to 0 after July 2017 because some services scheduled to start after DogVacay's shutdown were booked before the summer.

We measure competition between Rover and DogVacay at the local level to evaluate whether they divided the market, each owning 100% of a particular geography, or whether instead they competed in each geography. We consider zip codes with at least 50 transactions in 2016. We compute Rover's market share in a zip code as the ratio of Rover gross transaction volume in 2016 relative to the sum of Rover and DogVacay's volumes. In the average zip code in 2016, Rover had about 53.6% market share,[24] but there was substantial variation across zip codes. In 48% of zip codes, Rover had market shares between 25% and 75%. Zip codes with more transactions tended to be contested markets. Indeed 61% of zip codes with at least 200 transactions in 2016 had market shares between 25% and 75%.

The facts that both platforms intermediated the same type of services, they were similarly large, and they were present in the same geographies, suggest looking at how users substituted between the two platforms prior to the acquisition. In particular, we look at the extent to which users multi-home, i.e., actively use both platforms. Few users, and fewer buyers than sellers, multi-home across platforms. However, they account for a disproportionate share of transactions. Only 3.3% of buyers and 7.6% of sellers multi-home. Not surprisingly, multi-homing users tend to transact more frequently than single-homing users.

[24]In the aggregate in these zip codes Rover has 54.49% market share.

Table 1: Prices on Rover and DogVacay

	Seller Price (log)		
	(1)	(2)	(3)
DogVacay	0.067***	0.061***	−0.003
	(0.004)	(0.004)	(0.004)
Stay Duration FE	Yes	Yes	Yes
Zip code-year month FE	No	Yes	No
Provider-year month FE	No	No	Yes
Observations	1,567,740	1,567,740	1,567,740
R^2	0.814	0.884	0.928
Note:	Standard errors are clustered at the zip code level.		

Estimates from OLS regressions of seller prices on a dummy for whether the transaction occurred on DogVacay. The data include all successful transactions between 2012 and March 2017, when the acquisition was announced. Controls include fixed effects for the duration of the stay (columns 1-3), zip code and year-month fixed effects (column 2), and provider and year-month fixed effects (column 3). The variation that identifies the coefficient in column 3 comes from 236,170 matches from multi-homing sellers who transacted on both platforms within the same month.

27% of transactions are made by multi-homing sellers and 8% are made by multi-homing buyers.[25]

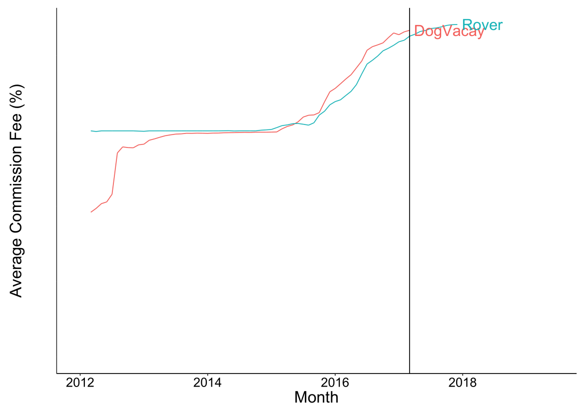
Multi-homing sellers treat the two platforms as close substitutes, at least judging by the price they charge, even though DogVacay's prices are higher on average.[26] Indeed, during the period before the acquisition, DogVacay sellers were expected to receive about $3.50 more per night than sellers on Rover, or 13% more. After controlling for geographic and time observables, the price difference decreases to about 6% but it completely disappears once we compare prices of multi-homing sellers transacting on both Rover and DogVacay within the same month (see Table 1). This suggests that sellers on DogVacay may have different qualities or costs compared to sellers on Rover, but that multi-homing sellers consider buyers from the two platforms as close substitutes.

Figure 3 plots the average commission fee on the two platforms, computed as the ratio of platform total fees over the price paid by buyers. The figure shows that commission fees

[25] Appendix Figure D.2 plots the share of a user's transactions occurring on DogVacay prior to the acquisition, separately for buyers and sellers. On average, only 4.2% of users are both buyers and sellers of services on any given year. Buyers rarely act as service providers on the platforms. In the years before the acquisition, on average 4.8% of buyers also transacted as sellers on any given year. Sellers are more often buying pet-sitting services on the platforms. Indeed, 25.8% of sellers also transacted as buyers on any given year.

[26] The payment that a seller receives is equal to what the buyer pays minus the platform commission fees. Tipping is not required, and is not recorded on the platform. However dog owners are not prevented from tipping sitters outside of the platform (`https://support.rover.com/hc/en-us/articles/206199686-Should-I-tip-my-sitter-`, accessed July 2019).

Figure 3: Average Fees



The figure plots the average commission fee, as a percentage of the price that buyers pay. The vertical line identifies March 2017, when the acquisition was publicly announced. Levels on the y-axis are hidden to protect company information.

were very similar across platforms, and they continued their pre-acquisition upward trend after Rover acquired DogVacay. The upward trend is due to the higher fee schedule for buyers and sellers who joined after September 2015 and March 2016, respectively, whose shares increased steadily over time. As is clear from the figure, commission fees did not increase discontinuously after the acquisition, suggesting that Rover did not take advantage of its increased market power to capture a higher share of surplus.

4 Theoretical Framework

This section presents a simple theoretical framework of online matching platforms. The goal is to measure consumers' utility from using a platform and how their utility changes as a function of a merger between two competing platforms. We will focus on buyers, but a symmetric analysis can be done for sellers. The results of this section will provide us with tests for the existence of network effects that we can take to the data.

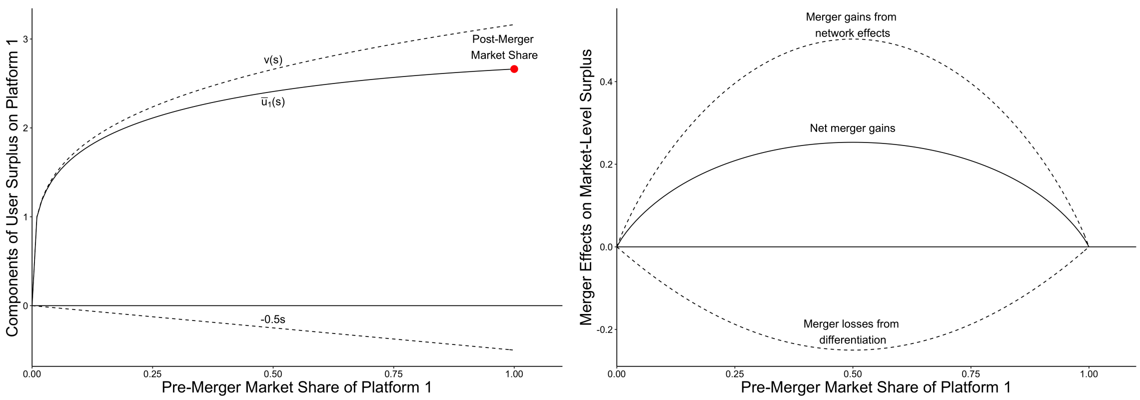
Our model is a simple Hotelling model with network effects. We define a market to be the activity of buyers and sellers within a local geography – e.g., a zip code – and short time period – e.g., a month. In a market there is a unit mass of sellers and a unit mass of buyers distributed uniformly on the (0,1) line. We assume that the number of buyers relative to sellers is fixed – equal to 1 for simplicity – and that buyers and sellers' utilities are such that competing platforms have the same ratio of participating buyers relative to sellers. Platform 1 is located at 0 while platform 2 is located at 1. A buyer located at point d_i has utility for platform 1 equal to $u_{i1}(s) = v(s) - d_i$, where s is the share of users using platform 1. Assuming that the market is always covered, i.e. nobody chooses the outside option, the share of users on platform 2 is $1 - s$ and the corresponding utility for user i is $u_{i2}(s) = v(1-s) - (1-d_i)$. *Network effects* exist whenever $v()$ is increasing in its argument. Horizontal preferences are given by the parameter d_i.

Consumers choose which platform to join as a function of platform utilities and a joining cost. We normalize platform 1's joining cost to 0, and we denote platform 2's joining cost c, which can be positive (i.e., higher cost relative to platform 1) or negative (i.e., lower cost relative to platform 1). This means that user i joins platform 1 if and only if $u_{i1}(s) \geq u_{i2}(s) - c$. Importantly, c is only present to rationalize different market shares across multiple geographies, but does not affect the utility obtained on the platforms after joining. Therefore, we will ignore c when computing the benefits of competition relative to a monopoly.

The equilibrium share of users joining platform 1 is given by the following indifference condition for the marginal user: $v(s) - s = v(1-s) - (1-s) - c$. Depending on $v()$, we can have a single or multiple equilibria. Additionally, $s = 1$ is also an equilibrium whenever $v(1) - 1 > v(0) - c$, i.e., the utility of users located at 0 from joining the farther platform if everybody else is on it is greater than being alone on the closest platform. Symmetrically, $s = 0$ is an additional equilibrium whenever $v(0) < v(1) - 1 - c$. For our purposes, equilibrium selection does not matter. Given an equilibrium s, the average utility provided by platform 1 is $\bar{u}_1(s) = v(s) - 0.5s$, the average utility provided by platform 2 is $\bar{u}_2(s) = v(1-s) - 0.5(1-s)$, and the average utility in the market is the weighted average of utilities from the two platforms, where the weights depend on the market shares: $s\bar{u}_1(s) + (1-s)\bar{u}_2(s)$.

When platform 1 acquires platform 2 and users from platform 2 are required to migrate to platform 1, the average utility provided by platform 1 is $\bar{u}_1(1) = v(1) - 0.5$, which also coincides with the market-level average utility. Figure 4a plots the average utility for users of platform 1 as a function of s. The figure shows how the component of utility that depends on platform size $v(s)$ is increasing in s, while the component of utility that depends on the distance from platform 1 is negative and decreasing in s.

Figure 4: Consumer Surplus at Platform and Market Level



(a) Platform-Level Surplus per Person (b) Market-Level Surplus per Person

The left panel plots surplus per user of users in platform 1, in aggregate and split into its two components. Average utility on platform 1 is $\bar{u}_i(s) = v(s) - 0.5s$. The solid line plots $\bar{u}_i(s)$, the dashed lines plot $v(s)$ – component of utility that depends on platform size – and $-0.5s$ – component of utility that depends on the distance from the platform. For the plot we assume $v(s) = (100s)^{0.25}$. Utility from platform 2 is exactly symmetric around 0.5. The right panel plots the change in market-level surplus after the merger as a function of platform 1's pre-merger market share. The post-merger utility per user is $\bar{u}_1(1) = v(1) - 0.5$, while the pre-merger utility is $s\bar{u}_1(s) + (1-s)\bar{u}_2(s) = sv(s) + (1-s)v(s) - (0.5s^2 + 0.5(1-s)^2)$. The positive dashed line plots $v(1) - [sv(s) + (1-s)v(s)]$, which represents the merger gains from network effects. The negative dashed line plots $-s(1-s)$, which represents the merger losses from reduction in platform differentiation. The solid line combines the two by plotting $\bar{u}_1(1) - [s\bar{u}_1(s) + (1-s)\bar{u}_2(s)]$.

To compare how utilities change after the merger of the two platforms, we start with users who were on platform 1 before the merger. Their average utility changes as follows:

$$\bar{u}_1^1(1, s) - \bar{u}_1(s) = v(1) - v(s),$$

where $\bar{u}_1^1(1, s) = v(1) - 0.5s$ denotes platform 1's utility after the merger to users who were on platform 1 before the merger. Network effects imply that the increase in utility for existing users of platform 1 is positive for any $s < 1$ and is decreasing in s:

$$\bar{u}_1^1(1, s) - \bar{u}_1(s) \text{ is decreasing in } s. \tag{1}$$

In words, the equation states that with network effects, the increase in average surplus for existing users of platform 1 is bigger in markets where platform 1 was smaller before the merger. That happens because the acquiring platform receives a bigger influx of users from platform 2 when s is small compared to when s is large.

Note that comparing the average utility of all users in platform 1 after the merger with the average utility of all users in platform 1 before the merger cannot separate network effects from selection effects. Specifically, $\bar{u}_1(1) - \bar{u}_1(s) = \left[\bar{u}_1^1(1, s) - \bar{u}_1(s)\right] - 0.5(1 - s)$. The first term in square brackets, $\bar{u}_1^1(1, s) - \bar{u}_1(s)$, represents the change in utility for the users who were already using platform 1 before the merger. The second term, $0.5(1 - s)$, represents the reduction in utility coming from the fact that the users migrating from platform 2 are located farther away from platform 1 than the existing users and thus have higher average travel costs.

To evaluate the role of horizontal preferences, we compare the post- and pre-merger utility of users who chose platform 2 before the merger:

$$\bar{u}_1^2(1, s) - \bar{u}_2(s) = v(1) - v(1 - s) - s, \tag{2}$$

where $\bar{u}_1^2(1, s) = v(1) - 0.5(1 + s)$ is platform 1's utility to users who were on platform 2 before the merger. Like before, the first component, $v(1) - v(1 - s)$, is the increase in utility due to network effects, which is positive and increasing in s. The second component is the increase in travel costs due to the migration to platform 1, again increasing in s in absolute value.

The predictions of how utility changes after the merger for users of platform 2 are ambiguous. Depending on whether network effects dominate over horizontal preferences, users of platform 2 may be better off or worse off after the merger. We note however, that there is a close relationship between the gains of users from platform 1 and platform 2. In particular, consider the change in utility for platform 1's users in a market where platform 1 has market share s and the change in utility for platform 2's users in a market where platform 1 has market share $1 - s$:

$$\left[\bar{u}_1^2(1, 1 - s) - \bar{u}_2(1 - s)\right] - \left[\bar{u}_1^1(1, s) - \bar{u}_1(s)\right] = -(1 - s).$$

The merger gains for users of platform 1 in a market where platform 1 has market share s are the same as the gains for users of platform 2 in a market where platform 1 has market share $1-s$ except for the increase in travel costs for platform 2 users. Note that the increase in travel costs $1-s$ is decreasing in s so the difference in gains, which is negative, is increasing in s:

$$\left[\bar{u}_1^2(1, 1-s) - \bar{u}_2(1-s)\right] - \left[\bar{u}_1^1(1, s) - \bar{u}_1(s)\right] \text{ is negative and increasing in } s. \tag{3}$$

Network effects have been used in the literature to justify that a single platform can create more value for users than two competing platforms, which is something that we can directly test. For network effects to be large enough to justify a single platform over two competitors, we need network effects to dominate over horizontal preferences. The change in market-level average utility from the merger is as follows:

$$\bar{u}(1) - [s\bar{u}_1(s) + (1-s)\bar{u}_2(s)] = [v(1) - sv(s) - (1-s)v(1-s)] - s(1-s).$$

The first term, $v(1) - sv(s) - (1-s)v(1-s)$, represents the gains from scale. The second term, $s(1-s)$, represents the losses from the reduction in platform differentiation. Figure 4b plots the two terms separately as dashed lines. The welfare-maximizing market structure – a single platform or two competing platforms – depends on which of the two terms dominates. If network effects dominate (as shown in Figure 4b), we have that $\bar{u}(1) - [s\bar{u}_1(s) + (1-s)\bar{u}_2(s)]$ is positive and reaches a maximum at $s = 0.5$:

$$\bar{u}(1) - [s\bar{u}_1(s) + (1-s)\bar{u}_2(s)] \text{ is decreasing in } |s - 0.5|. \tag{4}$$

Before we conclude, we provide a mapping between the model and our empirical analysis. Platform 1 is Rover, which eventually acquires DogVacay, or platform 2. A buyer's utility from using a dog sitting platform is a function of search costs that affect the probability of posting a request, the probability of matching conditional on posting a request, and the utility from the transaction net of price conditional on matching. Buyer's utility is increasing in match value and match rate, and decreasing in transaction prices and search costs.

The components of buyer's utility are in turn functions of the number of buyers and sellers participating on the platform. In particular, match value is increasing in the number of platform users if increasing both buyers and sellers at the same rate allows buyers to find a better match – because for example, they find somebody living closer to their home. The match rate is increasing in the number of users if increasing both buyers and sellers allows buyers to find a match with higher probability – because for example, it is more likely that they find somebody available for the required dates. Finally, search costs are decreasing in the number of users if increasing buyers and sellers makes it less costly to submit requests and open inquiries with sellers – because for example, the search results displayed by the platform offers choices of service providers that are better than alternative off-platform options.

The components of buyer's utility may also be functions of horizontal preferences for the two competing platforms. For certain users, search costs, match rates, and match values may be more favorable on one platform relative to the other if, for example, the type of sellers and the search results on the preferred platform are better tailored to their specific preferences.

Note that both our theory and estimation strategy below abstract away from changes in the number of buyers *relative* to sellers. In principle, that is not an innocuous assumption. The migration of DogVacay users may mean a doubling of sellers on Rover but a differential change in buyers relative to sellers across different geographies. When only 1:1 matches between buyers and sellers are allowed, Rover buyers would benefit more if the number of migrating DogVacay buyers for every migrating seller were lower, at least in the short-run. In practice, our context justifies the simplifying assumption. Indeed, pet sitters do not seem to have strong capacity constraints: they can host more than one dog on any given night (and some dog owners even prefer when their dog has company) and they do not seem to have strong preferences for specific pet characteristics. In addition, on average the difference in the number of buyers relative to sellers across the two platforms is only 0.11, with relatively little variation across geographies.

We can thus use Equations (1) through (4) separately on each component of buyers' utility to test for the existence of network effects and whether they are large enough to justify a single platform. We discuss extensions to this model in Appendix A, especially to motivate tests of heterogeneous effects presented in Section 6 and present the empirical approach in the next section.

5 Empirical Strategy and Identification

In this section we describe how to test our theory, which relies on variation in pre-merger market shares across geographies. Figure 5 shows the distribution of Rover's market shares in 2016 (in terms of gross transaction volume) across zip codes with at least 50 stays in that year. Because buyers and sellers' zip codes may differ, we use sellers' zip codes for our market definition. There is substantial variation in market shares, and at least part of that variation can be explained by the different expansion strategies that Rover and DogVacay adopted years earlier when they just started out.[27]

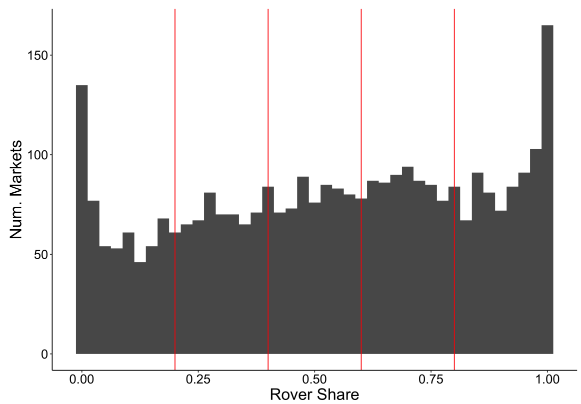
The substantial variation in market shares across geographies allows us to separate zip codes into 5 groups: zip codes where in 2016 Rover had market shares below 20%; between 20% and 40%; between 40% and 60%; between 60% and 80%; and above 80%. Merging the two platforms after the acquisition was effective in migrating DogVacay users to Rover. Zip codes with Rover market shares smaller than 10% experienced a median increase in users on Rover of 550% while markets above 90% had a median increase of 14% (Appendix Figure D.3).

If network effects exist, we would expect outcomes for users who were on Rover pre-merger to improve monotonically in the market share of DogVacay, the acquired platform (Equation 1). So we would expect outcomes to improve the most in zip codes with pre-merger market shares between 0 and 20% and the least in zip codes with market shares over 80%. That is because holding constant market size – which we ensure through matching zip codes, as described below – higher DogVacay's market shares imply a bigger influx of

[27] We find that part of the variation in 2016 market shares can be explained by which platform was the first mover in the market. Appendix Table D.1 shows that on average, Rover tends to have a 7% higher market share in zip codes where the first stay was booked on Rover rather than DogVacay. Due to confidentiality terms, we cannot disclose how the expansion strategies differed between Rover and DogVacay, although the two differed substantially in the way they targeted growth by expanding across geographies versus growing their user base within particular geographies.

users to Rover. If network effects are large enough to justify a dominant platform, we would expect the largest benefits from network effects to arise in the zip codes with shares between 40% and 60% (Equation 4). In a world with no platform differentiation where the two platforms are identical to consumers except for their market shares, zip codes where Rover had less than 20% or more than 80% of the market would in fact be indistinguishable from one another.

Figure 5: Rover Market Shares Pre-Acquisition



The figure plots the histogram of Rover market shares in 2016, the year prior to the acquisition. Each observation is a zip code with at least 50 transactions in 2016. The zip code's Rover market share is defined using gross transaction volume.

Because the merger may have affected user outcomes beyond the direct effects of platform differentiation and network effects, and because our hypotheses vary by pre-merger market share, we can control for other changes affecting all geographies uniformly by using certain zip codes as a control group. The zip codes where Rover was already dominant pre-merger are the best candidates as control group, since Rover remained the dominant platform after the merger. For this reason, we use zip codes where Rover had more than 80% of the pre-merger market as our control zip codes. Since Equation (1) is monotone in pre-merger market shares but Equation (4) is symmetric around 50% market share, we consider four separate treatment groups corresponding to the other four market share groups – 0-20%, 20%-40%, 40%-60%, and 60%-80% – displayed in Figure 5.

Zip codes where either Rover or DogVacay were dominant before the acquisition tend to be more rural, have fewer residents, lower population densities, and lower shares of college graduates. Areas where Rover is particularly successful also tend to have higher pet ownership rates. Appendix Figures D.4 and D.5, together with Appendix Table D.2, provide comparisons for a large set of observable characteristics, platform performance metrics, and their evolution over time. Given these differences, we may be concerned that the main assumption behind a difference-in-differences approach, that zip codes with different market shares have the same latent trends in platform performance, does not hold.

To ensure that zip codes in treated market share groups are as similar as possible to zip codes in the control group, we employ a matching estimator that accounts for covariate imbalance across groups (Imai et al., 2018). Recall that we consider zip codes with Rover market shares above 80% as the control group. We match one zip code from the control group to each "treated" zip code using covariate balancing propensity score matching (CBPS), introduced by Imai and Ratkovic (2014). Distances are calculated on the total number of active sellers in each month up to a year before the acquisition, where an active seller is defined as a seller who was involved in at least one booking inquiry in the given month. We hold the matched control group constant as we measure the effects of combining the two platforms across different outcomes of interest.

Appendix Table D.3, which provides descriptive statistics for the matched samples, shows that we are able to improve matching on a number of covariates that we do not explicitly use in the matching procedure.[28] However, platform performance metrics that are not explicitly considered in matching (e.g. prices, match rates, and share of repeat transactions) fail to balance across treatment and control group. Some of this imbalance is expected — for example we know that prices are higher on DogVacay and average prices will therefore be higher in markets with a higher DogVacay share. Other differences reflect the fact that platform performance metrics tend to positively correlate with a platform's market share. We should note however, that our empirical strategy, described below, does not require identical levels of pre-treatment outcomes, but rather parallel trends. The figures in the results section below provide support for this assumption.

Given matched zip codes, let y_{zt} be the outcome in treated zip code z and year-month t. Separately for each market share group $[0-20\%)$, $[20\%-40\%)$, $[40\%-60\%)$, and

[28] Appendix Table D.2 presents descriptives for the unmatched zip codes.

$[60\% - 80\%)$, we estimate the following regression:

$$y_{zt} - y_{z't} = \alpha_t + \epsilon_{z,z',t}, \tag{5}$$

where z is the treated zip code, and z' is the matched control zip code. The coefficients α_t should be interpreted as changes in the outcome variable relative to the control group, and relative to February 2017, the month before the acquisition announcement.

An econometric challenge that arises with this matching method is that a market in the control group may be matched to multiple markets from the treated group. As a result, each matched pair, or dyad, is no longer independently informative, as a single control market can impact the estimates of multiple dyads. We account for the resulting correlation in error terms with the cluster-robust variance estimation method from Aronow et al. (2015).

Equation (5) allows us to test Equations 1, 2, and 4. To test Equation (3) however, we need a different approach. Recall that in order to evaluate the role of platform differentiation, we need to estimate to what extent DogVacay users are worse off *relative to* Rover users who experienced the same change in platform size. Rover users in markets with Rover's pre-merger market share of s experience a change in platform size of $1 - s$. Symmetrically, DogVacay users in markets with Rover's pre-merger market share of $1 - s$ experience an identical change in platform size of $1 - s$. We attribute any difference in outcomes between Rover and DogVacay users of these symmetric markets to a reduction in platform differentiation.

Let $s \in \{0, 20\%, 40\%, 60\%, 80\%\}$ denote the lowest Rover's market share in each of our market share groups. For each of the five s, we consider the outcomes of Rover users in zip codes with market shares within $[s, s + 20\%)$ and the outcomes of DogVacay users in zip codes with market shares within $[80\% - s, 100\% - s)$. With these outcomes we estimate the following regression:

$$y_{zt} = \beta_t + \gamma_t \mathbb{1}\{z \text{ has market share in } [80\% - s, 100\% - s)\} + \nu_z + \epsilon_{zt}, \tag{6}$$

where y_{zt} is the outcome of Rover users in zip code z and year-month t if $z \in [s, s+20\%)$, and it is the outcome of DogVacay users in zip code z and year-month t if $z \in [80\% -$

$s, 100\% - s)$.

The coefficients γ_t measure the difference in outcomes between DogVacay and Rover users in markets where both users experienced the same change in market size, and in month t relative to February 2017. Given Equation (3), we expect the γ to be negative due to the loss of platform differentiation.

In estimating Equations (5) and (6), we look at a large number of outcomes proxying for the various components of user surplus. Buyers' utility is a function of the probability to find a sitter to transact with, the quality of the transaction, the price of the transaction, and search costs affecting the propensity of buyers to even post a request in the first place. We calculate the match rate of posted requests as the number of successful transactions in a given month and zip code divided by the number of posted requests for the same month and zip code. We compute the average nightly price of successful transactions as gross transaction volume divided by the number of transactions in a given month and zip code. We proxy for the average match quality with three metrics: the share of transactions in a given month and zip code whose buyer requests help again in the subsequent three months; the share of (non-repeat) transactions leading to a repeat stay in the future; and the share of transactions with a 5-star review submitted by the buyer. Because it is tricky to determine which buyers are potentially considering to post requests but end up choosing otherwise, we look at aggregate metrics to proxy for the propensity to post requests: total number of unique buyers posting requests and total number of posted requests in a given month and zip code. A metric aggregating these separate effects is the number of total transactions in a given month and zip code.

To test Equation (1) – are there network effects? – and Equation (3) – do users value platform differentiation? – we need to define users who were on Rover or DogVacay before the merger. For example, we define buyers as Rover buyers if all their booking inquiries during the year were on Rover, and DogVacay buyers if all their booking inquiries during the year were on DogVacay. The small share of multi-homers, those with inquires on both platforms in a given year, are analyzed separately in Appendix B.[29] We then measure the number of those users who post requests or engage in booking inquiries again in any given

[29]Multi-homing users are analyzed in Figure B.6.

month of the following calendar year.

To test Equation (4) – are network effects large enough to justify a dominant platform? – we compute market-level outcomes by aggregating Rover and DogVacay outcomes for all users pre-merger and considering Rover outcomes for all users post-merger. We also ensure that the results hold true for new users, by focusing on outcomes for users who had never posted requests on any platform or market prior to the given month.

The combination of many outcomes and subsets of users for which to measure these outcomes (especially if we include analogous outcomes from the sellers' perspective) would make our results section extremely long, but our main results can be summarized by just focusing on buyers and on two outcomes: request match rates and aggregate number of transactions. We present the other outcomes and a similar analysis for sellers in Appendix B. The results are also similar for more aggregated market definitions based on zip code clusters, which are less prone to potential violations of the stable unit treatment value assumption, but give rise to noisier estimates (Appendix B).

6 Results

This section presents our results testing Equations 1 through 4, focusing on buyers, and using only two outcomes: match rates of requests, and (log) total number of transactions.[30] Appendix B presents similar results on other outcomes.

We start with tests of Equation 1. In this case, y_{zt} is the outcome of buyers in zip code z and year-month t for buyers who had posted booking inquiries only on Rover in the calendar year preceding t. Figure 6a plots the results of estimating Equation (5) with log number of transactions and request match rates as the outcomes. As theory predicts, the top row shows that Rover buyers benefit more from the merger when the influx of users from DogVacay is larger. The effects on the top row imply a 26% increase in transactions for the markets with 0-20% market shares (left plot) and around 17% increase in transactions for markets with 20-40% or 40-60% market shares (second and third plot from the left).

[30] This section presents the results with event study plots. Appendix Tables B.1 through B.5 present the results of difference-in-differences regressions, aggregating the months in the pre-acquisition announcement period, those in between the announcement and the shut-down of DogVacay, and those after the shut-down of DogVacay.

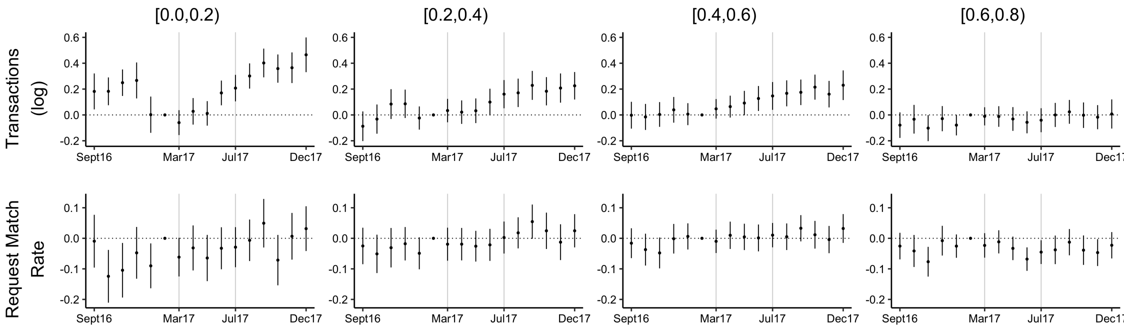
This increase in transactions is consistent with increased variety of sellers on the platform due to the migrating sitters from DogVacay. The increase in activity from Rover buyers entirely comes from the extensive margins – more users posting requests – rather than match quality or match rates. Indeed the bottom row of Figure 6a shows that Rover buyers did not experience an improvement in match rates, and the appendix confirms that our proxies for match quality remain unchanged (Appendix Figure B.1).

The top row of Figure 6a is our evidence that network effects exist. Buyers of the acquiring platform benefit from the influx of users from the acquired platform as evidenced by their increased propensity to post requests (and hence engage in more transactions) and by the fact that this increased propensity to post requests is larger in markets with a bigger shock to the number of users.

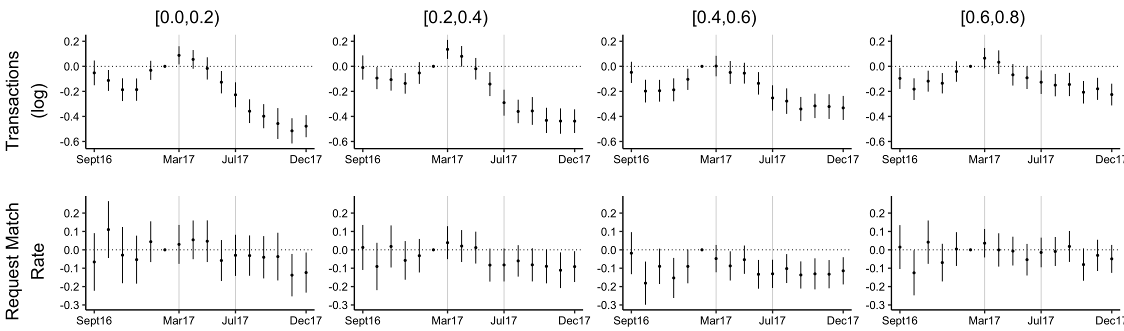
Next, we evaluate the effect of the merger on DogVacay users. Figure 6b estimates the change in proxies for the utility of DogVacay buyers, motivated by Equation (2) in the theoretical model. Here, y_{zt} is the outcome of buyers in zip code z and year-month t for buyers who had posted booking inquiries only on DogVacay in the calendar year preceding t. The top row of Figure 6b shows that DogVacay buyers experience higher attrition and lower match rates compared to before the acquisition and compared to DogVacay buyers in the zip-codes where Rover had 80-100% market share prior to the acquisition. The effects are particularly large in the 0-20% market share group, where there was a 33% reduction in the number of transactions. Appendix Figure B.2 shows that the reduction in transactions is largely due to a reduction in the number of buyers rather than the frequency of transactions per transacting buyer. The number of DogVacay buyers participating in the market decreases by 36% in the 0-20% market share group. Match rates of DogVacay buyers migrating to Rover are also lower, up to 7 percentage points lower in the zip codes where DogVacay was dominant.

The negative coefficients in Figure 6b seem to suggest that DogVacay buyers are worse off after the merger. However, the $v(1) - v(1 - s)$ component in Equation (2) is positive and largest in the control markets, which implies that DogVacay buyers in control markets experience the largest network effect benefits from combining with Rover users. This explains why DogVacay buyers in the treatment markets are worse off compared to DogVacay

Figure 6: Estimates of Merger Effects at the Platform Level



(a) Rover Users



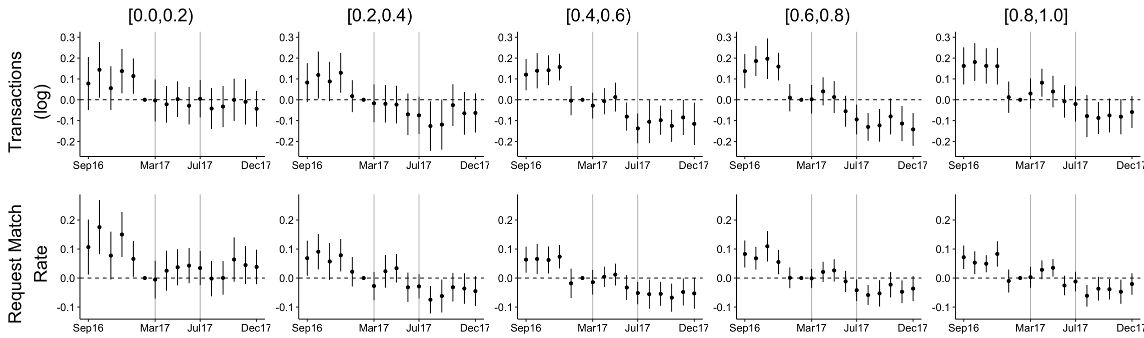
(b) DogVacay Users

Regression estimates of Equation (5)*. In the first panel we test Equation* (1)*. The first row displays results where the outcome is the (log) number of transactions from buyers who, in the prior calendar year, had only engaged in booking inquiries on Rover. The second row displays results for the match rate of those same Rover buyers, i.e., the number of stays divided by the number of requests posted by existing Rover buyers. Panel (b) displays analogous outcomes for users who, in the prior year, had only engaged in booking inquiries on DogVacay. An observation is a matched zip code-month. In each panel the regressions come from 2 different outcomes — stays and match rates — and 4 treatment groups — zip codes with Rover's market shares in the following bins: 0-20%, 20%-40%, 40%-60%, and 60%-80%. The control group from which matched zip codes are selected includes zip codes with Rover's market shares greater than 80%. Grey vertical lines denote March and July 2017, the months when the acquisition was announced and DogVacay was effectively shut down, respectively. Extensions, including other outcomes, results for multi-homing users, and estimates with clusters of zip codes as markets are in Appendix B.*

buyers in the matched control markets.

To evaluate the role of platform differentiation, we need to estimate Equation (6). The γ coefficients in that equation represent to what extent DogVacay buyers are worse off *relative to* Rover buyers who experienced the same potential change in platform size. Figure 7 plots the estimated γ coefficients for each month leading up to and after the acquisition. Across all market share groups, it is clear that DogVacay buyers experienced a reduction in the

Figure 7: Estimates of Merger Effects For DogVacay Users Relative to Rover Users



Regression estimates of Equation (6) *testing Equation* (3)*. The first row displays results where the outcome is the (log) number of transactions from buyers who, in the prior calendar year, had only engaged in booking inquiries on Rover or DogVacay. The second row displays results for the match rate of those same users, i.e., the number of stays divided by the number of requests submitted. Each column corresponds to a market share group* $(s, s+20\%)$*. Given* $(s, s+20\%)$ *the figure plots the estimated difference in outcomes between DogVacay users in markets with Rover market shares in* $(80\% - s, 100\% - s)$ *and Rover users in markets with Rover market shares in* $(s, s+20\%)$*. So for example, the top-left plot compares the (log) number of transactions that DogVacay users exchanged in markets where Rover had pre-merger market shares above 80% and the number of transactions that Rover users exchanged in markets Rover had pre-merger market shares below 20%.*

number of transactions (top row) and request match rate (bottom row) relative to Rover buyers in symmetric markets around the merger announcement. In fact, the decline in outcomes started occurring in January and February 2017, before the merger was announced but presumably during merger talks. This decline continued during the March-July 2017 period as DogVacay users started migrating to Rover. Outcomes drop more drastically after DogVacay was shut down and then stabilize. After DogVacay was shut down, the reduction in transactions of DogVacay buyers relative to Rover is at least 10% across all market share groups, and the reduction in match rates is at least 4 percentage points (Appendix Table B.3).

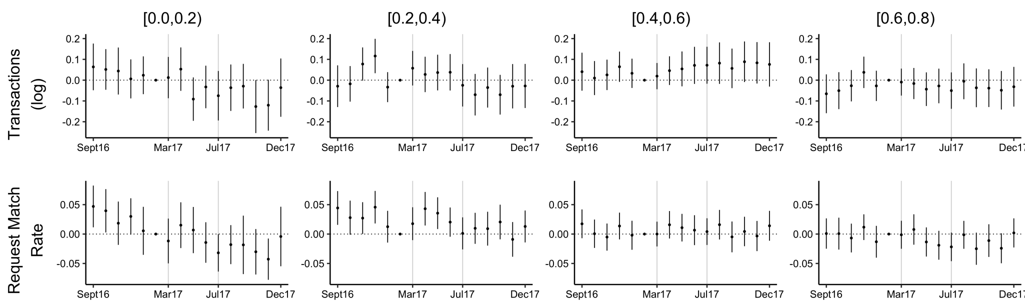
Equation (3) predicts that this decline is decreasing in absolute value as Rover's market share increases. Our empirical results are not fully aligned with that prediction. In fact, the largest declines in transactions and match rates are experienced in the markets with Rover shares between 20% and 80%. A model extension, which allows for a share of DogVacay users to leave the market instead of migrating to Rover and which is consistent with our empirical findings, can explain this pattern (see Appendix A).

The final step in our analysis is to test whether network effects are large enough that they more than offset the decline in platform differentiation, which reduces consumer surplus. Our theory provides Equation (4) as a test. Figure 8a plots the results of the test. The outcome in the first row is the (log) total number of transactions in a given zip code-month, regardless of whether they were intermediated by DogVacay or Rover. Like before, each column corresponds to a different treatment group. This time however, if network effects dominate the reduction in platform differentiation, we would expect the largest increase in the number of transactions to occur in the zip codes where Rover's market share was between 40% and 60% pre-merger (third plot in the first row). The effect should then be monotonically decreasing for the plots to the right and to the left. With symmetry of the two platforms, we expect that the group with Rover's market share between 0 and 20% (first plot from the left) to be indistinguishable from the control group. These patterns should be true not only for transactions, but also for request match rates (bottom row).

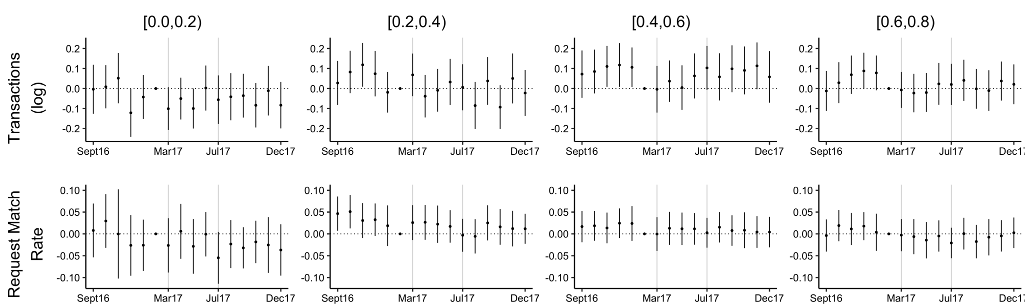
The first row of Figure 8a shows that indeed, there seems to be an uptick in the number of transactions after merging the two platforms in the zip codes with 40-60% market shares, but the estimated effect is noisy and often is indistinguishable from a null effect. Pooling together the months after DogVacay's shutdown to estimate a single difference-in-differences coefficient for each treatment group (Appendix Table B.4) confirms that the effect is not statistically significant. Zip codes with market shares farther away from 40%-60% are indistinguishable from the control group and, if anything, the difference-in-differences coefficient for 0-20% and 20-40% market share groups implies a marginally significant 7.5% decrease in the number of transactions. Similarly for the request match rate (second row of Figure 8a), we don't find any positive effect of the merger across market share groups. For zip codes where Rover had less than 20% market share, we even find a significant reduction in match rates of 3.5 percentage points. These results and the results in Appendix Figure B.4 suggest that buyers do not find matches of higher quality or at higher rates with the single merged platform compared to when there were two competing platforms.

The same conclusion rejecting the hypothesis that a single platform is better for users than two competitors is true when focusing on new users only. Figure 8b displays regression estimates of Equation (5) using transactions and match rates of new buyers, defined as those who never posted a request or were involved in a booking inquiry on any platform prior to the current month. The plots show surprisingly stable number of transactions and match rates after the merger across all treatment groups relative to the control group. This is a notable result, because it shows that horizontal preferences for platforms are not something that users develop *after* joining a particular platform, which would lead us to finding that a single dominant platform is on average preferred by new users than two competitors.

Figure 8: Net Effects at the Market Level



(a) Market Outcomes



(b) New Users

Regression estimates of Equation (5) *to test Equation* (4)*. Panel (a) presents market-level outcomes (log transactions and request match rate), while Panel (b) focuses on the same outcomes for new users, defined as users who never had a booking inquiry before the given month. Otherwise the plots are identical to Figure 6. Extensions and robustness checks are in Appendix B.*

6.1 Heterogeneous Effects Across Markets and Users

The results so far confirm the existence of network effects at the platform level but that the benefits from network effects are not enough for the average consumer to prefer a dominant platform over two competitors. In fact, our results suggest that the two options are, at least in the short-run, similar for consumer surplus. This is true on average, but network effects may dominate over platform differentiation in certain markets and not in others. We explore two dimensions of heterogeneity across markets: market size, and propensity to multi-home. We leave the theoretical discussion to Appendix A and histograms of these characteristics across zip codes in Appendix Figure D.6.

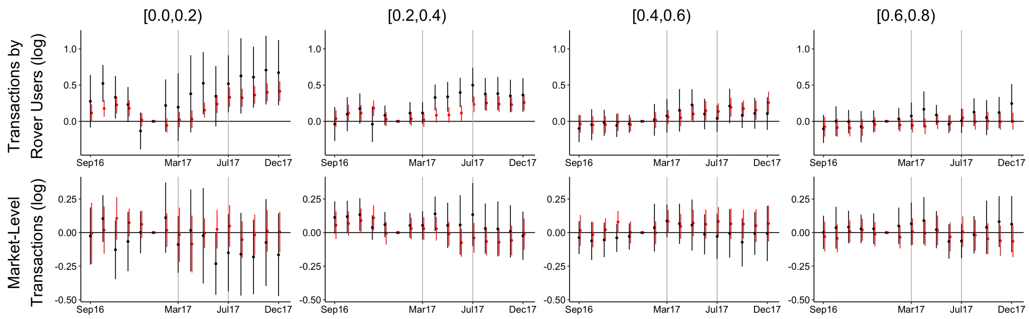
Markets differ in their total number of transactions. Among zip codes with at least 50 transactions in 2016, the average zip code had 171 stays in the same year, but with a standard deviation of 146, demonstrating that there is substantial heterogeneity across zip codes. It is possible that both platforms were already operating at an efficient scale in large markets but not in small markets. If this were the case, we would expect platform-level network effects to be larger after the merger in smaller markets. It would also be more likely that network effects are large enough to justify a single dominant platform in smaller markets compared to larger markets.

To test these hypotheses, we split zip codes into those with more or fewer than 250 transactions in 2016. A large share, 81%, of our zip codes are considered small markets. We focus on the log number of transactions for users who had posted requests on Rover the prior year, and for all users in a market. Figure 9a plots the estimates.[31] The red estimates are for small markets, while the black estimates are for large markets. We do not find much of a statistically significant difference between small and large markets: the transactions by existing Rover users go up monotonically in the influx of new users from the acquired platform, while the market-level transactions do not increase relative to the control group.

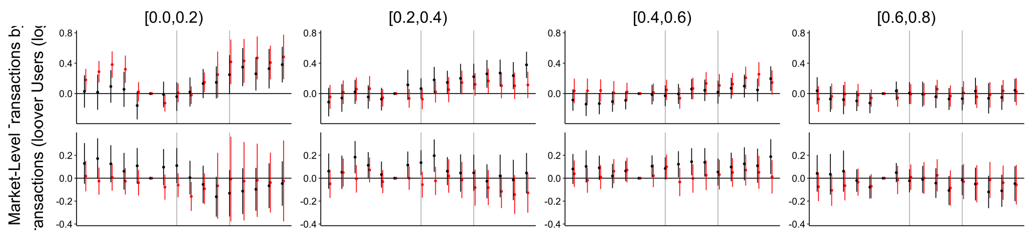
We should note that there is likely to be selection into the markets that experienced a small versus large number of transactions in 2016, so we have only suggestive evidence that our results are independent of market size. In other words, it may very well be that markets that were large in 2016 would have benefited more from a merger had it happened earlier, when the two platforms were smaller.

[31] Note that the matched samples differ from Figures 6 and 8 because we constrain each treated zip code to be matched to a control zip code within the same market size group.

Figure 9: Estimates of Merger Effects – Heterogeneity by Market Type



(a) *Small* versus *Large* Markets



(b) Markets with *Little* versus *Substantial* Multihoming

Estimates of Equation (5) *for different markets. In Panel (a) the zip codes are divided into two groups: markets with 50-250 transactions in 2016 (in red), and markets with more than 250 transactions (in black). In Panel (b), the zip codes are divided into two groups: markets whose share of 2016 transactions completed by multi-homing sellers is less than 10% (in red) and those whose share of transactions by multi-homing sellers is greater than the cutoff (in black). We focus on log number of transactions by buyers who only used Rover in the preceding calendar year (top row in each panel) and market-level log number of transactions (bottom row in each panel). Across all panels, coefficients in red denote zip codes where we would expect the improvements from the merger to be bigger (as per our theory extensions in Appendix A). Otherwise each panel is identical to the top rows of Figure 6a and Figure 8a.*

A second dimension of heterogeneity is the propensity to multi-home. In the extreme case and without capacity constraints, if one side of users – buyers or sellers – fully multi-home, every user has access to every other user in the market, so combining the two platforms should have no effect on the number and type of exchanges available to each user. Given that sellers are more likely to multi-home, we look at differential effects of merging the two platforms by sellers' propensity to multi-home. In the median zip code, 8.37% of 2016 transactions were supplied by multi-homing sellers. The heterogeneity across zip codes, with an average of 23.5% and a standard deviation of 29.9%, is quite large. We separate zip codes at the 10% cutoff, i.e., where 10% of transactions are supplied by multi-homing sellers. About half of the zip codes are at each side of the cutoff. We would expect larger benefits from merging the two platforms to occur in markets with a smaller propensity to multi-home.

Figure 9b displays the results of matched sample regressions for markets with low propensity (red) and high propensity to multi-home (black). Similarly to what we found for market size, transactions by Rover users increase monotonically in the market share of the acquired platform, while market-level transactions are similar between treatment and control groups, regardless of sellers' propensity to multi-home.

6.2 Predictors of User Behavior Post-Merger

In this subsection, we offer some suggestive evidence on potential reasons why DogVacay users, despite benefiting from the increase in platform size, are worse off relative Rover users who experience the same change in platform size. To do so, we match DogVacay users to similar Rover users and explore their activity after DogVacay was shut down. In what follows, we find that DogVacay buyers have 30% fewer transactions relative to similar Rover buyers after DogVacay was shut down. Switching costs do not seem to explain the result, which instead is consistent with two alternative explanations. The first is that DogVacay buyers may continue transacting with prior partners without using the platform (disintermediation). The second is that there may be coordination failures, so that DogVacay buyers are not able to find prior transaction partners on Rover, since those sellers do not switch platforms.

Our empirical strategy is based on matching Rover and DogVacay buyers who had at least one transaction in 2016, based on their activity throughout 2016. Each buyer is associated to a unique market corresponding to the modal zip code of the sellers with whom they communicated with in 2016. We use coarsened exact matching on the number of transactions and booking inquiries, the month of the last transaction, whether they had at least one transaction in 2016 with a repeat seller, the average nightly price of all 2016 transactions, and Rover's pre-merger market share in their market. For the latter, we match DogVacay buyers from market share group $[80\%-s, 100\%-s)$ with Rover users from market share group $[s, s+20\%)$. We then conduct regression analysis using the matching weights and excluding users for whom there was no match (Hong (2010)). Our outcome of interest is

Table 2: Transactions of Buyers After DogVacay is Shut Down

	# Transactions Post DogVacay Shutdown			
	(1)	(2)	(3)	(4)
DogVacay User	-0.2234***	-0.0978***	-0.1504***	-0.0346**
	(0.0065)	(0.0057)	(0.0101)	(0.0152)
# 2016 Stays	0.0750***	0.0802***	0.0804***	0.1370***
	(0.0033)	(0.0044)	(0.0044)	(0.0083)
Avg. Nightly Price (2016)	0.0016***	0.0016***	0.0016***	0.0016***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Has Repeat Stay		0.0727***	0.0729***	-0.0846***
		(0.0129)	(0.0129)	(0.0199)
DogVacay User × Has Repeat Stay		-0.2381***	-0.3899***	-0.1071***
		(0.0126)	(0.0204)	(0.0286)
DogVacay Seller Migrated			0.0634***	0.0622***
			(0.0103)	(0.0102)
Has Repeat Stay × DogVacay Seller Migrated			0.1712***	0.1716***
			(0.0200)	(0.0185)
DogVacay User × # 2016 Stays				-0.0937***
				(0.0093)
Mean of Y	0.74	0.74	0.74	0.74
R^2	0.02732	0.02928	0.03022	0.03509
Observations	212,817	212,817	212,817	212,817
Month of Last Stay FE	✓	✓	✓	✓
Platform Share FE	✓	✓	✓	✓

This table displays coefficients of regressions where the outcome is the number of transactions of a user post-DogVacay shut-down. Each observation is a single-homing buyer who had at least one transaction in 2016. The control variables include whether the user was on DogVacay in 2016, the number of stays in 2016, the average nightly price, whether a stay in 2016 was a repeat stay with a sitter from a prior transaction, and whether the seller migrated their profile to Rover post-merger (only applies to DogVacay users). A similar analysis for sellers is presented in D.4.

a buyer's total number of transactions between August and December 2017, after DogVacay was shut down.

Our first result, displayed in Table 2, column (1), shows that even among users with similar pre-merger behavior, DogVacay users are less likely to transact after DogVacay is shut-down. The average number of transactions is 0.74, and DogVacay buyers engage in 0.22 fewer transactions relative to Rover buyers. This effect is economically important, representing an almost 30% drop in transactions. The next columns in Table 2 break down the drop across a few potential explanations.

The first potential explanation is that dog owners prefer to engage in repeat transactions with prior sellers. This is a characteristic of many platforms for local services, like food delivery or childcare platforms, although it does not apply to all platforms, such as ride-sharing platforms. On average, 50.8% of 2016 transactions are between a buyer and a seller who had already transacted with each other before. If buyers and sellers trust each other, then they may be willing to disintermediate the platform and avoid paying commission fees. The shutdown of DogVacay could thus lead some users to disintermediate rather than migrating to Rover.

If disintermediation occurs, then we would expect that DogVacay buyers with repeat transactions would have fewer post-shutdown transactions relative to similar Rover buyers. Indeed, column (2) of Table 2 finds that this is the case. DogVacay buyers with a prior repeat stay have 0.24 fewer transactions post-shutdown compared to Rover buyers with prior repeat stays. For Rover buyers instead, having a prior repeat stay is positively correlated with subsequent transactions. Taken together, the estimates imply that while Rover buyers with repeat stays engage in more transactions in the second half of 2016 relative to buyers without repeat stays – consistent with repeat stays being a positive quality signal that the platform is providing value to its users – DogVacay buyers with repeat stays actually engage in fewer transactions than buyers without repeat stays, perhaps due to disintermediation.

Another explanation for why DogVacay users are worse off relative to Rover users is that DogVacay users may not be able to find each other on Rover. Both buyers and sellers need to migrate to the acquiring platform, but not all DogVacay sellers migrated to Rover. Buyers who did not find their prior sitter may have been induced to stop searching or send a request to a less preferred sitter. If this were true, then sellers' decisions to join Rover would be correlated with the post-shutdown transactions of the buyers with whom they interacted before the merger.

To study this coordination failure, we measure whether a DogVacay buyer's last seller in 2016 migrated their account on Rover post-merger. We add this dummy variable in column (3) of Table 2 . We see that DogVacay buyers have 0.06 more transactions on Rover if their most recent DogVacay seller migrated, and that having a prior repeat stay and a seller who migrated is associated with an additional 0.17 increase in the number of transactions. This is consistent with the presence of coordination failures in addition to disintermediation.

Finally, we show that simple switching costs are unlikely to be a primary reason for the drop in post-shutdown activity by DogVacay buyers. A one-time switching cost should be most salient for users who get the least utility from pet-sitting platforms. We proxy for the value that a user gets from a pet-sitting platform with the number of transactions they exchanged in 2016. We would expect that users who engage in many transactions should be more willing to incur switching costs and transfer to Rover than users with fewer prior transactions. To test for this, in column (4) of Table 2 we add an additional predictor: we interact an indicator for whether a buyer was on DogVacay in 2016 with their number of transactions in 2016. We find a negative correlation, implying that the more active DogVacay buyers also had fewer transactions after DogVacay was shut down. We interpret this as evidence against switching costs, since we would have expected that heavy DogVacay buyers would have been more willing to incur switching costs.

To summarize, DogVacay buyers use the combined platform less than similar Rover buyers after DogVacay was shut down. This drop seems to be at least in part explained by the role that repeat transactions play in the market for pet-sitting services, and the ease with which buyers and sellers can transact off the platform. We should note however, that this is only suggestive evidence of what may explain platform differentiation, and that interactions formed on DogVacay cannot fully explain platform differentiation. Indeed, new users do not have the opportunity to engage in repeat transactions or transact off the platform with existing service providers. Yet, we see that even for new users, network effects are not large enough to favor a single platform over two competitors.

7 Conclusions

There is a heated debate over antitrust regulation of online platforms (Scott Morton et al., 2019). To maximize user surplus, should we increase competition or allow monopolies? On one hand, competition among platforms may keep commission fees down so that the share of total surplus going to platform users—buyers and sellers—is maximized. Competition can also increase platform differentiation, which can benefit consumers with heterogeneous preferences. On the other hand, if network effects are large enough such that it is more efficient to have all users participating on a single platform rather than having users spread across multiple platforms, efficiency may counterbalance the costs of a monopolistic position.

In this paper, we show that while the risk of higher prices may not materialize (perhaps when two platforms merge while still growing by attracting new users), platform differentiation can be an important factor offsetting network effects even in industries where competing platforms appear very close substitutes. Using the merger of the two largest platforms for pet-sitting services into a single platform, we evaluate how combining two platforms differentially affects markets that were already effectively experiencing a single platform—because the acquiring platform already had over 80% of the market—versus markets where the two platforms were competing on equal grounds or where the acquired platform was dominant.

We find that the acquiring platform experienced sizable network effects. Indeed, existing users of the acquiring platform increased their platform activity, more so in locations experiencing a bigger influx of users from the acquired platform. Although network effects are often assumed to exist in digital platforms, we provide one of the few empirical confirmations of their existence and magnitude.

Despite the network benefits at the platform level, we find that on average at the market level, users are equally well off with one or two platforms, as evidenced by the constant number of transactions, match rates, and proxies for match quality. Combined with our evidence that platform prices did not increase post-acquisition, our results suggest that, on average, a single platform does not provide larger consumer surplus than the sum of two competing platforms.

The average market level result is a function of differential effects of merging the two platforms across users. In particular, we find that while existing users of both platforms benefit from aggregating user participation on a single platform, users of the acquired platform are worse off relative to users of the acquiring platform. Indeed, they match at lower rates and complete fewer transactions. Some of this difference is likely driven by the importance of repeat transactions (which may lead to disintermediation) and switching costs. However, our finding that even for new users a dominant platform is not better than two competitors suggests that horizontal preferences do not simply originate from experience in using a particular platform.

Our study focuses on two platforms that intermediate local and time-sensitive services.

Other platforms with similar features include ride-sharing platforms (Lyft), food delivery platforms (Doordash), home-improvement platforms (HomeAdvisor), and child care platforms (Care.com). These platforms are well suited for a similar causal analysis of network effects because they are comprised of geographically separate markets exchanging services. The specific result in our study, that platform differentiation perfectly offsets the benefits of network effects, may or may not generalize. Our analysis of user attrition post-merger shows that repeat transactions play an important role counterbalancing network effects. As a result, platform differentiation may be more even important on child care platforms than in out setting, where repeat transactions are more frequent, and less important on ride-sharing platforms, where repeat transactions are rarer.

These results have important implications for platform competition and antitrust regulation. In our context, competition between two platforms and a single platform are comparable in terms of prices charged as well as the quantity and quality of services exchanged. Together with the fact that platform commission fees did not increase after the acquisition and that kennels and dog hotels still constitute a large share of the market for pet-sitting services, our results point to the merged platform being better able to compete with larger incumbents by reducing fixed and variable costs, such as technology investments, customer acquisition costs, and labor costs. These considerations would of course be different in a context where the acquiring platform were the only option to access pet-sitting services.

The null effect at the market level occurs despite the presence of network effects that exist at the platform level, and despite the fact that the two platforms appear so similar in the way they intermediate services. In other contexts where mergers occur between platforms that are not as close substitutes, horizontal preferences and user attrition are likely to play an even bigger role when comparing a single dominant platform versus multiple competitors. In those cases, it may be particularly important to ensure platform competition.

Given the difficulty of causally linking a merger in 2017 to events occurring many months later, our evidence concerns just the short-run. Extending theories and empirical approaches to estimate the effects of mergers beyond the first few months would be crucial to assess the costs and benefits of acquisitions of early stage competitors by incumbent platforms.

We have also focused on local, as opposed to global effects. Many important platforms also enjoy global network effects across geographies, such as platforms for virtual work like Upwork, or app platforms like iOS and Android. We are able to measure whether people living in the same geography are better off with two competing platforms versus a single platform. Our paper does not speak to whether it is better for consumers to have two platforms with non-overlapping geographic presence or a single platform active in all geographies (Zhu et al., 2019), nor are we able to measure cost efficiencies from the acquisition. Expanding our analysis to estimate externalities across geographic clusters and cost savings is a fruitful avenue for future research.

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APPENDIX TO "Dog Eat Dog: Measuring Network Effects Using a Digital Platform Merger"

By Chiara Farronato, Jessica Fong, Andrey Fradkin

A Extensions to the Theory Model

In this Appendix, we discuss one extension to the theory model from Section 4 that relaxes the assumption that the market is covered and thus all users of platform 2 migrate to platform 1 after the acquisition. We also discuss two additional extensions – varying market size and allowing for multi-homing – that motivate some heterogeneous effects that we test in Section 6.

In the first extension, we assume that a $\lambda \in (0, 1)$ share of platform 2 users do not migrate to platform 1 after the acquisition. This means that when the platforms merge in a market where platform 1 has market share s, a mass of $s + (1 - \lambda)(1 - s) = 1 - \lambda(1 - s)$ will use platform 1. In this case the predictions for how the utility of platform 1 users change after the merger (Equation (1)) remain the same. What is different is the implication for the change in utility experienced by users of platform 2 in markets with share $1 - s$ relative to users of platform 1 in markets with share s (Equation (3)). In particular, since $\bar{u}_2(1-s)$ and $\bar{u}_1(s)$ have the same network effects component $v(s)$, we have that $\left[\bar{u}_1^2(1, 1-s) - \bar{u}_2(1-s)\right] - \left[\bar{u}_1^1(1, s) - \bar{u}_1(s)\right] = v(1 - \lambda s) - v\left(1 - \lambda(1 - s)\right) - (1 - s)$. The first component $v(1 - \lambda s) - v\left(1 - \lambda(1 - s)\right)$ starts positive for s=0, decreases in s, and ends negative for $s = 1$. The second component, $-(1 - s)$ is instead always negative and increasing towards 0 as s increases. The sum of the two results in a difference in utilities between platform 2 and platform 1 users that is not necessarily always negative and increasing in s.

Allowing for platform 2 users not to migrate to platform 1 also changes the implications for the market level benefits from network effects. In particular, the average utility from network effects in Equation (4) changes to $v\left(1 - \lambda(1 - s)\right) - sv(s) - (1 - s)v(1 - s)$, which, instead of reaching a peak at $s = 0.5$, reaches a peak at a point $s > 0.5$. This result justifies our empirical strategy of breaking market shares into 5 groups and allowing for non-linearities in the relationship between our outcomes of interest and market share.

The second extension relates to total market size. In Section 4 we have assumed a unit-mass of buyers, but what happens if the mass of consumers increases? Let us denote n the mass of consumers. We then have that $\bar{u}_1(s,n) = v(sn) - 0.5s$ and $\bar{u}_2(s,n) = v\left((1-s)n\right) - 0.5(1-s)$. Equation (1) then becomes $\bar{u}_1^1(1,s,n) - \bar{u}_1(s,n) = v(n) - v(sn)$. One possibility is that $v()$ is increasing as long as the number of platform participants is less than a maximum threshold T, and is flat after that: $v(sN) = v(min\{sN,T\})$. In other words, the first T users to a platform contribute to increasing value for everyone else, but then the marginal effect of every additional user is null.

If $v(sN) = v(min\{sN,T\})$, the change in utility for platform 1 users, which is equal to $\bar{u}_1^1(1,s,n) - \bar{u}_1(s,n) = v(n) - v(sn)$, is non-monotone in n (dashed line in Figure A.1a). In particular, it will be positive and increasing in n if $n \leq T$; it will be positive but decreasing in n for $sn < T < n$; and it will be zero for $sn \geq T$. On average, the network effects benefits from the merger will be bigger when n is smaller. The comparative statics are similar at the market level (solid line in Figure A.1a). The market-level change in average utility after the merger is $\bar{u}(1,n) - [s\bar{u}_1(s,n) + (1-s)\bar{u}_2(s,n)] = [v(n) - sv(sn) - (1-s)v\left((1-s)n\right)] - s(1-s)$. The network effects term, $v(n) - sv(sn) - (1-s)v\left((1-s)n\right)$, depends on n while the horizontal preferences term, $s(1-s)$, is independent of n. This implies that the change in market-level utility after the merger will be bigger on average when n is smaller.

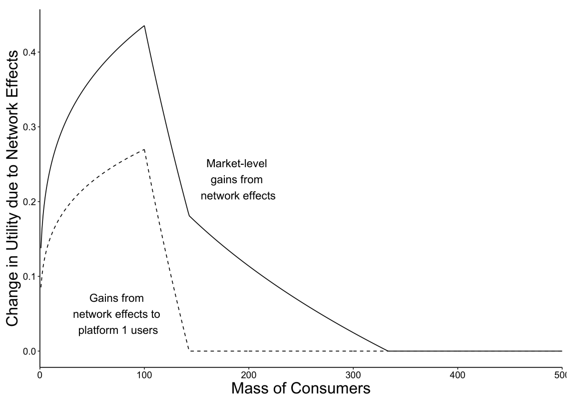
The third and final extension relates to the degree of multi-homing. In Section 4 we have assumed no multi-homing, but what happens if a share of users is available on both platforms before the merger? Multi-homing can be incorporated in our model by assuming that users can choose to join any platform whose utility, which is $u_{i1}(s) = v(s) - d_i$ for platform 1 and $u_{i2}(s) - c = v(1-s) - (1-d_i) - c$ for platform 2, is greater than a constant k. If a user multi-homes, we further assume that their average utility is a simple average of the utilities from the two platforms.

Let γ denote the share of multi-homers, i.e. all i for which $u_{i1}(s) \geq k$ and $u_{i2}(s) - c \geq k$. All else equal, a lower k will increase multi-homing. As before, s denotes the point of indifference between $u_{i1}(s)$ and $u_{i2}(s) - c$. With multi-homing, as long as users located at

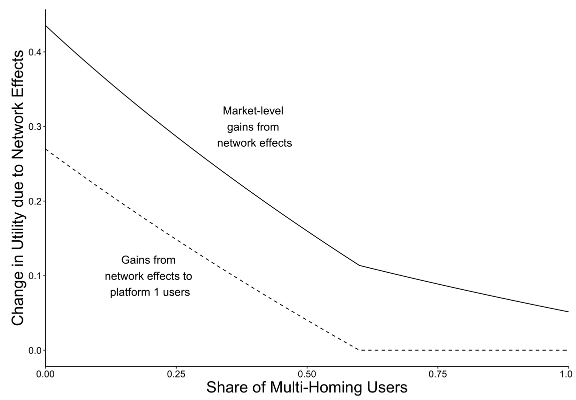
0 and 1 do not multi-home, the point s is located on the $(0,1)$ line such that exactly half of multi-homing users are to the left of s and the other half are to the right.

The change in utility for single-homing platform 1 users is equal to $\bar{u}_1^1(1,s,\gamma)-\bar{u}_1(s,\gamma) = v(1)-v\left(min\{s+\gamma/2,1\}\right)$ and is decreasing in γ. When computing the market-level change in average utility after the merger, $\bar{u}(1,n)-[s\bar{u}_1(s,n)+(1-s)\bar{u}_2(s,n)]$, the network effects term can be simplified to $v(1)-sv(s+0.5*\gamma)-(1-s)v(1-s+0.5*\gamma)$, which is also decreasing in γ. These comparative statics imply that the change in platform level and market level utility due to network effects will be bigger on average when γ is small (Figure A.1b).

Figure A.1: Heterogeneous Effects of the Merger



(a) Heterogeneous Effects by Market Size



(b) Market-Level Surplus per Person

Both panels plot platform-level (dashed lines) and market-level (solid lines) changes in surplus due to network effects as a function of market size n (Panel a) and share of multi-homing users γ (Panel b). In Panel (a), the solid line plots $\bar{u}_1^1(1,s,n)-\bar{u}_1(s,n) = v(n)-v(sn)$, while the dashed line plots the network effect component in $\bar{u}(1,n)-[s\bar{u}_1(s,n)+(1-s)\bar{u}_2(s,n)]$, which is equal to $v(sn)-sv(sn)-(1-s)v\left((1-s)n\right)$. For the plot we assume $v(s) = min\{sn,100\}^{0.25}$, we set $s = 0.7$, and we let the mass of consumers n vary between 1 and 500. In Panel (b) The solid line plots $\bar{u}_1^1(1,s,\gamma)-\bar{u}_1(s,\gamma) = v(1)-v(s+0.5*\gamma)$, while the dashed line plots the network effect component in $\bar{u}(1)-[s\bar{u}_1(s,\gamma)+(1-s)\bar{u}_2(s,\gamma)]$, which is equal to $v(1)-sv(s+0.5*\gamma)-(1-s)v(1-s+0.5*\gamma)$. For this plot we assume $v(s) = (100s)^{0.25}$, we set $s = 0.7$, and we let the share of multi-homers γ vary between 0 and 1.

B Extensions to the Empirical Results

In this appendix, we provide additional results to Section 6.

First, we provide results on additional outcomes for the results presented in Figure 6. Figure B.1 presents additional outcomes for users who were involved in booking inquiries only on Rover in the calendar year precending the current month. Figure B.2 is analogous for existing DogVacay users.

Second, Figure B.3 provides results on additional outcomes for the results presented in Figure 7.

Third, we provide results on additional outcomes for the results presented in Figure 8. Figure B.4 presents additional outcomes at the market level (i.e., aggregating outcomes across the two competing platforms). Figure B.5 provides additional outcomes for users who were involved in a booking inquiry (on Rover or DogVacay) for the first time in the current month.

Fourth, we provide results for multi-homing users, i.e. users who were involved in booking inquiries on both platforms in the previous calendar year, in Figure B.6.

Fifth, we present the coefficients from the matching regressions in tables for better readability. Instead of estimating a coefficient for each month, as in Equation (5), we estimate a coefficient for the transition period (March to June 2017) and post-acquisition (July to December 2017). Instead of normalizing February 2017 to 0, we normalize all 3 months before the acquisition (December 2016 - February 2017) to 0. We refer to this period as the baseline. We also estimate a pre-trend coefficient for the 3 months before the baseline. The interpretation of each coefficient is the average difference between the treated market and a matched control unit in the respective time period, relative to the baseline period. Note that if all matched markets had identical pre-trends, we would expect the coefficient for the 3 months before the baseline to be not statistically different from 0. The below regression is estimated separately for each Rover market share group.

$$\begin{aligned} y_{zt} - y_{z't} = \alpha + \beta_1 \mathbf{1}\{t \in 3\ Months\ PreBaseline\} + \beta_2 \mathbf{1}\{t \in\ Transition\} \\ + \beta_3 \mathbf{1}\{t \in PostMerger\} + \epsilon_{z,z',t} \quad (7) \end{aligned}$$

Results are presented in the five Tables B.1 through B.5.

Sixth, we provide results using a simple estimation without matching zip codes, which accounts for differential pre-trends across market share groups. We replace Equation (5) with the following, un-matched, equation:

$$y_{zt} = \beta_{s(z)t} + \gamma_{s(z)}t + \delta_{s(z)}\mathbb{1}\{t \geq Dec2016\} + \mu_t + \mu_z + \epsilon_{zt}. \tag{8}$$

By adding $\gamma_{s(z)}t + \delta_{s(z)}\mathbb{1}\{t \geq Dec2016\}$, we allow for the observations in the treatment and control groups to have a different linear pre-trend. Results are presented in Figure B.7.

Finally, in the paper we have defined markets at the zip code level. The problem with this definition is that zip codes are not independent of each other. There are over 20 zip codes in Seattle, and dog owners may search for sitters across many zip codes within their city. It is possible that in zip code A, Rover had 50% of the market before the acquisition, and in neighboring zip code B it had 75% of the market. After the acquisition, the bigger increase in options in zip code A may cause some dog owners to substitute away from sitters in B towards sitters in A. This would amplify the post-acquisition outcome differences between A and B. The above example demonstrates how the stable unit treatment value assumption (SUTVA) of causal inference does not hold. This bias has been studied in the context of online marketplaces for inferences from A/B experiments (Holtz and Aral, 2018).

To reduce bias from violations of SUTVA, we form clusters of zip codes separately for each CBSA. The construction of clusters must balance two competing objectives. On one hand, larger clusters reduce interactions between units of observation. On the other hand, larger clusters mean fewer observations and less statistical power. For this reason, we choose a clustering procedure that allows us to explore this trade-off.

We use a geographically constrained hierarchical clustering algorithm,[32] which allows us to impose that a cluster be formed by a spatially contiguous set of zip codes. A key advantage of this algorithm is that more aggregated clustering nests less aggregated clustering — i.e. all zip codes belonging to one cluster when the clustering is less aggregated map to the same (larger) cluster when the clustering is more aggregated. Therefore, it is easy to vary the desired size of clusters to evaluate the bias-precision trade-off.

[32] We use the R package *ClustGeo* (Chavent et al., 2018).

The clustering procedure takes in two dissimilarity matrices. The first matrix gives dissimilarities in the "feature space" and it is computed from data on co-occurrence of searches,[33] i.e. cases when a dog owner sees listings from two zip codes in the same set of search results. The more frequently the two zip codes co-occur, the more similar they are. The second matrix gives the dissimilarities in the "constrained space", and each element is 0 or 1 depending on whether two zip codes are geographically contiguous. There is a final parameter, α, which controls the importance of each dissimilarity matrix — higher α increases the importance of the geographic distances. We also have the freedom to choose the number of clusters in a given CBSA. We choose α and the number of clusters to maximize the number of observations — clusters — subject to a threshold on the level of interactions among distinct clusters.

Specifically, we implement the Ward-like hierarchical clustering method with spatial constraints proposed by Chavent et al. (2018). The algorithm takes in the following inputs:

- A dissimilarity matrix D_0 composed of distances $(d_{0,ij})$ between zip codes i and j. The distances are based on how frequently two zip codes occur together in search results.[34] We measure co-occurrences in the following way. For each search s, we take the corresponding search results and create all unique zip code pairings. For the pair of zip codes i and j we compute the probability of obtaining the pair i, j out of a draw of two search results from search s.[35] The probability $p_{s,ij}$ takes values between 0—if i or j do not appear in the search results from search s—and .5 —if search s has only two results, one from zip code i and the other from zip code j. We aggregate at the zip code-pair level by summing over searches, and we normalize by the minimum number of searches with results from zip code i or zip code j. We call this the co-occurrence share. The distance $d_{0,ij}$ is equal to the reciprocal of the co-occurrence share:

$$d_{0,ij} = \frac{min(\sum_s \mathbb{1}\{\text{search } s \text{ contains zip code } i\}, \sum_s \mathbb{1}\{\text{search } s \text{ contains zip code } j\})}{\sum_s \mathbb{1}\{\text{search } s \text{ contains zip codes } i \text{ and } j\} p_{s,ij}}$$

  Infinite values are set to $2 \max_{d_{0,ij}<\infty} d_{0,ij}$. This guarantees that after normalizing the

[33] We use 2017 search results from Rover to construct the matrix of dissimilarity in the feature space.
[34] We have search results data from 2017 for Rover.
[35] For computational ease, we sample search results with replacement to compute $p_{s,ij}$.

dissimilarity matrix $\frac{D_0}{max(D_0)}$, the distance values are either 1 (for zip codes with no co-occurrences) or between 0 and .5. The diagonal values are set to 0.

- A matrix D_1 of geographic distances $(d_{1,ij})$ between zip codes i and j. The distance $d_{1,ij}$ is equal to 1 if zip codes i and j are not geographic neighbors, and it is equal to 0 otherwise. Every zip code has a distance 0 from itself so the diagonal is once again set to 0.

- A set of weights (w_i), one for each zip code. We set $w_i = 1$ for all zip codes.

- A parameter, α, which determines the importance of the geographic distance matrix D_1 relative to the co-occurrence distance matrix D_0.

The values in the normalized matrix $\frac{D_0}{max(D_0)}$ and in D_1 are all between 0 and 1 so the matrices have the same order of magnitude. The algorithm then proceeds in steps starting from a partition $\mathcal{P}_n^\alpha$ where each of the n zip codes is a separate cluster. At each following step k, for each cluster $\mathcal{C}_k^\alpha$ we compute the mixed pseudo inertia as

$$I_\alpha\left(\mathcal{C}_k^\alpha\right) = (1-\alpha)\sum_{i\in\mathcal{C}_k^\alpha}\sum_{j\in\mathcal{C}_k^\alpha}\frac{w_i w_j}{2\mu_k^\alpha}d_{0,ij}^2 + \alpha\sum_{i\in\mathcal{C}_k^\alpha}\sum_{j\in\mathcal{C}_k^\alpha}\frac{w_i w_j}{2\mu_k^\alpha}d_{1,ij}^2,$$

where $\mu_k^\alpha = \sum_{i\in\mathcal{C}_k^\alpha} w_i$ is the aggregate weight of cluster $\mathcal{C}_k^\alpha$. The mixed pseudo inertia is a measure of homogeneity within a cluster, which is a function of the dissimilarity values in characteristics and geography. In order to obtain a new partition $\mathcal{P}_k^\alpha$ in k clusters from a given partition $\mathcal{P}_{k+1}^\alpha$ in $k+1$ clusters, we choose to combine clusters $\mathcal{A}$ and $\mathcal{B}$ belonging to $\mathcal{P}_{k+1}^\alpha$ to minimize mixed within cluster inertia:

$$\arg \min_{\mathcal{A},\mathcal{B}\in\mathcal{P}_{k+1}^\alpha} I_\alpha\left(\mathcal{A}\cup\mathcal{B}\right) - I_\alpha\left(\mathcal{A}\right) - I_\alpha\left(\mathcal{B}\right).$$

We can graphically represent the hierarchically-nested set of partitions $\{\mathcal{P}_n^\alpha, ..., \mathcal{P}_k^\alpha, ...\mathcal{P}_1^\alpha\}$ with a tree. We are free to choose where to 'cut' the tree, i.e. the number k of clusters to include in our partition. We are also free to choose α. To select α and k we implement the following algorithm:

1. We divide zip codes into Core-Based Statistical Areas (CBSAs). We perform steps

2-4 separately for each CBSA, which means that we choose α, k separately for each CBSA.[36]

2. We implement the hierarchical clustering with spatial constraints for a grid of values for $\alpha \in \{.25, .5, .75, 1\}$ and for k between 1 and $min(100, n)$, where n is the number of zip codes in the CBSA.[37]

3. Our measure of cluster quality Q_k^α is derived from the search data in a similar manner to the dissimilarity matrix. For each cluster in partition $\mathcal{P}_k^\alpha$ we compute the weighted number of search co-occurrences within each cluster and divide it by the weighted total co-occurrences in the CBSA. We then sum across clusters within CBSA to get the cluster quality.

$$Q_{k,CBSA}^\alpha = \frac{\sum_{c \in \mathcal{C}_k^\alpha} \sum_{i,j \in c} \sum_s \mathbb{1}\{\text{search } s \text{ contains zip codes } i \text{ and } j\} p_{k,ij}}{\sum_{i,j \in CBSA} \sum_s \mathbb{1}\{\text{search } s \text{ contains zip codes } i \text{ and } j\} p_{k,ij}}.$$

If all co-occurrences are within cluster, then $Q_k^\alpha = 1$, representing a perfect clustering. In practice, some co-occurrences inevitably occur across clusters. These are driven by the dispersion of search results shown by Rover's ranking algorithm and by the willingness of owners to consider many zip codes.

4. We pick the partition $\mathcal{P}_k^\alpha$ with the highest k subject to $Q_k^\alpha > .65$.

Intuitively we find the partition with the most distinct clusters subject to a minimum quality threshold that controls the potential interdependencies across clusters. Setting the threshold at 65% means that on average 65% of requests have booking inquiries only within the cluster. Note that this threshold is far from 100%. 100% means that all booking inquiries for the same request happen within the same cluster.

Figure B.8 plots the clusters that our procedure finds in four of the largest cities in our data. The clusters are reasonably contiguous in space, and in general much larger than individual zip codes. On average each cluster has 6.26 zip codes. There are also a

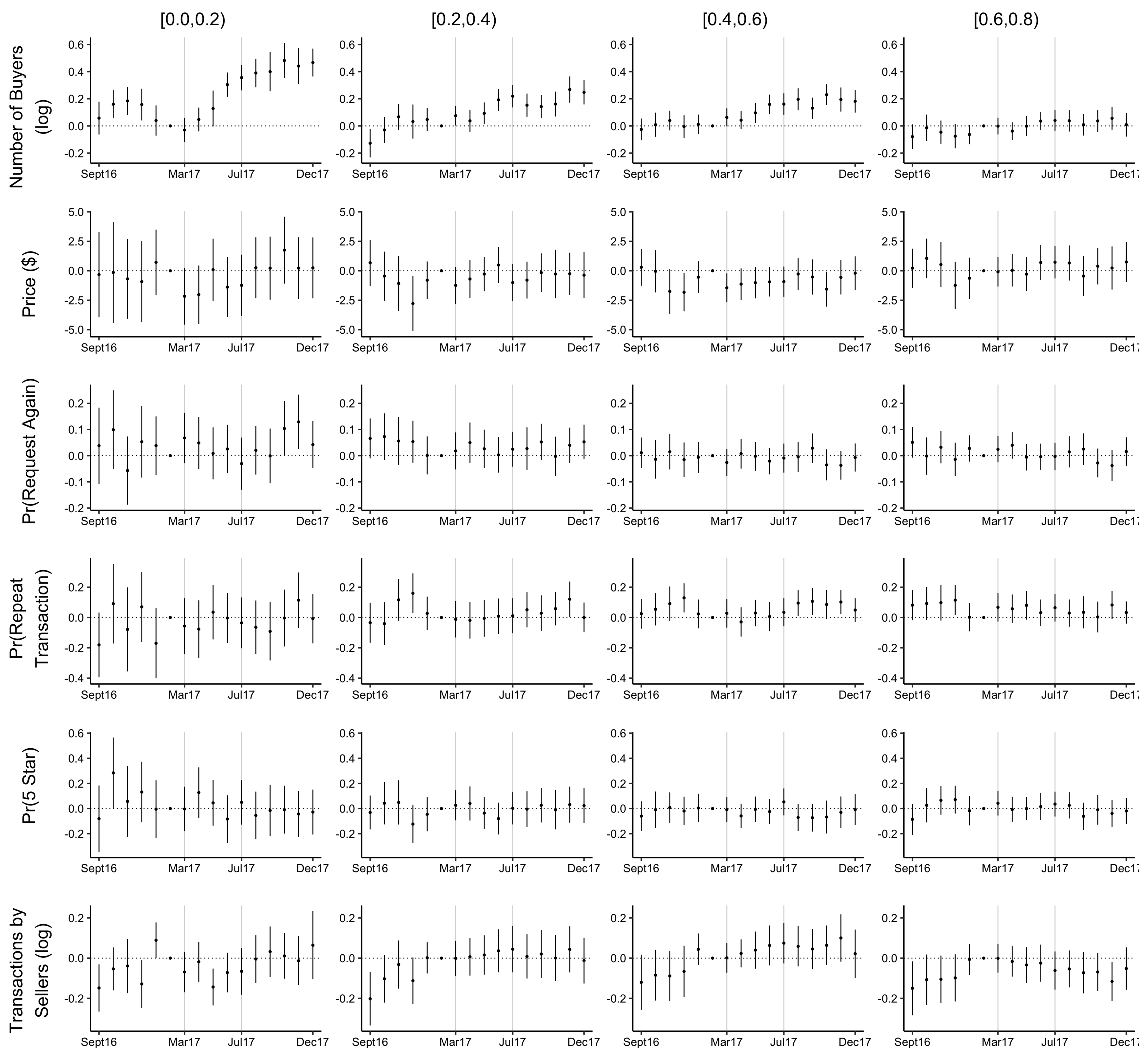
[36] A handful of CBSAs have zip codes with no neighbors. For example, Odessa, TX, has a zip code that only borders an airport. These zip codes pose a problem for the Ward-based algorithm. In this case we cluster zip codes ignoring the geographic dissimilarity matrix. So for these CBSAs, we set $\alpha = 0$.

[37] For CBSAs with more than 200 zip codes the 25 limit can be binding in practice, so we use k between 1 and $min(50, n)$, where n is the number of zip codes in the CBSA.

few separate clusters in each city, implying that not all zip codes in a CBSA are equally substitutable between one another.

We then estimate Equation (5) with cluster-month as unit of observation. Results are presented in Figure B.9.

Figure B.1: Estimates of Merger Effects – Additional Outcomes for Rover Users



Regression estimates of Equation (5) *for additional outcomes of users who posted requests only on Rover in the previous calendar year. The first five rows focus on outcomes of existing Rover buyers, while the last row considers current transactions involving existing Rover sellers. Otherwise the figure is identical to Figure 6a. Outcomes for multi-homing users are in Appendix Figure B.6.*

Table B.1: Estimates of Merger Effects - Rover Users

Period	Rover Share	Transactions by Buyers (log)	Request Match Rate	Number of Buyers (log)	Price ($)	Pr(Request Again)	Pr(Repeat Transaction)	Pr(5 Star)	Transactions by Sellers (log)
3 Months Before Baseline	[0.0,0.2)	0.114***	-0.034	0.066	-0.446	-0.003	-0.039	0.029	-0.068*
	[0.2,0.4)	-0.034	-0.014	-0.058*	0.786	0.051*	-0.042	0.057	-0.073*
	[0.4,0.6)	-0.02	-0.035**	0.006	0.25	0.011	0.011	-0.019	-0.089**
	[0.6,0.8)	-0.037	-0.037**	-0.002	1.157*	0.022	0.054	-0.019	-0.082**
Transition	[0.0,0.2)	-0.053	-0.005	0.047	-1.356	0.01	0.022	-0.02	-0.065*
	[0.2,0.4)	0.025	-0.001	0.072**	0.588	0.01	-0.053	0.026	0.052
	[0.4,0.6)	0.067**	0	0.088***	-0.41	-0.004	-0.035	-0.02	0.039
	[0.6,0.8)	0.007	-0.023**	0.044**	0.684	0.008	0.024	-0.002	0.018
Post-Merger	[0.0,0.2)	0.263***	0.041*	0.358***	0.17	0.016	0.018	-0.042	0.012
	[0.2,0.4)	0.174***	0.039**	0.171***	0.538	0.018	-0.005	0.055	0.055
	[0.4,0.6)	0.167***	0.013	0.18***	0.053	-0.004	0.032	-0.024	0.069*
	[0.6,0.8)	0.028	-0.024*	0.075***	1.013*	-0.007	0.008	-0.022	-0.032

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table displays the estimates of Equation (7) for buyers who engaged in a booking inquiry on Rover in 2015, 2016 and is analogous to Figure 6a. The baseline is the 3 months before the merger announcement (December 2016 - February 2017).

Table B.2: Estimates of Merger Effects - DogVacay Users

Period	Rover Share	Transactions by Buyers (log)	Request Match Rate	Number of Buyers (log)	Price ($)	Pr(Request Again)	Pr(Repeat Transaction)	Pr(5 Star)	Transactions by Sellers (log)
3 Months Before Baseline	[0.0,0.2)	-0.044	-0.014	0.008	-3.375	0.043	-0.06	0.087	0.128***
	[0.2,0.4)	-0.006	0.012	0.03	-2.336	-0.006	0.157*	-0.043	-0.002
	[0.4,0.6)	-0.05*	-0.022	0.02	1.133	-0.018	0.038	-0.068	-0.069**
	[0.6,0.8)	-0.073***	0	-0.06**	-2.234	0.04	0.134*	0.003	-0.082***
Transition	[0.0,0.2)	0.074***	0.009	-0.001	-0.327	-0.064	-0.144**	-0.006	0.1***
	[0.2,0.4)	0.077***	0.019	-0.008	0.964	-0.029	-0.07	-0.052	0.123***
	[0.4,0.6)	0.038	-0.01	-0.032	-0.279	-0.034	-0.016	0.057	0.096***
	[0.6,0.8)	0.043*	0.006	-0.01	-1.053	0.057	0.041	-0.036	0.117***
Post-Merger	[0.0,0.2)	-0.332***	-0.072**	-0.362***	-0.485	-0.085*	-0.126*	0.026	-0.042
	[0.2,0.4)	-0.322***	-0.057**	-0.366***	1.037	-0.044	-0.106**	0.008	-0.039
	[0.4,0.6)	-0.21***	-0.051**	-0.245***	-0.011	-0.032	-0.003	0.022	-0.032
	[0.6,0.8)	-0.113***	-0.01	-0.176***	-1.346	0.04	-0.011	0.055	0.029

Note: *p<0.1; **p<0.05; ***p<0.01

This table displays the estimates of Equation (7) for buyers who engaged in a booking inquiry on DogVacay in 2015, 2016 and is analogous to Figure 6b. The baseline is the 3 months before the merger announcement (December 2016 - February 2017).

Table B.3: Estimates of Merger Effects - DogVacay Users Relative to Rover Users

Period	Rover Share	Transactions by Buyers (log)	Request Match Rate	Buyers (log)	Price ($)	Pr(Request Again)	Pr(Repeat Again)	Pr(5 Star)	Transactions by Sellers (log)
3 Months Before Baseline	[0.0,0.2)	0.01	0.05*	-0.063**	2.361**	-0.002	-0.066	-0.008	0.012
	[0.2,0.4)	0.051	0.042**	-0.005	0.422	0.001	0.06*	0.022	-0.004
	[0.4,0.6)	0.085***	0.045***	0.029	0.952**	0.003	-0.004	0.008	0.071*
	[0.6,0.8)	0.126***	0.072***	0.045**	0.576	-0.013	0.021	0.004	0.128***
	[0.8,1.0]	0.12***	0.036***	0.1***	0.109	0.021	0.006	0.018	0.179***
Transition	[0.0,0.2)	-0.094***	-0.041**	-0.073***	0.337	-0.006	-0.025	0.005	-0.073**
	[0.2,0.4)	-0.084***	-0.035**	-0.053**	-0.554	0.009	0.017	-0.027	-0.068**
	[0.4,0.6)	-0.078***	-0.027**	-0.051***	0.394	-0.009	-0.035*	0.008	-0.088***
	[0.6,0.8)	-0.054**	-0.01	-0.039**	0.032	-0.017	-0.045**	-0.045*	-0.084***
	[0.8,1.0]	-0.021	-0.013	-0.007	0.21	-0.022**	-0.042*	-0.007	-0.043**
Post-Merger	[0.0,0.2)	-0.103***	-0.039**	-0.08***	-0.666	0.015	-0.007	0.043	-0.063
	[0.2,0.4)	-0.129***	-0.08***	-0.036	-1.844***	0.028	0.004	0.057*	-0.069**
	[0.4,0.6)	-0.164***	-0.074***	-0.065***	-0.879**	0.003	-0.037*	0.046**	-0.146***
	[0.6,0.8)	-0.168***	-0.062***	-0.092***	-1.345***	0.013	-0.057**	-0.003	-0.073**
	[0.8,1.0]	-0.129***	-0.061***	-0.049*	-1.33***	-0.024*	-0.049*	0.012	-0.05

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table displays the regression estimates of Equation 6, and is analogous to Figure 7. The baseline is the 3 months before the merger announcement (December 2016 - February 2017). The regression includes platform, year-month, and zip code fixed effects. Standard errors are clustered at the CBSA level.

Table B.4: Estimates of Merger Effects - Market Level

Period	Rover Share	Number of Buyers (log)	Number of Sellers (log)	Transactions (log)	Request Match Rate	Price ($)	Pr(Request Again)	Pr(Repeat Transaction)	Pr(5 star)
3 Months Before Baseline	[0.0,0.2)	-0.002	0.025	0.043	0.023	0.45	-0.01	-0.008	0.031
	[0.2,0.4)	-0.042	-0.018	-0.017	0.014	0.645*	-0.013	-0.013	-0.004
	[0.4,0.6)	-0.009	-0.006	-0.007	0	0.428	-0.007	-0.008	-0.007
	[0.6,0.8)	-0.042*	-0.038**	-0.05*	-0.001	0.128	0.001	0.025*	-0.004
Transition	[0.0,0.2)	-0.015	0.014	-0.023	-0.013	-0.186	-0.034*	-0.006	-0.019
	[0.2,0.4)	-0.006	0.001	0.013	0.01	0.386	-0.01	-0.03*	-0.018
	[0.4,0.6)	-0.005	0.006	0.015	0.004	0.04	0.006	-0.021	-0.02
	[0.6,0.8)	-0.015	0.009	-0.027	-0.006	0.165	0.004	0	-0.038***
Post-Merger	[0.0,0.2)	-0.021	-0.036	-0.077*	-0.035***	-1.622***	-0.028	0.012	-0.015
	[0.2,0.4)	-0.043	-0.046**	-0.073*	-0.012	-0.624*	-0.012	-0.018	-0.022
	[0.4,0.6)	0.039	-0.009	0.044	0.001	-0.133	0.005	0	-0.015
	[0.6,0.8)	0	0.006	-0.036	-0.012	0.018	0.004	0.011	0

Note: *p<0.1; **p<0.05; ***p<0.01

This table displays the estimated coefficients of each period in Equation (7) and is analogous to Figure 8a. The baseline is the 3 months before the merger announcement (December 2016 - February 2017).

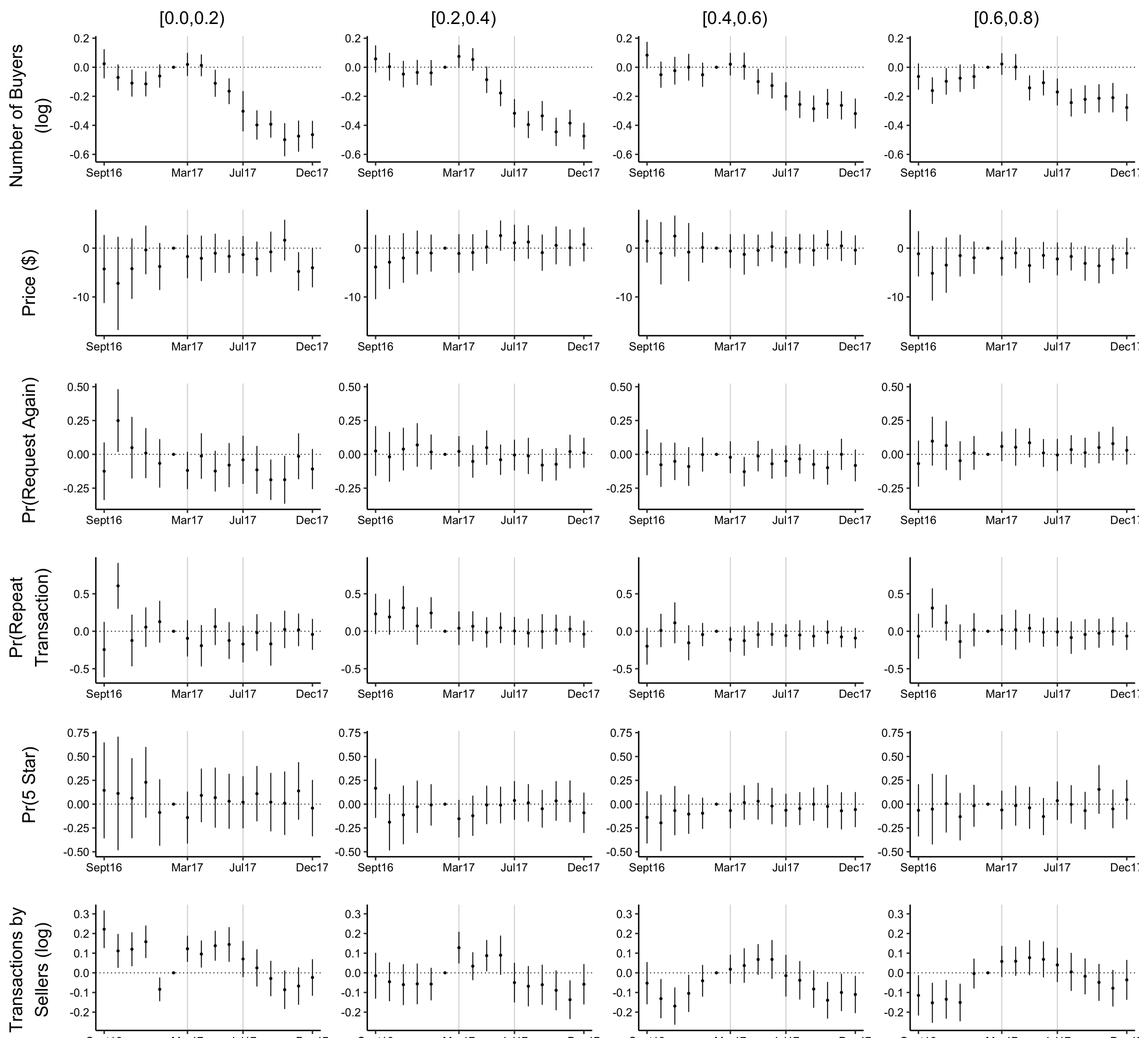
Table B.5: Estimates of Merger Effects - New Users

Period	Rover Share	Number of Buyers (log)	Number of Sellers (log)	Transactions (log)	Request Match Rate	Price ($)	Pr(Request Again)	Pr(Repeat Transaction)	Pr(5 star)
3 Months Before Baseline	[0.0,0.2)	-0.01	0.025	0.074**	0.03	1.284	-0.018	0.007	0.021
	[0.2,0.4)	-0.021	0.055**	0.058*	0.025**	0.53	0.021	-0.019	-0.021
	[0.4,0.6)	0.006	0.005	0.015	0	-0.089	-0.001	-0.018	-0.002
	[0.6,0.8)	-0.027	0.018	-0.023	0.004	-0.084	0.038*	-0.007	0.028
Transition	[0.0,0.2)	-0.048	-0.01	-0.007	0.005	1.273	-0.015	0.011	0.003
	[0.2,0.4)	-0.038	0.023	-0.004	0.006	0.239	-0.025	-0.046**	-0.008
	[0.4,0.6)	-0.048	-0.004	-0.049	-0.007	-0.014	0.005	-0.029	-0.008
	[0.6,0.8)	-0.03	0	-0.06**	-0.013	-0.5	0.019	-0.02	-0.024
Post-Merger	[0.0,0.2)	0.016	-0.026	0.006	-0.013	0.129	0.037	0.023	-0.023
	[0.2,0.4)	-0.03	-0.019	-0.037	-0.008	0.524	0.014	-0.012	-0.026
	[0.4,0.6)	0.023	-0.015	0.013	-0.009	-0.25	0.027	-0.003	-0.002
	[0.6,0.8)	0.01	-0.014	-0.034	-0.014	0.368	0.045**	-0.005	0.005

Note: *p<0.1; **p<0.05; ***p<0.01

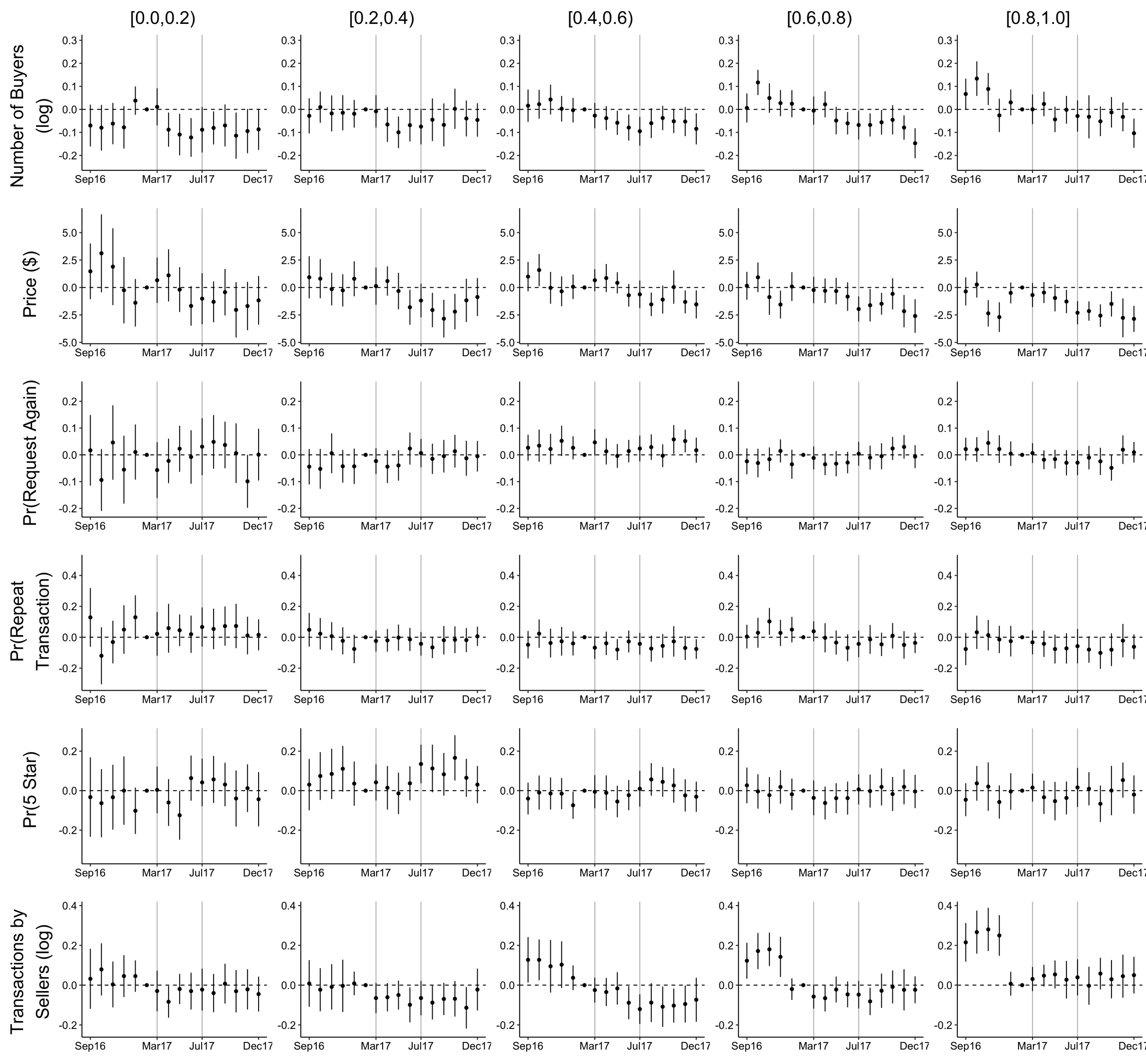
This table displays the estimates of Equation (7) for buyers who never posted a request or were involved in a booking inquiry on any platform prior to the current month and is analogous to Figure 8b. The baseline is the 3 months before the merger announcement (December 2016 - February 2017).

Figure B.2: Estimates of Merger Effects – Additional Outcomes for DogVacay Users



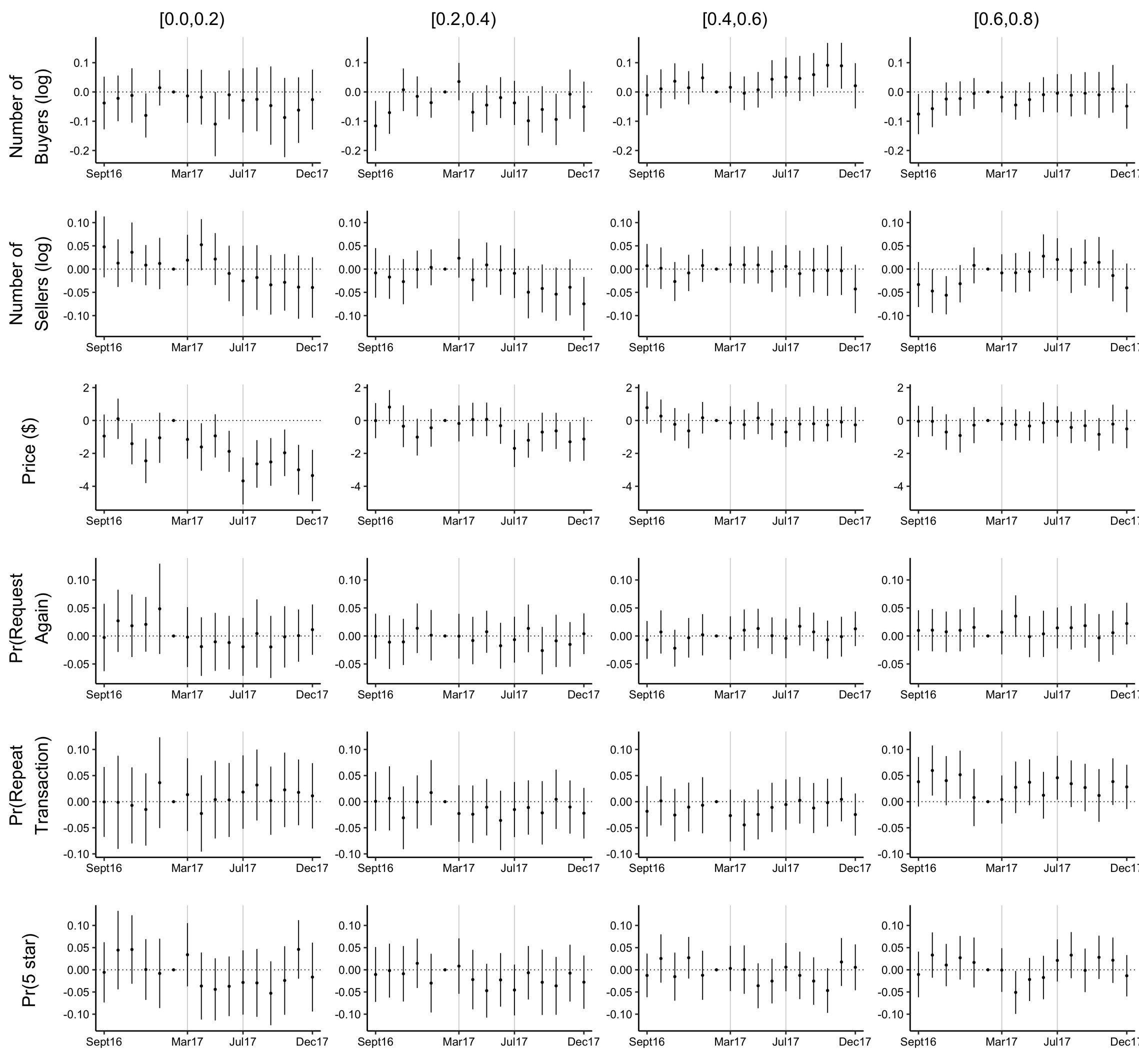
Regression estimates of Equation (5) *for additional outcomes of users who posted requests only on DogVacay in the previous calendar year. The first five rows focus on outcomes of existing DogVacay buyers, while the last row considers current transactions involving existing DogVacay sellers. Otherwise the figure is identical to Figure 6b. Outcomes for multi-homing users are in Appendix Figure B.6.*

Figure B.3: Estimates of Merger Effects – Additional Outcomes for the Comparison of DogVacay and Rover Users



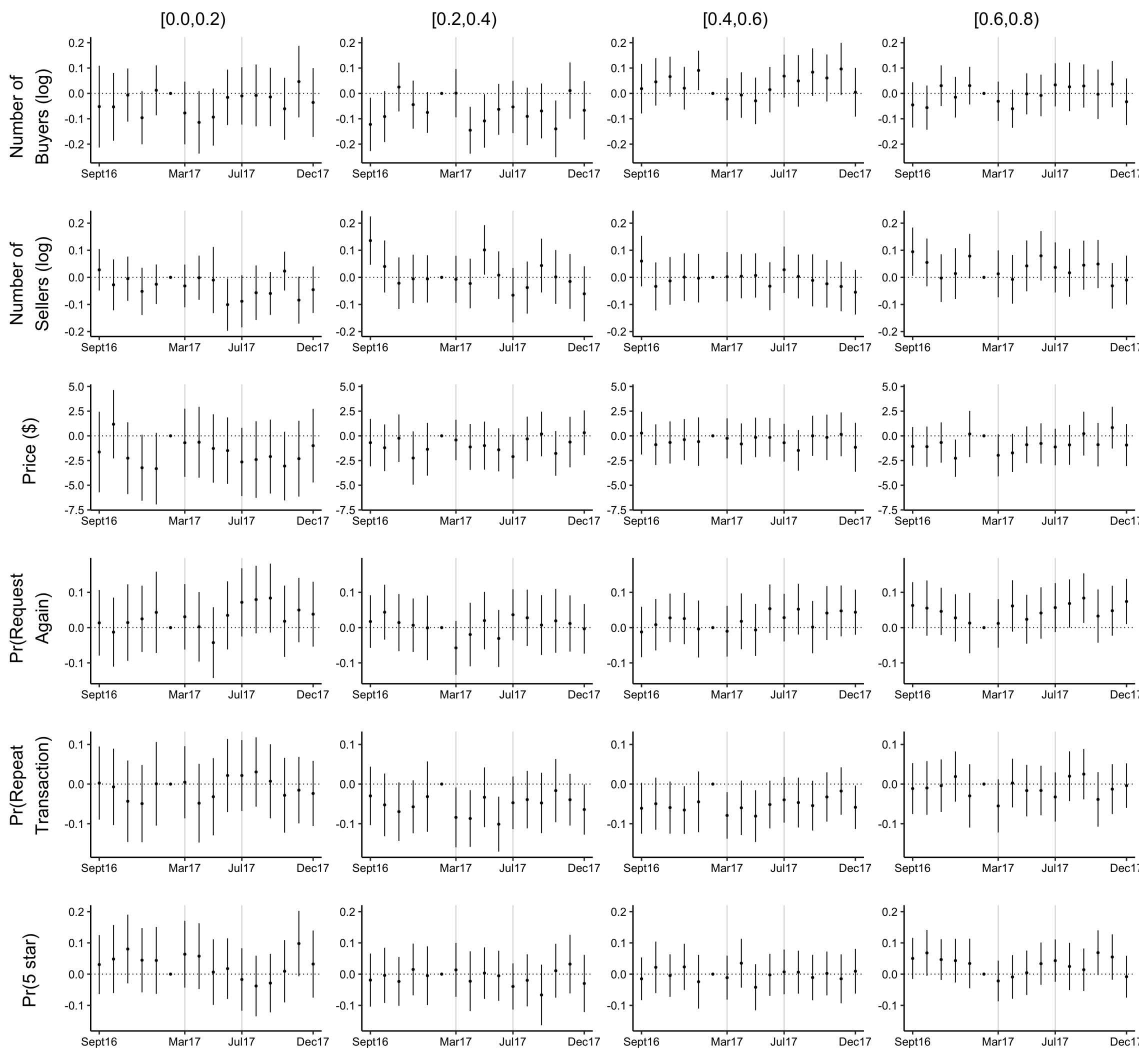
Regression estimates of Equation (6) *for additional outcomes of users who posted requests only on DogVacay or Rover in the previous calendar year. The first five rows focus on outcomes of existing buyers, while the last row considers current transactions involving existing sellers. Otherwise the figure is identical to Figure 7.*

Figure B.4: Estimates of Merger Effects – Additional Market-Level Outcomes



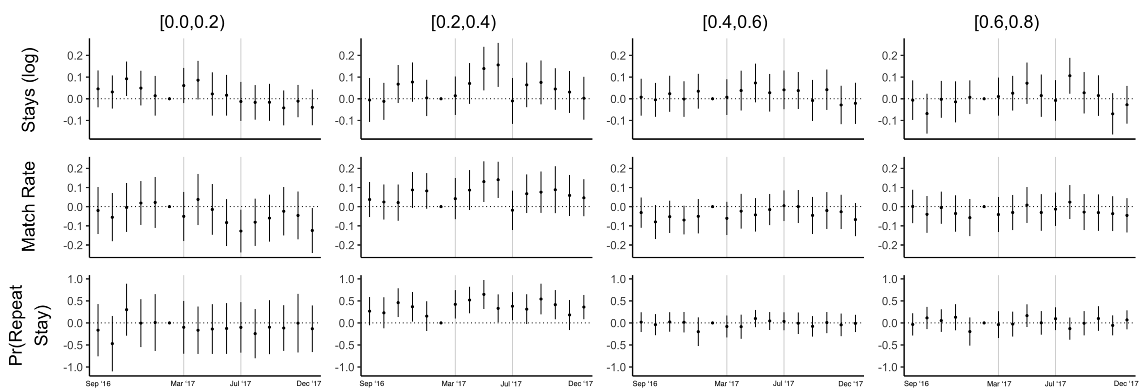
Regression estimates of Equation (5) *for additional outcomes calculated at the market level. Otherwise the figure is identical to Figure 8a.*

Figure B.5: Estimates of Merger Effects – Additional Outcomes for New Users



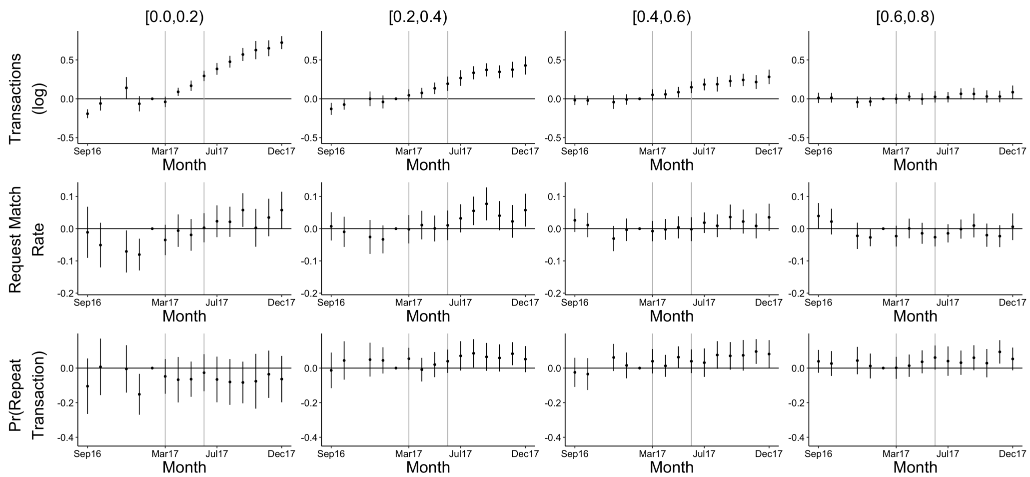
Regression estimates of Equation (5) *for additional outcomes of new users. Otherwise the figure is identical to Figure 8b.*

Figure B.6: Estimates of Merger Effects By User Type – Multihoming Users

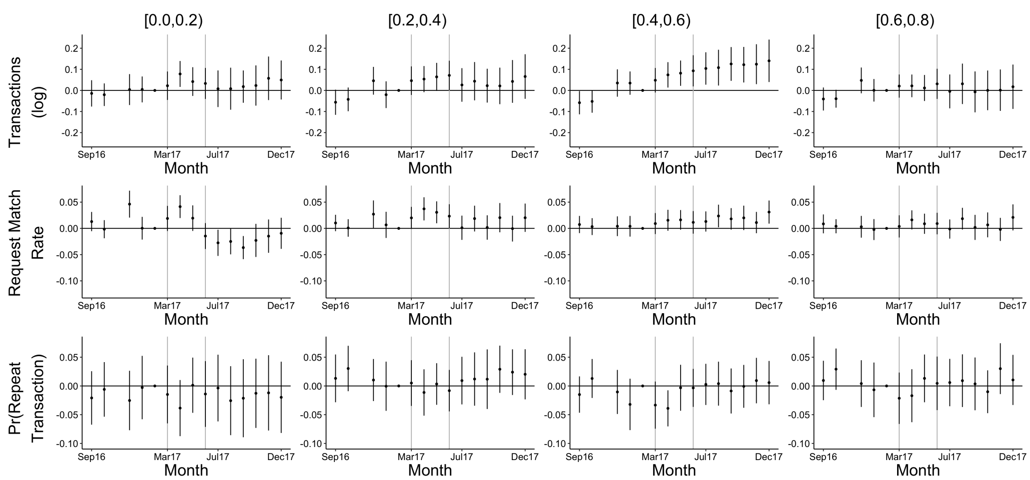


This figure displays results for multi-homing users. Multi-homing users are defined as those who engaged in booking inquiries on both Rover and DogVacay in the previous year. Otherwise the figure is identical to Figure 6 and Appendix **??**.

Figure B.7: Estimates of Merger Effects – Unmatched



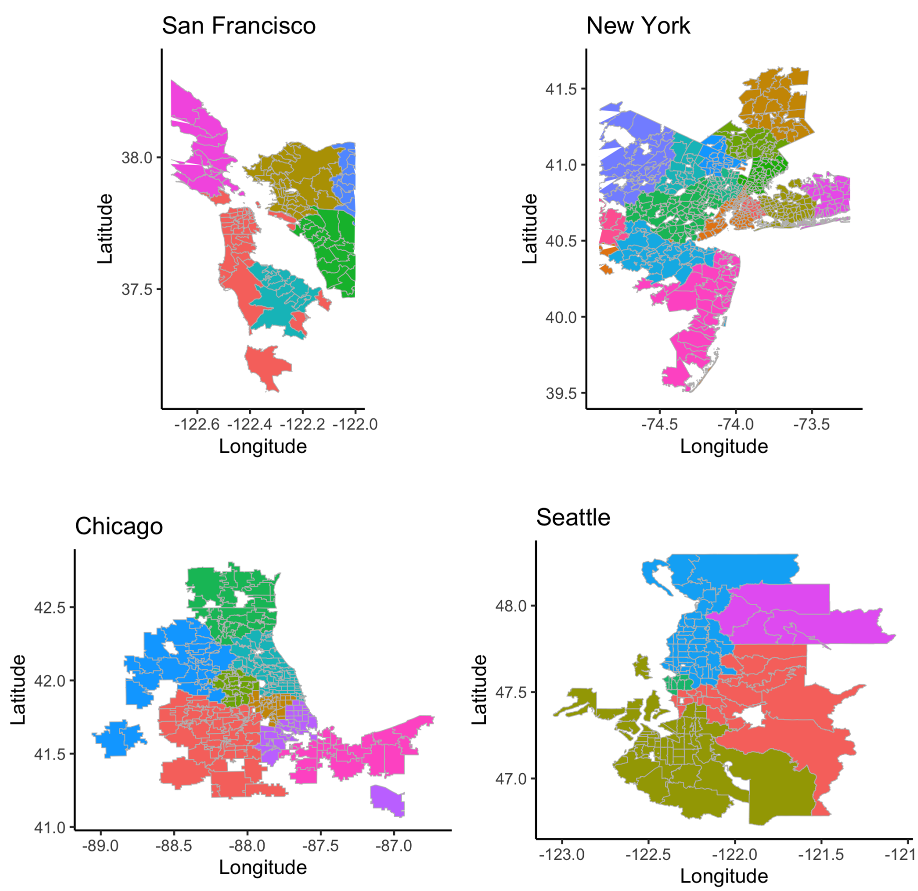
(a) Outcomes for Rover Users



(b) Market Outcomes

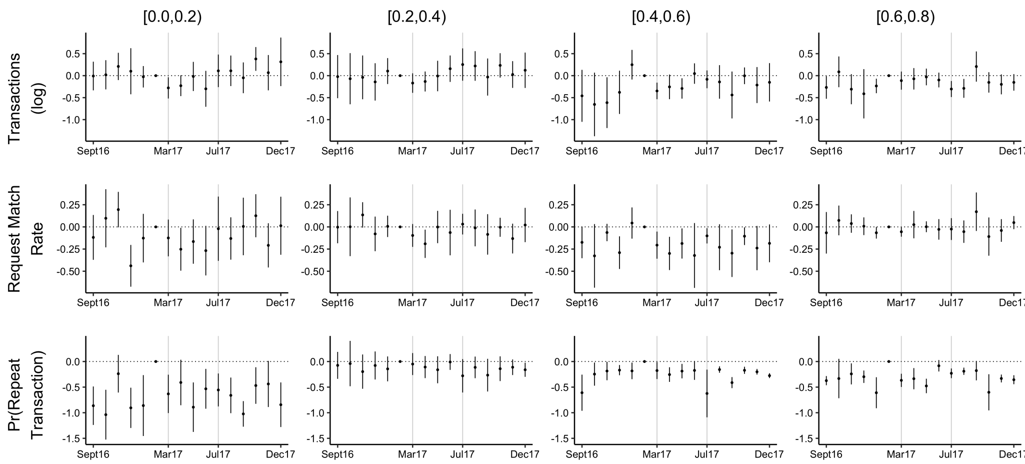
Regression estimates of Equation (8). *Otherwise Panel a is identical to Figure 6a and Panel b is identical to Figure 8a.*

Figure B.8: Cluster Maps - CBSAs

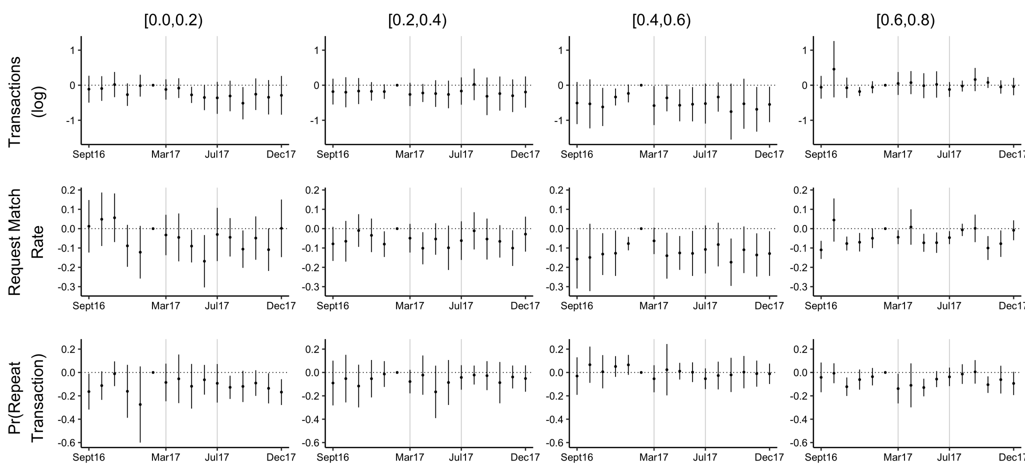


The figures plot the clusters for four Core-Based Statistical Areas (CBSAs) formed by aggregating zip codes using hierarchical clustering with geographic constraints.

Figure B.9: Estimates of Merger Effects – Geographic Clusters



(a) Outcomes for Rover Users



(b) Market Outcomes

Regression estimates of Equation (5) *with geographic clusters as markets instead of zip codes. Otherwise Panel a is identical to Figure 6a and Panel b is identical to Figure 8a.*

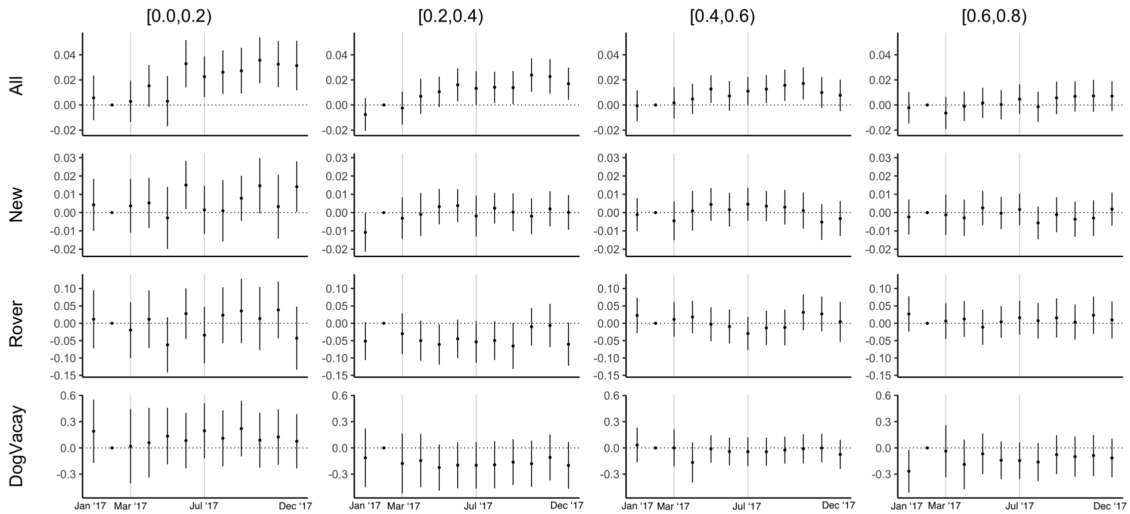
C Additional Results Based on Search Data

The discussion in the main body of the paper has focused on booking inquiries and stays. However, there may also be effects of the merger on the probability that a search leads to a booking inquiry. Intuitively, searchers should be more likely to find suitable sitters in markets with more sitters. We have data on search behavior only starting in 2017 and only for the Rover platform. As a result, we can only compute platform level rather than market level outcomes related to search. This limits our ability to say how search conversion changed at a market level, but does allow us to measure changes in platform efficiency.

We observe data on search requests, which are queries into the Rover search engine, and search results, which are results returned for those queries. We are also able to observe the mapping between a search and a user in the database for a subset of queries. For other queries, we cannot map the search to a user, either because the user did not have an account or because the platform was not able to successfully map the search to a user. We attribute the search to a location by using the first zip searched by the searcher in a given month. Lastly, we define a conversion (either to a booking inquiry or to a stay) as a binary variable that takes the value of 1 when a searching user has at least one booking inquiry or stay initiated in that year-month.

Using the above definitions and matched sample, we estimate the effect of merging the two platforms on platform conversion rates (Figure C.1) from search to booking inquiry. The first row shows that conversion rates increase by up to 3 percentage points in markets with the lowest Rover market share pre-acquisition (first plot on the first row), but we do not see significant differences post-acquisition in conversion rates for existing or new users (last three rows of Figure C.1).

Figure C.1: Merger Effects for Conversion from Search to Booking Inquiry



Regression estimates of Equation (5). The first row displays results where the outcome is the conversion rate of searches to booking inquiries for all searchers. The second row displays results only for users who have not previously made a request or searchers who are unknown. The third row displays results only for users who made requests exclusively on Rover in 2016. The fourth row displays results for users who made requests exclusively on DogVacay in 2016.

Table C.1: Estimates of Merger Effects for Conversion from Search to Request

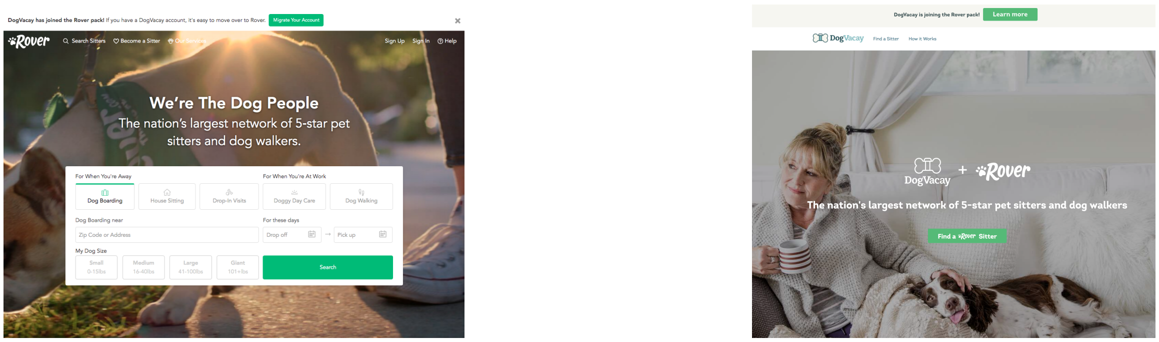
Period	Rover Share	All	New	Rover	DogVacay
Transition	[0.0,0.2)	0.011*	0.003	-0.017	0.015
	[0.2,0.4)	0.012**	0.006	-0.02	-0.137
	[0.4,0.6)	0.007*	0.001	-0.007	-0.054
	[0.6,0.8)	0	0.001	-0.011	0.024
Post-Merger	[0.0,0.2)	0.026***	0.005	0	0.049
	[0.2,0.4)	0.021***	0.006	-0.015	-0.109
	[0.4,0.6)	0.013***	0.001	-0.01	-0.05
	[0.6,0.8)	0.006	0	-0.001	0.017

Note: *p<0.1; **p<0.05; ***p<0.01

This table displays the estimates of Equation (7). The outcome variables are the search to request rate for various types of users. This table is analogous to Figure C.1.

D Additional Figures and Tables

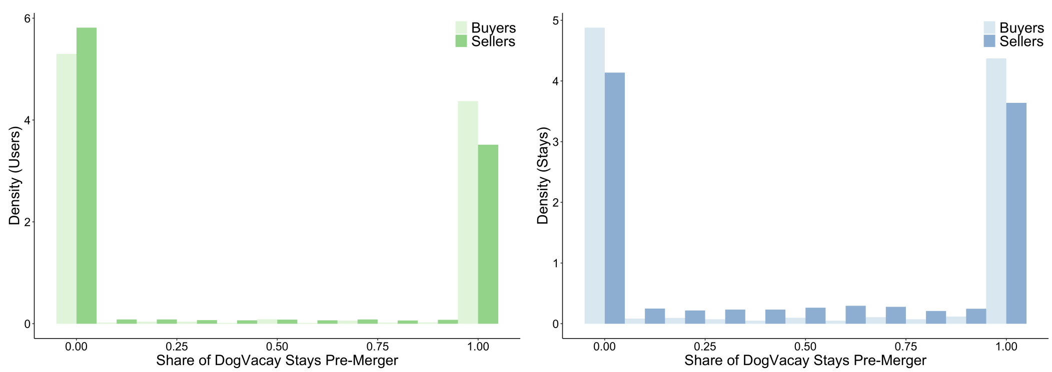
Figure D.1: Rover's and DogVacay's Landing Pages After the Merger



(a) Rover.com, July 2017. (b) Dogvacay.com, July 2017.

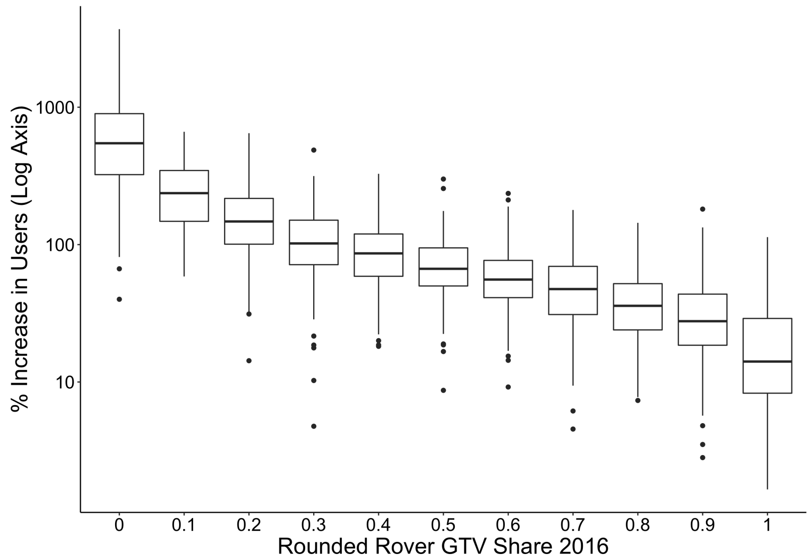
The figures show the landing page of Rover and DogVacay after the merger of the two platforms was completed. The screenshots are accessible on Wayback Machine (`https://web.archive.org/web/20170714115852/https://www.rover.com/` *and* `https://web.archive.org/web/20170704144306/https://dogvacay.com/`*). In July 2017 (right panel), DogVacay users could migrate to Rover by clicking on "Migrate Your Account" at the top.*

Figure D.2: Multi-Homing



The figures plot the distribution of transactions between Rover and DogVacay for users active before the acquisition. On the left panel, an observation is a user (buyer in light, seller in dark). The histogram plots the share of users' transactions occurring on DogVacay. Users at 1 are those who only transacted on DogVacay prior to the acquisition, while those at 0 only transacted on Rover. Those in between multi-home, i.e. transact on both platforms prior to the acquisition. The right-hand panel weighs each seller by the number of transactions. The comparison between the left and right plots shows that multi-homing users transact more than single-homers.

Figure D.3: Transactions from DogVacay Users as Share of Prior Rover Users



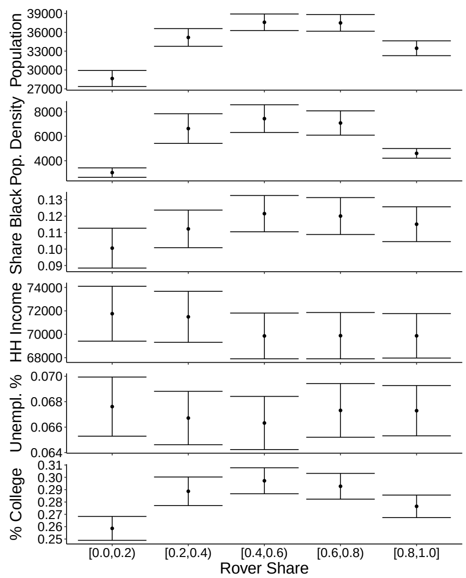
Box plot of the percentage change in the number of transacting users post-acquisition due to DogVacay users switching to Rover as a function of Rover market shares in 2016. Specifically, the percentage change in users is the number of DogVacay users who migrated their profiles to Rover and transacted after '2017-04-01' over the number of Rover users transacting between '2016-01-01' and '2017-04-01'. The zip code's Rover market share is defined using gross transaction volume and is rounded to the nearest 0.1.

Table D.1: First Movers and Rover Market Share

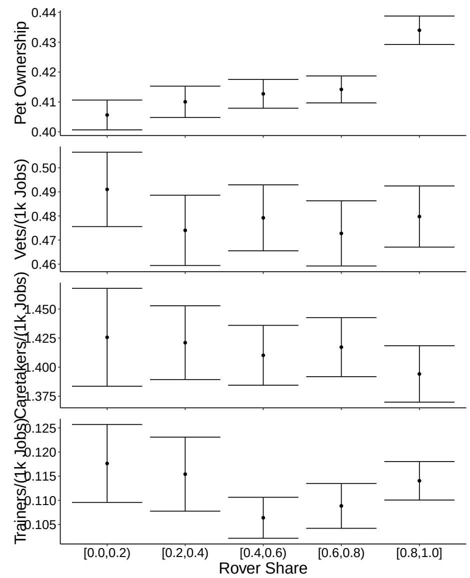
	Dependent variable:			
	2016 Rover Market Share			
	(1)	(2)	(3)	(4)
1{First Mover = Rover}	0.081***	0.078***	0.069***	0.071***
	(0.007)	(0.007)	(0.007)	(0.007)
State FE	N	Y	N	N
CBSA FE	N	N	Y	Y
Year Month FE	N	N	N	Y
Observations	8,200	8,200	8,200	8,200
R^2	0.017	0.055	0.155	0.162
Adjusted R^2	0.017	0.049	0.124	0.125
Note:				*p<0.1; **p<0.05; ***p<0.01

The table displays the OLS estimates of Rover's market share in 2016 on whether Rover was the first mover in the market for all markets where both Rover and DogVacay had at least one transaction before 2016 and the market had more than 50 transactions during 2016. Each market is a zip code. Rover is defined to be the first mover in the market if the first transaction was booked on Rover. Results also hold for when the first mover is defined to be the first platform to reach 10 transactions in the market. **p<0.1;* ***p<0.05;* ****p<0.01.*

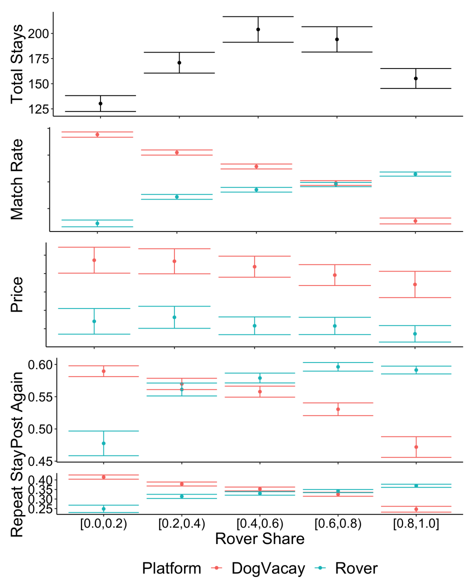
Figure D.4: Differences Across Zip Codes



(a) Population Demographics.



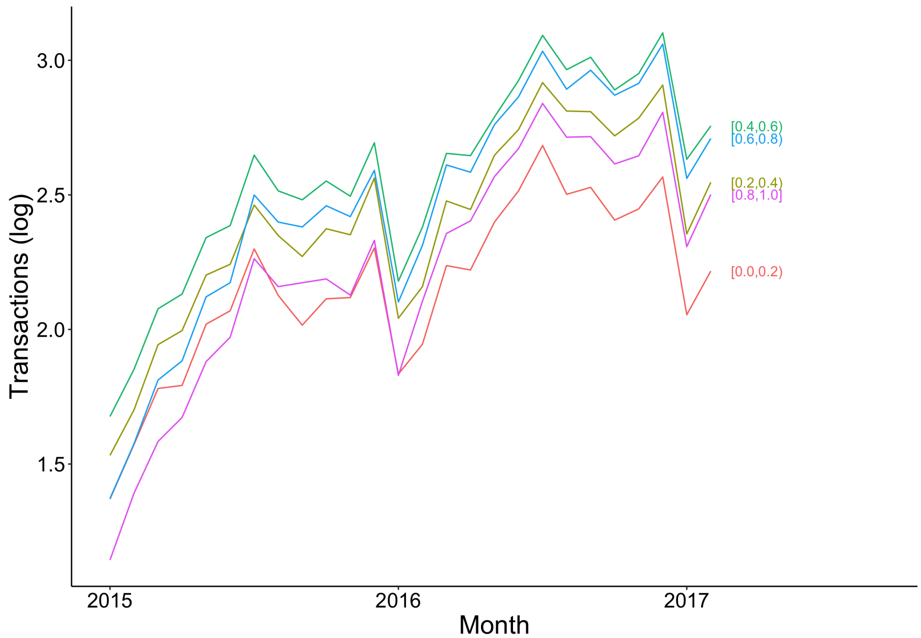
(b) Pet Ownership and Services.



(c) Platforms' Performance.

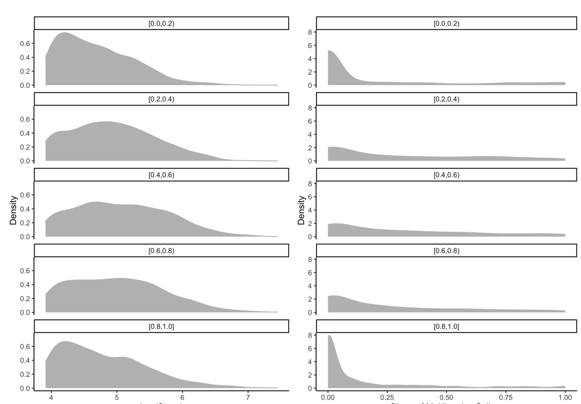
Differences across zip codes in population demographics (left), pet ownership and services (right), and Rover and DogVacay's performance (bottom). Each zip code is grouped by market share – the groupings are defined in Figure 5. The plot on the left shows average population demographics within each market group: population and population density, share of black residents, median household income, unemployment rate, share of the population with a college degree. The plot on the right shows the share of households with pets, as well as jobs related to pet services: number of veterinarians, animal caretakers, and animal trainer per 1,000 jobs. Data come from the 2016 American Community Survey and Bureau of Labor Statistics Occupational Employment Statistics. The plot on the bottom shows average (Rover + DogVacay) stays, ad well as other performance metrics broken down by platform: price; match rates; share of buyer requesting again within 3 months; share of buyers transacting again with the current seller (conditional on the current transaction being a new relationship). Vertical bars correspond to 95% confidence intervals. The absolute levels of price and match rates are omitted to protect company information.

Figure D.5: Matches over Time



The figure plots the average number of monthly stays across market share groups.

Figure D.6: Heterogeneity Across Market Share Groups



The figure plots the density of dimensions of heterogeneity across markets. An observation is a zip code, and zip codes are divided across rows depending on Rover's market share in 2016. The left column plots the log number of (Rover + DogVacay) transactions in a zip code in 2016. The right column plots the share of sellers in a zipcode who transacted on both platforms in 2016.

Table D.2: Comparison Across Market Share Groups

	[0.8,1.0]	[0.0,0.2)	[0.2,0.4)	[0.4,0.6)	[0.6,0.8)
Panel A: Population Demographics					
Population	33,463	-4,815***	1,717*	4,131***	4,032***
Land Area (sq. miles)	22.58	10.54***	1.67	-0.17	-3.12
Population Density	4,600	-1,572**	2,028***	2,839***	2,482***
Share Asian	0.09	-0.03***	-0.01***	-0.01**	-0.00
Share Black	0.12	-0.01*	-0.00	0.01	0.00
Share White	0.70	0.07***	0.02**	0.01	-0.01
Average Income ($)	87,898	2,496	2,787	-179	-292
Median Income ($)	69,872	1,888	1,621	-11	12
Unemployment Rate	0.07	0.00	-0.00	-0.00	0.00
Share Uninsured	0.10	-0.00	0.00	0.01**	0.01*
Share Non Citizen	0.09	-0.02***	-0.00	0.00	0.01***
Share with College	0.28	-0.02**	0.01*	0.02***	0.02**
Share Poor	0.04	-0.00	-0.00	-0.00	-0.00
Share with Pets††	0.43	-0.03***	-0.02***	-0.02***	-0.02***
Vets/1,000 jobs††	0.48	0.01	-0.01	-0.00	-0.01
Animal Caretakers/1,000 jobs††	1.39	0.03	0.03	0.02	0.02
Animal Trainers/1,000 jobs††	0.11	0.00	0.00	-0.01*	-0.01
Panel B: Market Performance					
Stays	155	-25***	16**	49***	39***
Nightly Price (log $)†	–	0.09***	0.07***	0.05***	0.03***
Match Rate†	–	0.11***	0.03***	-0.01	-0.02***
Share Repeat Transactions	0.48	0.09***	0.00	-0.02***	-0.03***
Share Requesting Again	0.58	-0.00	-0.02***	-0.01***	-0.00
Share Transacting with Same Sitter	0.36	0.03***	-0.01	-0.02***	-0.02***
Panel C: Rover Performance					
Stays	141	-128***	-86***	-35***	-4
Nightly Price (log $)†	–	0.01	0.02**	0.01	0.01
Match Rate (rel. to Panel B)†	0.02	-0.18***	-0.09***	-0.06***	-0.04***
Share Repeat Transactions	0.49	-0.22***	-0.09***	-0.05***	-0.03***
Share Requesting Again	0.59	-0.11***	-0.03***	-0.01*	0.00
Share Transacting with Same Sitter	0.37	-0.12***	-0.06***	-0.04***	-0.03***
Panel D: DogVacay Performance					
Stays	14	103***	102***	83***	42***
Nightly Price (log $)†	–	0.04***	0.04***	0.04***	0.03**
Match Rate (rel. to Panel B)†	-0.16	0.32***	0.26***	0.20***	0.14***
Share Repeat Transactions	0.27	0.32***	0.25***	0.21***	0.14***
Share Requesting Again	0.47	0.12***	0.10***	0.09***	0.06***
Share Transacting with Same Sitter	0.25	0.17***	0.13***	0.11***	0.08***
N	793	577	560	639	692

The table compares zip code-level demographics and platform performance across market share groups. Demographics data are obtained from the US Census Bureau. For each of the characteristics, the first column displays the average value in the control group. The other columns display the difference of a particular market share bin compared to the control group, and whether the difference is statistically significant at standard confidence levels. Panels separate variables into the following 4 groups: population demographics; aggregate platform performance (Rover + DogVacay); Rover performance; and DogVacay performance. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

† *:The level of nightly price is not displayed for the control group to protect company information. We only show log differences across market share groups. Analogously, the match rate is not displayed for the control group in Panel B. For Panel C and D the control group column displays the percentage point difference in match rates between the zip code average match rate and the match rates in each of the two separate platforms.*

††*: CBSA-level variables. Each zip code is assigned the value of its CBSA, and then mean and standard deviation are computed with zip code as units of observation.*

Table D.3: Comparison Across Matched Market Share Groups

	[0.0,0.2)		[0.2,0.4)		[0.4,0.6)		[0.6,0.8)	
	Control	Treated	Control	Treated	Control	Treated	Control	Treated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Population Demographics								
Population	30,968	-2,320**	33,728	1,451	35,012	2,582**	33,775	3,720***
Land Area (sq. miles)	26.20	6.93**	22.83	1.42	22.94	-0.53	23.50	-4.04
Population Density	3,545	-517*	4,564	2,064***	4,819	2,620***	4,438	2,644***
Share Asian	0.09	-0.03***	0.08	-0.01	0.09	-0.01	0.08	0.00
Share Black	0.12	-0.02*	0.12	-0.01	0.12	0.00	0.11	0.01
Share White	0.70	0.06***	0.70	0.02*	0.70	0.00	0.71	-0.02
Average Income ($)	88,882	1,512	86,266	4,420*	88,104	-385	87,467	139
Median Income ($)	70,551	1,209	69,122	2,371	70,039	-179	68,977	906
Unemployment Rate	0.07	-0.00	0.07	-0.00	0.07	-0.00	0.07	-0.00
Share Uninsured	0.10	-0.00	0.11	0.00	0.10	0.01*	0.10	0.01*
Share Non Citizen	0.08	-0.02***	0.09	-0.00	0.08	0.01	0.08	0.01***
Share with College	0.26	-0.00	0.27	0.01	0.28	0.02*	0.28	0.01
Share Poor	0.04	-0.00	0.04	-0.00*	0.04	-0.00	0.04	-0.00
Share with Pets††	0.43	-0.03***	0.44	-0.03***	0.44	-0.03***	0.44	-0.03***
Vets/1,000 jobs††	0.47	0.02	0.49	-0.02	0.47	0.00	0.50	-0.03**
Animal Caretakers/1,000 jobs††	1.38	0.04	1.42	-0.00	1.39	0.02	1.42	-0.00
Animal Trainers/1,000 jobs††	0.11	0.01	0.12	-0.00	0.12	-0.01**	0.12	-0.01*
Panel B: Market Performance								
Stays	125	5	153	18**	172	32***	164	30***
Nightly Price (log $)†	–	0.09***	–	0.08***	–	0.05***	–	0.03***
Match Rate†	–	0.08***	–	0.02***	–	0.00	–	-0.02***
Share Repeat Transactions	0.58	-0.00	0.58	-0.01*	0.59	-0.02***	0.58	-0.00
Share Requesting Again	0.38	0.01	0.36	-0.01	0.35	-0.01	0.35	-0.02***
Share Transacting with Same Sitter	0.50	0.07***	0.48	0.01	0.47	-0.01	0.47	-0.02***
Panel C: Rover Performance								
Stays	115	-102***	139	-83***	156	-49***	149	-11
Nightly Price (log $)†	–	0.02	–	0.03**	–	0.02	–	0.02*
Match Rate†	–	-0.21***	–	-0.09***	–	-0.05***	–	-0.03***
Share Repeat Transactions	0.59	-0.11***	0.59	-0.03***	0.59	-0.01**	0.59	0.01
Share Requesting Again	0.39	-0.15***	0.37	-0.06***	0.36	-0.03***	0.36	-0.02***
Share Transacting with Same Sitter	0.51	-0.24***	0.49	-0.09***	0.49	-0.05***	0.48	-0.02***
Panel D: DogVacay Performance								
Stays	10	107***	14	102***	16	81***	15	41***
Nightly Price (log $)†	–	0.03	–	0.05***	–	0.03*	–	0.04***
Match Rate†	–	0.32***	–	0.26***	–	0.20***	–	0.14***
Share Repeat Transactions	0.47	0.12***	0.45	0.12***	0.48	0.07***	0.48	0.05***
Share Requesting Again	0.26	0.15***	0.24	0.14***	0.24	0.11***	0.25	0.08***
Share Transacting with Same Sitter	0.27	-0.02	0.26	0.21***	0.26	0.20***	0.27	0.13***
N	323	577	376	560	372	639	414	692

The table compares zip code-level demographics and platform performance across markets in each Rover market share group and its respective matched control markets. Demographics data are obtained from the US Census Bureau. For each of the "treated" market share groups, the odd-numbered columns display the average value in the control group. The even-numbered columns display the difference of the average of a particular market share bin compared to the average of the corresponding control group markets, and whether the difference is statistically significant at standard confidence levels. Panels A through D separate variables into the following 4 groups: population demographics; aggregate platform performance (Rover + DogVacay); Rover performance; and DogVacay performance. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

† *:The level of nightly price is not displayed for the control group to protect company information. We only show log differences across market share groups. Analogously, the match rate is not displayed for the control groups. The displayed match rates are the percentage point differences between the respective treated and control groups.*

††*: CBSA-level variables. Each zip code is assigned the value of its CBSA, and then mean and standard deviation are computed with zip codes as units of observation.*

Table D.4: Transactions of Sellers After DogVacay is Shut Down

	# Transactions Post DogVacay Shutdown			
	(1)	(2)	(3)	(4)
DogVacay User	-2.742***	-0.9202***	-1.306***	-0.5079***
	(0.2715)	(0.1464)	(0.1531)	(0.1904)
# 2016 Stays	0.1507***	0.1607***	0.1609***	0.3353***
	(0.0173)	(0.0200)	(0.0198)	(0.0543)
Avg. Nightly Price (2016)	0.0319***	0.0320***	0.0302***	0.0165*
	(0.0094)	(0.0095)	(0.0094)	(0.0087)
Has Repeat Stay		0.6405***	0.6383***	-1.490***
		(0.2379)	(0.2356)	(0.4175)
DogVacay User × Has Repeat Stay		-2.794***	-4.317***	-0.3801
		(0.3633)	(0.5598)	(0.5844)
Share Buyers Migrated			0.7543***	0.7835***
			(0.2007)	(0.2024)
Has Repeat Stay × Share Buyers Migrated			2.439***	2.447***
			(0.7425)	(0.5843)
DogVacay User × # 2016 Stays				-0.2662***
				(0.0580)
Mean of Y	4.66	4.66	4.66	4.66
R^2	0.08066	0.08494	0.08694	0.11798
Observations	28,103	28,103	28,103	28,103
Month of Last Stay fixed effects	✓	✓	✓	✓
Platform Share fixed effects	✓	✓	✓	✓

This table displays coefficients of regressions where the outcome is the number of transactions of a user post-DogVacay shut-down. Each observation is a single-homing seller who had at least one transaction in 2016. The control variables include whether the user was on DogVacay in 2016, the number of stays in 2016, the average nightly price, whether a stay in 2016 was a repeat stay with a sitter from a prior transaction, and whether the average of whether the seller's 2016 buyers migrated their profile to Rover post-merger (only applies to DogVacay users).