

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

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Abstract

Large digital platforms are economically important and are increasingly the subject of regulatory scrutiny. In comparison to markets with multiple competitors, a single platform may increase consumer welfare if network effects are large or may decrease welfare due to higher prices or a reduction in product variety. We measure this trade-off in the context of the merger between the two largest platforms for pet-sitting services. We use the following intuition and a difference-in-differences approach to causally estimate network effects. In local markets where the acquiring platform is already dominant, the merger has little effect on the size of the combined platform. On the other hand, in markets where the two competing platforms are of similar sizes, combining the users should lead to sizable improvements in user outcomes because of network effects. We find that users of the acquiring platform benefited from the union due to network effects. However, users of the acquired platform were more likely to leave the market and those who stayed experienced a reduction in match rates. This is likely due to a reduction in product variety and switching costs. Overall, consumers are, on average, not substantially better off with a single combined platform than with two separate and competing platforms.

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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 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 users on the platform. The stronger the network effects, the more likely that there will be winner-take-all equilibria, where all users join a single platform. This monopolistic position may thus be efficient because it maximizes total surplus. We study these issues in the 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 efficiency improvements experienced by the acquiring platform. 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 platforms, 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 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

¹The 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>.

two online platforms for pet sitting services, in which 1) a unique platform emerged from the acquisition by the largest platform of its biggest platform 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 measuring network effects. 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. Fourth, 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 its 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 preventing market outcomes from fully equilibrating across platforms. Prices, for example, tend to be persistently higher on one platform compared to the other, even if providers charge identical prices when selling on both platforms. 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 identification strategy is motivated by a theoretical result and an empirical fact. The theoretical result from the existing literature is that because of network effects, one would expect that a single platform generates higher aggregate user value than two separate platforms. The empirical fact is that pre-acquisition market shares vary across geographies. In a geography where each platform had 50% of the market, merging the two platforms could lead to large increases in user value by doubling the number of users interacting with one another. On the other hand, in a geography where one platform already had 90% of the market, merging the two platforms would have a smaller effect on aggregate user value because one platform was already dominant. We can thus use a difference-in-differences strategy to measure the effect of the merging 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 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 we use coarser market definitions based on users’ search behavior.

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.

²Some 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.

While we do not find evidence of large network effects at the *market* level, we do find evidence of network effects at the *platform* level. When we look at user outcomes on the acquiring platform, we find that the number of transactions and the match rate of requests into transactions improves more in geographies that received a bigger influx of users from the acquired platform. This increase is due to two main reasons. First, network effects causally improve users' outcomes. Second, the acquisition caused a change in the number and *composition* of users in the market. We are able to provide separate evidence for both of these explanations by studying the effects of merging the two platforms on three user groups: existing users of the acquiring platform (Rover), existing users of the acquired platform (DogVacay), and new users.

In support of the network effects explanation, we find that existing buyers and sellers on Rover increased their usage of the platform. However, we fail to find evidence of increased usage for DogVacay users and for new users. In fact, DogVacay users exited the market due to the merger. Many of these users chose not to migrate their profile to Rover and those who migrated used the platform less frequently. This attrition was at least partially offset by increased usage of Rover users.

We then consider the effects of merging the two platforms on request match rates. Prior to the acquisition, each platform matched its own users at higher rates in the markets where it was dominant. Rover users matched at higher rates in markets where Rover had high market shares, compared to both Rover users in other geographies and to DogVacay users in the same geographies. The same was true for DogVacay. After the acquisition, these differences persisted on the combined platform, but our data allows us to separate the effect of these compositional changes from true network effects.

Looking at match rates separately for each user group, we find that merging the two platforms did not cause match rates to substantially change for Rover users and new users. However, the acquisition reduced match rates of DogVacay users. These results are consistent with the two platforms serving consumers with heterogeneous horizontal preferences and switching costs.

Taken together, 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. Although we do not study this, there may be other benefits from merging competing platforms related to the costs of user acquisition, technology investments and employees' wages, which we discuss in the conclusion.

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 literature on the economics of platforms 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), Hagiw 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), find that platform competition has ambiguous effects on consumer surplus

in the presence of product variety, prices, and network effects. Our work adds an empirical focus to this literature, by estimating whether user outcomes improve with the number of other participating users. 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 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), which show early evidence that network effects are present, respectively, in federal computer procurement, in the adoption of computer spreadsheet programs, and in banks' adoption of ATMs. 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, and Berry and Waldfogel (1999) and Jeziorski (2014a,b), who study radio stations. 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, respectively.

Our context is distinct from the existing literature for three reasons. First, similar to Li and Netessine (Forthcoming), we exploit the combination 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

³The exception is the known consumer and merchant behavior over credit card use. See Bakos and Halaburda (2019) for survey evidence.

dimensions, from the extensive margins – i.e. number of transactions – to the intensive margins – i.e. search costs 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 affordable 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 grooming, but their largest category is dog boarding. Competitors include other online platforms such as Wag, more traditional businesses like kennels and dog hotels, and more informal alternatives such as friends and family.

A comparison of Figure 1a and Figure 1b highlights the high degree of similarity between the two platforms before they combined into one. 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,⁷ 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

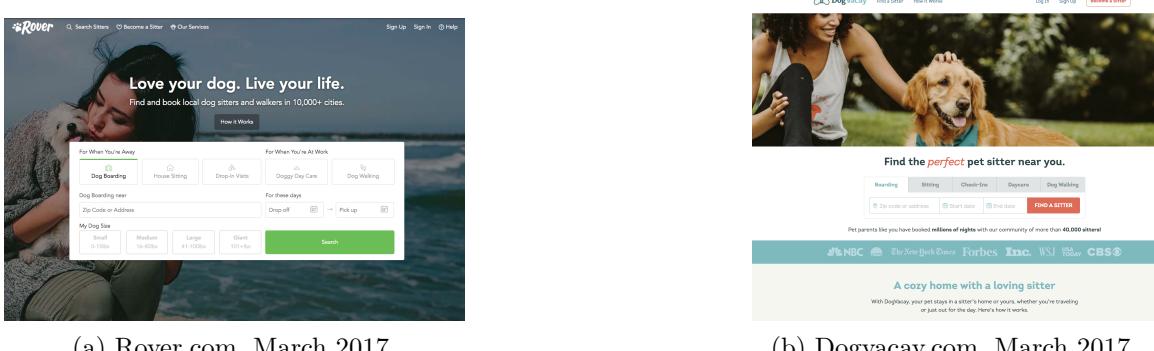
⁴<https://www.wsj.com/articles/rover-raises-125-million-as-dog-sitting-war-heats-up-1527166801> (accessed July 2019).

⁵<https://www.americanpetproducts.org/pr> (accessed April 2020).

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

⁷The service categories include pet overnight-boarding, sitting, drop-ins, daycare, and walking.

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/>)

determined by the companies’ proprietary algorithms. For each provider, 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. 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 booking value 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 \$25 per booking for owners who joined after September 2015.⁸ DogVacay had a very similar fee structure and its commissions closely tracked those of Rover throughout the period between 2012 and 2017.

⁸The information is available at <https://support.rover.com/hc/en-us/articles/205385304-What-are-the-service-fees-> (accessed July 2019).

3.1 The Acquisition

On March 29, 2017, Rover announced it would buy DogVacay.⁹ 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 company, it was not a *killer acquisition*¹⁰ 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.¹¹

Rover acquired DogVacay in an all-stock deal.¹² 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.¹³

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 to see a single platform survive after it acquires its competitor. 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,¹⁴ the decision to fully absorb DogVacay into the Rover brand was a consequence of the rapid growth that Rover

⁹<https://techcrunch.com/2017/03/29/rover-dogvacay-merge/> (accessed July 2019).

¹⁰Cunningham 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.

¹¹<https://www.latimes.com/business/technology/la-fi-tn-dogvacay-rover-20170329-story.html> (accessed June 2020).

¹²<https://techcrunch.com/2017/03/29/rover-dogvacay-merge/> (accessed April 2020).

¹³<https://www.ftc.gov/news-events/media-resources/mergers-and-competition/merger-review> and <https://www.justice.gov/atr/merger-enforcement> (accessed April 2020).

¹⁴<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).

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 early May, Rover announced that DogVacay would be shut down.¹⁵ 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.¹⁶

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.

3.2 Data

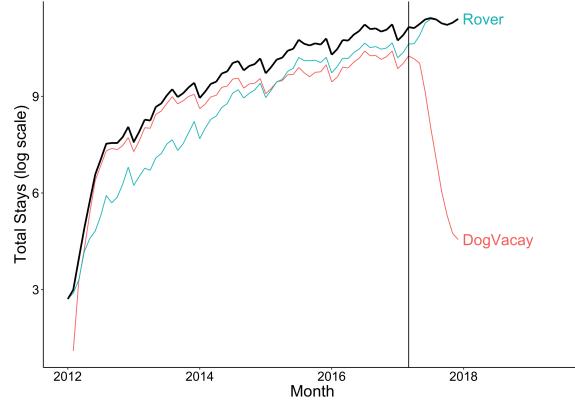
We have proprietary data from Rover, which retained pre-acquisition data from DogVacay. This allows us to have visibility into all service requests, buyer-seller booking inquiries, matches, and reviews from both platforms before and after the acquisition. A *request* refers to a buyer’s need for a sitter (e.g. dog boarding in Seattle from August 16th until August 18th) and it 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*. 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 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

¹⁵Based on the publish date of this website: <https://www.rover.com/joining-forces/>

¹⁶Appendix Figure D.1 displays Rover’s and DogVacay’s landing pages after the merger.

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.

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 sizes 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.¹⁷

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.¹⁸ 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,¹⁹ 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. 27% of transactions are made by a multi-homing seller, and 8% are made by a multi-homing buyer.²⁰

¹⁷Across all service categories, Rover was 62% larger than DogVacay.

¹⁸CBSA stands for Core-Based Statistical Area, which roughly coincides with metropolitan and micropolitan areas. See <https://www.census.gov/topics/housing/housing-patterns/about/core-based-statistical-areas.html> for more details.

¹⁹In the aggregate in these zip codes Rover has 54.49% market share.

²⁰Appendix 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

Table 1: Prices on Rover and DogVacay

	Seller Price (log)		
	(1)	(2)	(3)
DogVacay	0.067*** (0.004)	0.061*** (0.004)	-0.003 (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.

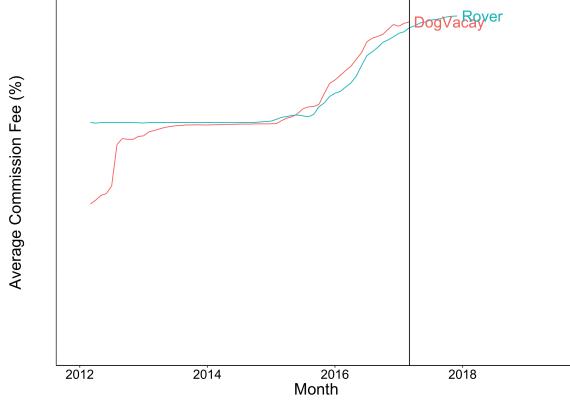
Multi-homing sellers treat the two platforms as perfect substitutes, at least judging by the price they charge, even though DogVacay's prices are higher on average.²¹ On average, across the months before the acquisition, DogVacay sellers were expected to receive about \$3.50 more than sellers on Rover, or 13% more. After controlling for geographic and time observables, the price difference is around 6% but it 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 considered buyers from the different 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 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

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.

²¹The 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.

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 since the data provide suggestive evidence that sellers do not have heterogeneous preferences for dogs.²² The results of this section will provide us with tests for the existence of network effects that we can take to the data.

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. We assume buyers in a market each have one need for pet sitting services. A buyer's ex-ante utility from finding help on a platform is the probability of finding a match, denoted q , multiplied by the expected utility v net of price p conditional on matching: $u = (v - p)q$. Buyer's utility is increasing in v and

²²Sellers' decision to reject service requests are not explained by observable request characteristics, but rather their own schedule and availability.

q , and decreasing in p . The three components of buyer's utility are in turn a function of the number of buyers and sellers participating on the platform. Let N denote the number of participating sellers. We assume that the number of buyers relative to sellers is fixed and equal across markets and competing platforms. This means that once we know N , we can derive the number of buyers directly by multiplying N by the number of buyers for every seller. Appendix A extends this model to allow for varying number of buyers relative to sellers. We assume that each component of $u(N)$ is twice continuously differentiable.

We further let $v(N)$ and $q(N)$ be functions of the number of platform participants. We assume that $v(N)$ is increasing in N . This means that doubling both buyers and sellers allows buyers to find a better match – because for example, they find somebody living closer to their home. We also assume that match probability $q(N)$ is increasing in N . This means that doubling 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, we assume that price is independent of N . This assumption means that doubling both the number of buyers and sellers does not affect average prices.²³ Given these assumptions, we can define what we mean by *network effects*. Network effects exist whenever u is increasing in N because of an increase in v or q or both.

When two platforms exist, let $\pi \geq 0.5$ denote the share of sellers using the larger platform in a market and let us further assume that the matching and pricing technologies are not too different across the two platforms, so u is not platform specific. This means that conditional on exactly the same number of buyers and sellers, the two platforms match buyers and sellers at similar rates, with similar prices and average match quality levels. In a geography where two platforms exist, the market-level match rates, values, and prices are going to be a weighted average of the outcomes in the two platforms, where the weights depend on the relative size of the two platforms. On average in the market, the per-person surplus will be equal to $\pi u(\pi N) + (1 - \pi)u((1 - \pi)N)$. Assuming all participants remain active when the two platforms merge, the per-person surplus will increase to $u(N)$.

We want to compare two geographies with different shares of users across the two plat-

²³Whether this assumption holds exactly depends on the nature of competition between sellers. On the one hand, increasing N results in more options for buyers, which should decrease prices. On the other hand, increasing N may result in buyers who have more idiosyncratic utility for a particular seller, increasing that seller's market power and prices. In the data, we reject large changes in prices post-acquisition.

forms, but identical number of users in the market. In both markets we have N number of sellers, but in market 1 the larger platform has a share of users π_1 , while in market 2 it has a share π_2 , with $\pi_1 > \pi_2 \geq 0.5$. Let us first consider what happens to users in the acquiring platform, which without loss of generality we assume is the larger platform. The surplus created by the acquiring platform increases by $u(N) - u(\pi_1 N)$ in market 1. Network effects at the platform level imply that the increase in consumer surplus for users of the larger platform is bigger in market 2 than in market 1:

$$u(N) - u(\pi_2 N) > u(N) - u(\pi_1 N). \quad (1)$$

When Equation (1) holds, we say that *platform efficiency* increases after a merger because of network effects.

In addition to increasing platform efficiency, 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. In our setting, with network effects, users in market 2 would gain more from the merger than users in market 1. Indeed, because of network effects, market 1 had higher utility – both aggregate and per person – with two competing platforms than market 2. So we have that

$$u(N) - [\pi_2 u(\pi_2 N) + (1 - \pi_2)u((1 - \pi_2)N)] > u(N) - [\pi_1 u(\pi_1 N) + (1 - \pi_1)u((1 - \pi_1)N)]. \quad (2)$$

When Equation (2) holds, we say that *market efficiency* increases after a merger because of network effects.

The inequalities in both Equations (1) and (2) motivate difference-in-differences tests of the existence of network effects at the platform and market level. Equation (2) can be tested by comparing outcomes for both platforms' users before and after the acquisition and across markets with different pre-acquisition market shares. Equation (1) can be applied to outcomes for users of a single platform, which is the acquiring platform in our case.

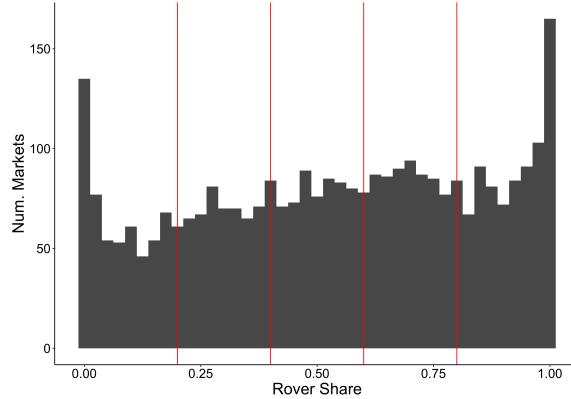
Note that we could very well have a situation where we find support for Equation (1) but not for Equation (2). This would imply that even if network effects exist so that platform efficiency increases after a merger, other considerations – such as differences in matching

and pricing technologies, or heterogeneity in user preferences – counterbalance the benefits of platform size at the market level. We discuss extensions to this model in Appendix A. In the next sections, we empirically test Equations (1) and (2).

5 Empirical Strategy and Identification

The combination of two platforms affects many aspects of the acquiring company. We study the effects of this merger on local marketplace efficiencies. We do not study the effects of the acquisition that operate uniformly across the platform. For example, the acquisition may have created operational efficiencies and cost savings. To the extent that these affect all geographies, we cannot statistically differentiate these effects from time effects. Instead, we study differences in outcomes across local markets that are differentially affected by combining the two platforms, in line with our theoretical framework.²⁴

Figure 4: 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.

Figure 4 shows the distribution of Rover's market shares (in terms of gross transaction volume) across zip codes with at least 50 stays in 2016. 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%.

²⁴Appendix Figure D.3 provides a graphical intuition of our theoretical framework.

We would expect the largest benefits from network effects to arise in the zip codes with shares between 40% and 60%. In a world where the two platforms are identical except for their market shares, zip codes where Rover had 10% or 90% of the market would be indistinguishable from one another. Since that may not be true in practice, we keep the 0-20% and 80%-100% market share groups separate. We do the same for the 20%-40% and 60%-80% market share groups.

Merging the two platforms 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.4). To exploit this differential user migration, we take a difference-in-differences approach and compare outcomes in the months immediately before and after the acquisition across market share groups.

Zip codes where either Rover or DogVacay were dominant before the acquisition tend to be 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.5 and D.6, together with Appendix Table D.1, 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 our 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 across market share groups are as similar as possible, we employ a matching estimator that accounts for covariate imbalance across groups (Imai et al., 2018). We consider zip codes with Rover market shares above 80% as the control group. Separately for each of the other market share groups, 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.²⁵ We find a separate control group from zip codes with Rover market shares above 80% for each of the other “treated” market share groups. Let y_{zt} be the outcome in zip code z and year-month t . For each

²⁵An active seller is defined as a seller who was involved in at least one booking inquiry in the given month.

market share group, we estimate the following regression

$$y_{zt} - y_{z't} = \beta_t + \epsilon_{c,c',t} \quad (3)$$

where z is the “treated” zip code, and z' is the matched “control” zip code. The coefficients β_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).

We look at a large number of outcomes. On the extensive margins, we look at total number of transactions in a given zip code and month. On the intensive margins, we look at the match rate of posted requests and the share of transactions leading to a repeated stay in the future, which we take as a measure of match quality. We look at these outcomes for the market as a whole and for the Rover platform only. So for example, when looking at transactions, we look at transactions completed in a given zip code-month separately for all buyers and only for buyers using Rover.²⁶

We hold the matched control groups constant as we measure the effects of combining the two platforms across different outcomes of interest. Table 2, which provides descriptive statistics for the matched samples, shows that we are able to improve matching on many covariates that we do not explicitly use in the matching procedure.²⁷ However, platform performance metrics that are not explicitly considered in matching (e.g. prices, matching rates, and 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

²⁶We explore other outcomes, such as total number of buyers and sellers, transaction prices, retention rates, and share of stays whose sitter received a 5-star review. These additional analyses are presented in Appendix B. The results are consistent with those presented in the main body of the paper.

²⁷Appendix Table D.1 presents descriptives for the unmatched zip codes.

Table 2: Comparison Across Matched Market Share Groups

	[0,0,0.2)		[0.2,0.4)		[0.4,0.6)		[0.6,0.8)	
	Control (1)	Treated (2)	Control (3)	Treated (4)	Control (5)	Treated (6)	Control (7)	Treated (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.

differences reflect the fact that platform performance metrics tend to positively correlate with a platform’s market share. We should note however, that our difference-in-differences strategy does not require identical levels of pre-treatment outcomes, but rather parallel trends, appropriately defined. The figures in the next section provide support for this

assumption.

6 Results

This section presents the main results on the effect of merging the two platforms on the market as a whole and on Rover specifically. We then disaggregate results by user type and present heterogeneous effects across different markets.²⁸

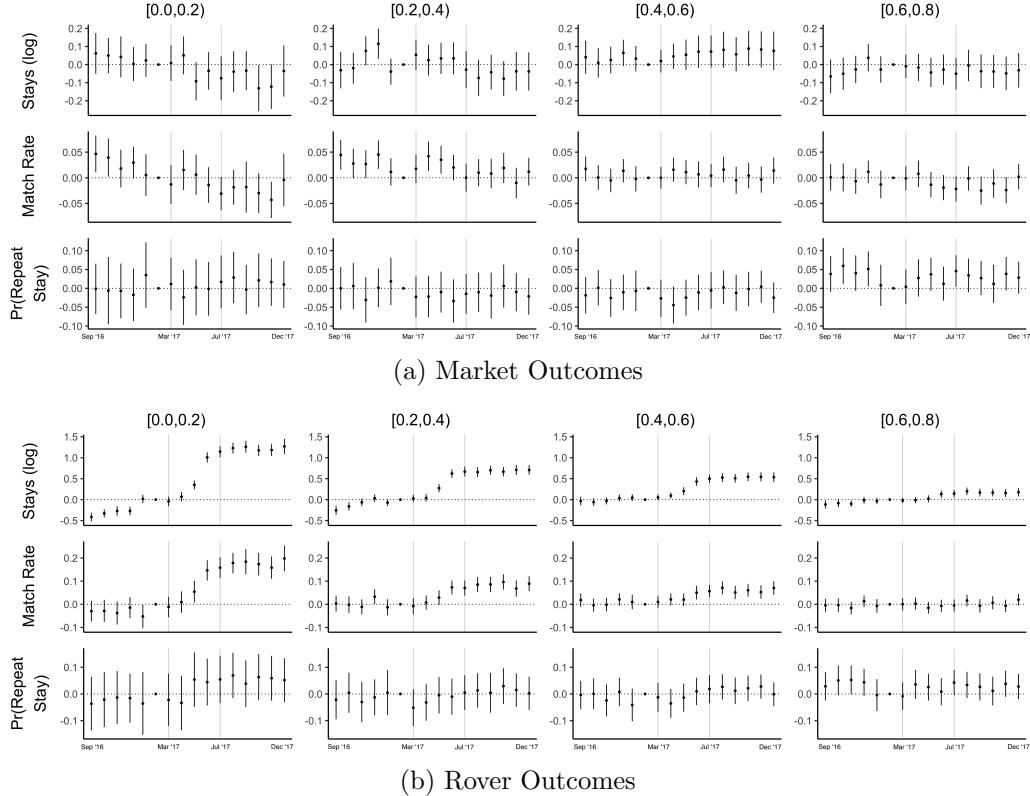
We start with market-level outcomes to test whether merging the two platforms increased the overall number of matches, match rates, and match quality more in zip codes where Rover and DogVacay split the market relatively equally before the merger compared to zip codes in which Rover was already dominant.

Figure 5a plots the results. The outcome in the first row is the (log) total number of transactions (stays) in a given zip code-month, regardless of whether they were intermediated by DogVacay or Rover. Each column corresponds to a different treatment group, and 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% in 2016 (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 the other outcomes: number of transactions divided by number of requests (match rate, second row) and share of new transactions leading to a repeat stay in the future (third row).²⁹

²⁸This section presents the results with event study plots. Appendix Tables B.1 through B.6 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.

²⁹From this last outcome we exclude transactions between buyers and sellers who had transacted with each other in the past. This is to avoid attributing relationships found in the past to current match quality. Repeat transactions are a good measure of match quality, at least as measured by the dog owner's willingness to transact again with a particular sitter. Although this is likely correlated with dog welfare, in this setting we cannot directly measure the latter (Singer, 2015).

Figure 5: Estimates of Merger Effects



Regression estimates of Equation (3). An observation is a matched zip code-month. Panel (a) presents market level outcomes, while Panel (b) presents Rover-level outcomes. In each panel the regressions come from 3 different outcomes — stays, match rates, and share of stays leading to a repeat transaction in the future — 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 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 and estimates with clusters of zip codes as markets are in Appendix B. For more aggregated difference-in-differences coefficients, see Appendix Tables B.1 and B.2.

The first row 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.1) confirms that the effect is not statistically significant. Zip codes with market shares 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 other outcomes, we don't find any differential 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 (Appendix Table B.1). The results 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. That is, we do not find evidence supporting the hypothesis that a single platform is better for users than two separate and competing platforms.

Does the absence of efficiency gains at the market level necessarily imply absence of network effects? No, and in fact the results focusing on the Rover platform suggest that there are network effects. Figure 5b plots the same outcomes for the Rover platform. We now look at transactions occurring on the Rover platform only. Similarly, we look at the match rate for requests submitted on the Rover platform only and the share of new transactions leading to a repeated stay. Rover received a bigger influx of users in markets where it had a smaller share of the market, so it's not surprising to see that the number of transactions increases the most in markets with a low Rover market share pre-acquisition. Relative to the control group, the number of Rover stays increase by 50% in markets where Rover had 40-60% share, they increase by 70% in markets where Rover had 20-40% share, and they increase by 130% in markets where Rover had only 0-20% share.

What is more interesting are the estimates on the intensive margins: match rates and the probability that a current transaction leads to a repeat stay. For both measures, the post-acquisition improvement compared to the control group is larger where Rover was smaller pre-acquisition, i.e., where Rover experienced a larger influx of users migrating from the acquired platform. We find substantial effects, with up to 20 percentage point increase in match rates for the zip codes where Rover had less than 20% market share. The results are similar for other outcomes and for more aggregated market definitions based on zip code clusters, which are less prone to potential violations of the stable unit treatment value assumption. Appendix B provides these and other extensions to our empirical results.

What explains this apparently contradictory finding, that there exist network effects at the platform level, but that users on average are not finding more and better matches

with a single platform compared to two competing platforms? We first note that DogVacay users – both buyers and sellers – are more likely to leave the platform after the merger, in particular in markets where DogVacay had a relatively larger market share. Appendix Table B.5 indicates that markets experienced at least a 13 percentage point increase in attrition after the merger compared to the control markets, and as high as a 36 percentage point increase for buyers in markets where DogVacay had over 80% market share. This level of attrition is consistent with switching costs, a preference for the DogVacay brand, or an expectation of lower match quality on Rover.

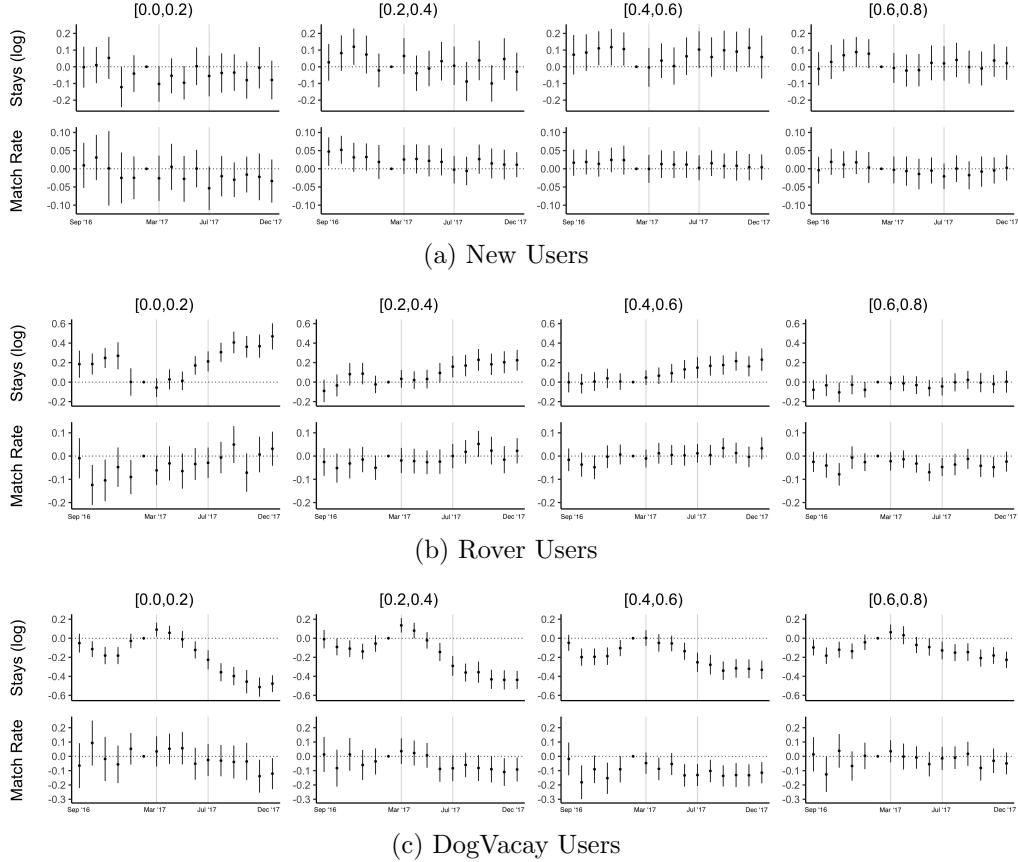
To investigate this further, we separately look at outcomes for different users: new users, users who used DogVacay before the acquisition, and users who used Rover before the acquisition. We first focus on new users. We define a user as new if they never engaged in a booking inquiry or posted a request before. We want to explore whether new users are better off when finding help after merging the two platforms compared to before and whether the improvement was bigger in zip codes where Rover and DogVacay split the market equally compared to markets where Rover was dominant. Figure 6a plots the number of new buyers submitting requests in a zip code-month, as well as the match rate of those requests. There are no significant differences across zip codes with different market shares on the extensive or the intensive margins.

We then look at Rover and DogVacay users. We define these users according to their activity across the two platforms. We consider all users who engaged in a booking inquiry in a calendar year. We define them as Rover users if all their booking inquiries during the year were on Rover, as DogVacay users if all their booking inquiries were on DogVacay, and multi-homers otherwise.³⁰ We then measure the number of those users who post requests or engage in booking inquiries again in any given month of the following calendar year, the total number of transactions they exchange, and the match rate of their requests. By including 2016 and 2017 we can compare the behavior of 2015 users who came back in 2016 with 2016 users who came back in 2017 while the merger took place.

Figure 6b shows that Rover users benefit from merging the two platforms when the influx of users from DogVacay is larger. The effects imply a 26% increase in stays for the

³⁰The analysis for multi-homing users is in Appendix Figure B.3.

Figure 6: Estimates of Merger Effects By User Type



Regression estimates of Equation (3). In the first panel the first row displays results where the outcome is the (log) number of stays from buyers who never posted a request before. The second row displays results for the match rate of new buyers, i.e., the number of stays divided by the number of requests by buyers who never posted a request before. Panel (b) displays the same outcomes for users who, in the prior year, had only engaged in booking inquiries on Rover. Panel (c) displays the outcomes for users who, in the prior year, had only engaged in booking inquiries on DogVacay. Otherwise the figure is identical to Figure 5. Results for other outcomes are in Appendix Figure B.2. Results for multi-homing users are in Appendix Figure B.3. For more aggregated difference-in-differences coefficients, see Appendix Tables B.3, B.4, and B.5.

markets with 0-20% market shares and around 17% increase in stays for markets with 20-40% or 40-60% market shares. This increase in stays is consistent with a role of increased variety of sellers on the platform due to the incoming DogVacay sitters, thus confirming the presence of network effects. The increase in activity from Rover users entirely comes from the extensive margins – more users posting requests – rather than match quality or match rates.

Figure 6c shows the opposite for DogVacay users, who 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 attrition. The number of DogVacay buyers participating in the market decreases by 36% in the 0-20% market share group. Match rates of DogVacay users migrating to Rover are also lower, up to 7 percentage points lower in the zip codes where DogVacay was dominant.³¹

Why do DogVacay users attrit more and match at lower rates? In general, buyers prefer to engage in repeat transactions with prior sitters who were good matches and this is especially true on DogVacay. On average, 50.8% of 2016 transactions are between a buyer and a seller who had already transacted before. This share is a little higher on DogVacay (54.5% versus 48%), and it's especially higher where the platform is successful. Indeed, 63.3% of DogVacay transactions in zip codes where DogVacay had at least 80% market share were repeat transactions. This pattern is even more pronounced post-acquisition — 79.8% of DogVacay buyers' transactions on Rover in these zip codes are repeat transactions with DogVacay sitters.

When repeat transactions are so important, 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 may have sent a request to a worse quality match. The evidence in Table 3 is consistent with the above story. This table displays regressions where an observation is a DogVacay buyer. We regress a series of outcomes on the market share group of the buyer's zip code and whether the buyer's most recent seller migrated to Rover. Buyers are more likely to migrate their profiles, initiate booking inquiries, and transact if their most recent seller also migrated their profile to Rover. Column 4 shows that this effect is driven by repeat transactions on Rover with the seller previously found on DogVacay. The interaction terms with market share groups show that the presence of prior sellers is less important for DogVacay buyers in high Rover share

³¹Appendix C finds very similar results on match rates for new, Rover, and DogVacay users using search data from Rover.

³¹DogVacay buyers are defined as those who transacted on DogVacay in 2016 and repeat DogVacay sitters are those with whom the buyer previously transacted on the DogVacay platform.

Table 3: DogVacay Buyer Outcomes as a Function of Seller Migration to Rover

	Migrated	Conversed	Transacted	Repeat Stay	Matched
	(1)	(2)	(3)	(4)	(5)
Seller Migrated	0.102*** (0.011)	0.093*** (0.011)	0.117*** (0.011)	0.152*** (0.010)	0.157*** (0.017)
Seller Migrated * Share = [.2, .4]	-0.029** (0.015)	-0.033** (0.014)	-0.041*** (0.014)	-0.049*** (0.012)	-0.074*** (0.021)
Seller Migrated * Share = [.4, .6]	-0.001 (0.014)	-0.009 (0.014)	-0.028** (0.014)	-0.039*** (0.012)	-0.095*** (0.021)
Seller Migrated * Share = [.6, .8]	-0.033** (0.015)	-0.028* (0.015)	-0.044*** (0.014)	-0.063*** (0.013)	-0.088*** (0.022)
Seller Migrated * Share = [.8, 1]	-0.054*** (0.018)	-0.048*** (0.018)	-0.067*** (0.017)	-0.083*** (0.016)	-0.099*** (0.026)
Mean of Y	0.56	0.4	0.34	0.25	0.85
Num.Obs.	86478	86478	86478	86478	34588
R-Squared	0.107	0.131	0.134	0.150	0.030

This table displays coefficients of regressions for DogVacay buyer outcomes post-acquisition. Each observation is a DogVacay buyer. The outcome ‘Migrated’ indicated that the user has claimed or merged an account on Rover. ‘Conversed’ indicates that the user has started a booking inquiry, ‘Transacted’ that the user has successfully transacted, and ‘Repeat Stay’ that a user has transacted with their previous seller on DogVacay. ‘Matched’ indicates that the user Transacted conditional on sending a booking inquiry. ‘Seller Migrated’ indicates that the buyer’s last seller on DogVacay migrated their profiles. Fixed effects for market share group and month of last DogVacay stay are included. The data used for this regression comprise all DogVacay buyers between April 2016 and April 2017. Standard errors are clustered on the previous provider of the buyer.

markets. This can be explained by the fact that there are more Rover sellers in high Rover share markets, which may provide good alternatives for the buyer. While this pattern is consistent with buyers attriting and having lower match rates due to unavailability of their previous sitter, the correlation may also be driven by reverse causality, coordination or simply rational expectations that the other side of users will behave similarly when deciding whether to migrate accounts.³²

³²Nonetheless, we note that sellers have more of an incentive than buyers to join the new platform to make money. Therefore, their participation decision should be less reliant on the presence of a previous buyer. Indeed, more sellers migrate their profiles than buyers — while 56% of buyers migrate their profile, 82% of

Another potential explanation for increased DogVacay attrition post-acquisition is that merging the two platforms may have caused DogVacay users to disintermediate the platform, i.e., to transact with the same service provider outside of the platform. This mechanism is important to consider because it would imply that our data is missing transactions and underestimating market surplus. Since, by definition, disintermediation is hard to measure, we cannot conclusively rule it out.

When we look at match rates for Rover, DogVacay, and new buyers separately (second row of plots in all panels in Figure 6), one thing jumps to our attention: no set of buyers see their match rates increase after merging the two platforms. Then why do we see an increase in match rates for the Rover platform in zip codes where Rover is smaller (Figure 5b)? Compositional differences are the main reason. Before the acquisition, DogVacay buyers matched at higher rates in markets where DogVacay was dominant. The migration of these buyers to Rover increases the average match rate, even though no user is more likely to match after merging the two platforms compared to before. So the change in match rates is not evidence of network effects in this case. The strongest evidence we have of network effects is the increase in participation by users of the acquiring platform, which translates into an increase in the number of their transactions.

6.1 Heterogeneous Effects across Market and Users

Network effects may manifest differently across different markets. We explore three dimensions of heterogeneity across markets: market size, propensity to multi-home, and differences in the buyer-to-seller ratio. We leave the theoretical discussion to Appendix A and histograms of these characteristics across zip codes in Appendix Figure D.7.

Markets differ in their total number of transactions. The average zip code has 171 stays in 2016, but with a standard deviation of 146 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, which could benefit from merging the two platforms. This would occur if the consumer surplus curve is more convex in smaller markets (Appendix Figure D.3). If this were the case, we would expect that both Rover and market-level

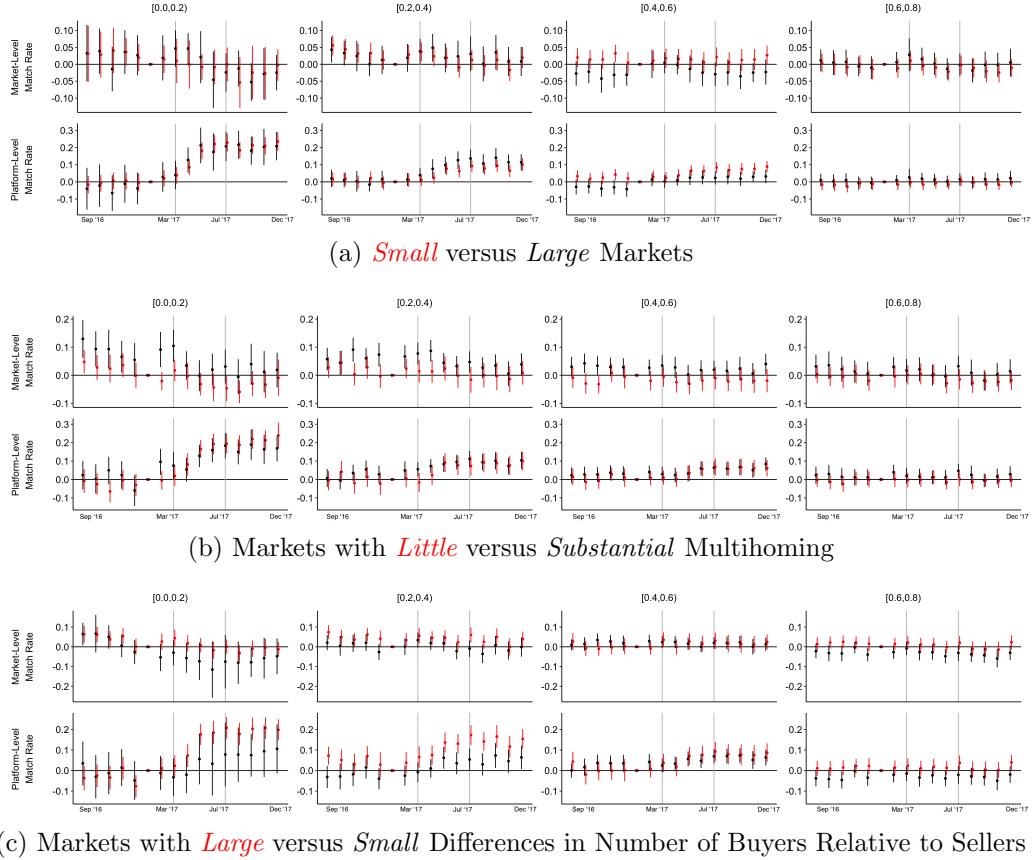
their sellers do so.

efficiency change more in small markets than in large markets as a function of pre-acquisition market shares.

To test these hypotheses, we split zip codes into zip codes with more or fewer than 250 transactions in 2016. We focus on Rover-specific and market-level match rates although Appendix B confirms that the conclusions do not change when we look at additional outcomes. Figure 7a plots the estimates.³³ The red estimates are for small markets, while the black estimates are for large markets. We do not find much of a difference between small and large markets: the Rover match rate goes up monotonically in the influx of new users from the acquired platform, while the market-level match rate does not improve relative to the control group.

³³Note that the matched samples differ from Figures 5b and 5a because we constrain that each “treated” zip code is matched to a control zip code within the same market size group.

Figure 7: Estimates of Merger Effects – Heterogeneity by Market Type



Estimates of Equation (3) for different markets. In the top panel the zip codes are divided into two groups: markets with at most 250 transactions in 2016 (in red), and market with more than 250 transactions (in black). In the middle panel, 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). In the bottom panel, the zip codes are divided into two groups: markets where the difference between Rover and DogVacay in the number of buyers relative to sellers is larger than 1.5 (in red) and those where the difference is lower than the cutoff (in black). We focus on market-level match rates and match rates on the Rover platform. 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 the figure is identical to Figure 5. Other outcomes are presented in Appendix Figures B.4, B.5, and B.6.

A second dimension of heterogeneity is the propensity to multi-home. In the extreme case and aside from 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 services 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. We would expect larger benefits from merging the two platforms to occur in markets with a smaller propensity to multi-home.

Figure 7b 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, Rover match rates increase monotonically in the market share of the acquired platform, while market-level match rates are similar between treatment and control groups, regardless of sellers' propensity to multi-home.

Lastly, we consider heterogeneity by the differences in the buyer to seller ratio. As discussed in Appendix A, we would expect that the gains from merging the two platforms are greatest for markets with the largest differences in the number of buyers relative to sellers across the two competing platforms. In Figure 7c we display the treatment effects split by whether the differences in the number of buyers for every seller is greater than 1.5. We find some evidence that merging the two platforms led to larger benefits to the Rover match rate in the markets with a larger difference in the relative number of buyers per seller (red), although the results are noisy.

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 keeps commission fees down so that the share of total surplus going to platform users—buyers and sellers—is maximized. 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. The choice is a trade-off between maximizing total surplus and maximizing the share of that surplus going to users.

In this paper, we show that there might not be a trade-off after all, but not because of the absence of network effects. We exploit the merger of the two largest platforms for pet sitting services into a single platform. The local nature of the services exchanged gives us the opportunity to evaluate how merging 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.

We find that the acquiring platform experiences network effects, as evidenced by increased participation of existing users who see their choice sets expand from the influx of users from the acquired platform. However, on average, 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 substantially 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 users of the acquiring platforms benefit from the merger at the expense of users of the acquired platform, who are leaving the market. Some of this attrition is likely driven by the importance of repeat transactions. Buyers who do not find their past providers on the acquiring platform are less likely to transact. Lastly, we cannot rule out that the merger caused some disintermediation — in which case measured activity using platform data would underestimate the true amount of surplus created in the market.

Our study focuses on platforms that intermediate local and time sensitive services. These platforms are well-suited for causal analysis of network effects because they allow us to observe geographically separate markets exchanging services under similar platform rules. Our results and methods are most likely generalizable to other local platforms such as Lyft and Uber, or Doordash and Uber Eats. 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. For these platforms, a different empirical strategy would be required to estimate network effects.

These results have important implications for platform competition and antitrust regulation. In our context, competition between two platforms and a single platform is 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 incumbents by reducing fixed and customer acquisition 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 let both platforms remain operational. Beyond the context of pet sitting platforms, we provide a road-map to measure network effects in other settings and to evaluate important heterogeneities across user groups and market types.

We have also focused on local, as opposed to global effects. 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). Our paper also does not speak to cost savings generated by the acquisition. Extending our analysis to estimate externalities across geographic clusters and cost savings is a fruitful avenue for future research.

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APPENDIX

A Extensions to the Theory Model

In this Appendix, we discuss some extensions of the theory model from Section 4, which motivate some heterogeneous effects that we test in Section 6. In the theory model, we have assumed that the proportion of buyers relative to sellers is held constant. But in a two-sided platform where buyers choose from the same set of service providers, we would expect that more sellers, holding constant the number of buyers, will be beneficial for each individual buyer by increasing the expected match value v and the match probability q , and by decreasing the transacted price p . We let N denote the number of sellers in a market, as in Section 4. Here we add γ to denote the number of buyers for every seller, so that the total number of buyers is γN . So now we have $v(N, \gamma)$, $p(N, \gamma)$, and $q(N, \gamma)$.

We make the following assumptions.

1. *$p(N, \gamma)$, price, is independent of N and is increasing in γ .* This assumption means that average prices increase if buyers increase relative to sellers – because for example, sellers have heterogeneous costs and the marginal seller sets the market clearing price – but that doubling both the number of buyers and sellers does not affect average prices – because for example, the new sellers and buyers are drawn from the same distributions as the existing participants.
2. *$v(N, \gamma)$, the buyer's match value, is increasing in N and independent of γ .* Doubling both buyers and sellers allows buyers to find a better match – because for example, they find somebody living closer to their home, but an increase in buyers relative to sellers does not change the match value, conditional on matching.
3. *$q(N, \gamma)$, the match probability, is increasing in N and decreasing in γ .* Doubling 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 – but increasing only the number of buyers reduces the value of the match – because for example, the available sitter is now transacting with another buyer.

4. *Buyers and sellers do not multi-home.*

Assumptions 1-3 lead to the following: (1) network effects imply that u is increasing in N because of an increase in v or q or both, while leaving the price unchanged, and (2) u is decreasing in γ because of a decrease in q and an increase in p . Assumption 4 is made for simplicity: participants on the merged platform are the sum of the participants in each of the two separate platforms.

Intuitively, if two merging platforms have a different number of buyers relative to sellers, the merger will shock buyers from the two platforms in opposite directions. Both sets of buyers will see an increase in the seller pool, but if one platform had 2 buyers for every seller and the other platform had 3 buyers for every seller, the merged platform would have a number of buyers for every seller between 2 and 3, depending on their market shares. This means that after controlling for the increase in market size, buyers in the first platform will be relatively worse off – because they now need to compete with relatively more buyers for the sellers available compared to before – while buyers in the second platform would be better off.

As long as the utility function has decreasing marginal returns to each additional user then the benefits from the merger are bigger in markets where the two platforms have very different relative proportions of buyers and sellers. This is because the average utility can be written as a function of the total number of sellers N and of the number of buyers relative to sellers γ . Assuming that $\gamma N u(N, \gamma)$ is twice continuously differentiable, has increasing returns to scale, and has decreasing returns to each individual buyer or seller implies that its first derivatives with respect to both N and γ are positive, but while the second derivative with respect to N is positive, the second derivative with respect to γ is negative. $u(N, \gamma)$ is thus concave in γ . Let's now assume that both competing platforms have the same number of sellers, $0.5N$, but the larger platform has a share $\pi \geq 0.5$ of buyers. This means that the larger platform has a number of buyers relative to sellers equal to $\pi\gamma$ where γ is the market-level number of buyers per seller. Analogously the smaller platform, which has the remaining buyers, has a number of buyers relative to sellers equal to $(1 - \pi)\gamma$. So the aggregate utility in the market, which is the sum of the utilities of both platforms, will be equal to $\pi\gamma 0.5N u(0.5N, \pi\gamma) + (1 - \pi)\gamma 0.5N u(0.5N, (1 - \pi)\gamma)$. After the platforms merge,

the combined market has N sellers, and γN buyers, and thus, aggregate utility when the platforms merge is $\gamma N u(N, \gamma)$ regardless of the pre-merger share of buyers π . However, due to Jensen's inequality, the closer π is to 1, the lower the aggregate pre-merger utility from the two separate platforms: $\pi\gamma 0.5 N u(0.5N, \pi\gamma) + (1-\pi)\gamma 0.5 N u(0.5N, (1-\pi)\gamma)$. Therefore the increase in benefits from the merger is greater in markets with higher π .

Relaxing Assumption 4, to the extent that a share of sellers multi-home, we would expect the benefits from the merger to be lower. So we can test whether network effects are larger in markets where a lower share of sellers multi-home.

Finally, we have compared markets with the same number of participants but different proportions of participants across the two competing platforms. To the extent that increasing returns to scale are higher for markets with a smaller number of participants (smaller N), we would expect the benefits from the merger to be concentrated in geographies with fewer participants.

B Extensions to the Empirical Results

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

First, we provide results on additional outcomes in Figure B.1.

Second, we provide additional results separately for new users, Rover users, DogVacay users (Figure B.2), and multi-homing users (Figure B.3).

Third, we provide additional results for large versus small markets, for market with little versus substantial multihoming, and for markets with little versus large differences in the relative proportions of buyers and sellers across the two competing platforms. the results are in Figure B.4, Figure B.5, and Figure B.6.

Fourth, we present the coefficients from the matching regressions in tables for better readability. Instead of estimating a coefficient for each month, as in Equation (3), 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.

$$y_{zt} - y_{z't} = \alpha + \beta_1 \mathbf{1}\{t \in 3 \text{ Months PreBaseline}\} + \beta_2 \mathbf{1}\{t \in \text{Transition}\} + \beta_3 \mathbf{1}\{t \in \text{PostMerger}\} + \epsilon_{z,z',t} \quad (4)$$

Results are presented in Tables B.1 through B.6.

Fifth, we provide results using a simple difference-in-differences estimation with no matching, which accounts for differential pre-trends across market share groups. We replace Equation (3) with the following, un-matched, equation:

$$y_{zt} = \beta_{s(z)t} + \gamma_{s(z)} t + \delta_{s(z)} \mathbf{1}\{t \geq \text{Dec2016}\} + \mu_t + \mu_z + \epsilon_{zt}. \quad (5)$$

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.

Sixth and 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,³⁴ 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.

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,³⁵ 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

³⁴We use the R package *ClustGeo* (Chavent et al., 2018).

³⁵We use 2017 search results from Rover to construct the matrix of dissimilarity in the feature space.

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.³⁶ 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 .³⁷ 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 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

³⁶We have search results data from 2017 for Rover.

³⁷For computational ease, we sample search results with replacement to compute $p_{s,ij}$.

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^α where each of the n zip codes is a separate cluster. At each following step k , for each cluster \mathcal{C}_k^α we compute the mixed pseudo inertia as

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

where $\mu_k^\alpha = \sum_{i \in \mathcal{C}_k^\alpha} w_i$ is the aggregate weight of cluster \mathcal{C}_k^α . 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^α in k clusters from a given partition \mathcal{P}_{k+1}^α in $k+1$ clusters, we choose to combine clusters \mathcal{A} and \mathcal{B} belonging to \mathcal{P}_{k+1}^α to minimize mixed within cluster inertia:

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

We can graphically represent the hierarchically-nested set of partitions $\{\mathcal{P}_n^\alpha, \dots, \mathcal{P}_k^\alpha, \dots, \mathcal{P}_1^\alpha\}$ 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.³⁸

³⁸A 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 $\alpha = 0$.

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.³⁹
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^α 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^α 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 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 (3) with cluster-month as unit of observation. Results are presented in Figure B.9.

³⁹For 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.

Table B.1: Estimates of Merger Effects - Market Level

Period	Rover Share	Buyers (log)	Sitters (log)	Stays (log)	Match Rate	Price	Pr(Request Again)	Pr(Repeat Stay)	Pr(5 star)
3 Mons 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

* p<0.1; ** p<0.05; *** p<0.01
Note:
This table displays the estimated coefficients of each period in Equation (4) and is analogous to Figure 5a.

Table B.2: Estimates of Merger Effects - Rover

Period	Rover Share	Buyers (log)	Sitters (log)	Rover Stays (log)	Rover Match Rate	Price	Pr(Request Again)	Pr(Repeat Stay)	Pr(5 star)
3 Mons Before Baseline	[0,0,0.2)	-0.244***	-0.035	-0.253***	-0.011	-0.138	0.021	-0.008	0.008
	[0.2,0.4)	-0.113***	-0.03*	-0.148***	-0.01	0.646*	0.016	-0.012	-0.016
	[0.4,0.6)	-0.037	-0.026	-0.069**	-0.006	-0.115	0.013	0	-0.018
	[0.6,0.8)	-0.054**	-0.042***	-0.082***	-0.01	0.382	0	0.03*	-0.009
Transition	[0,0,0.2)	0.455***	0.24***	0.434***	0.077***	-0.253	0.048***	0.035	-0.015
	[0.2,0.4)	0.229***	0.133***	0.255***	0.019**	0.249	-0.005	-0.021	-0.01
	[0.4,0.6)	0.142***	0.093***	0.167***	0.015*	-0.215	0	-0.003	-0.014
	[0.6,0.8)	0.063***	0.072***	0.046*	-0.006	-0.097	-0.005	0.002	-0.029*
Post-Merger	[0,0,0.2)	1.192***	0.451***	1.301***	0.197***	0.724	0.08***	0.072***	-0.035
	[0.2,0.4)	0.56***	0.237***	0.699***	0.076***	0.687*	0.01	0.014	-0.029
	[0.4,0.6)	0.401***	0.178***	0.499***	0.05***	0.36	0.011	0.027*	-0.013
	[0.6,0.8)	0.192***	0.132***	0.188***	0.003	0.37	-0.005	0.016	0.001

Note:

This table is the same as Table B.1, except the outcomes are for Rover only. These results are analogous to Figure 5b.

* p<0.1; ** p<0.05; *** p<0.01

Table B.3: Estimates of Merger Effects - New Users

Period	Rover Share	New Buyers (log)	New Sitters (log)	New Buyer Stays (log)	Match Rate (New Buyers)	Price (New Buyers)	Pr(Request Again) (New Buyers)	Pr(Repeat Stay) (New Buyers)	Pr(5 star) (New Buyers)
3 Mons Before Baseline	[0,0,0.2) [0,2,0.4) [0,4,0.6) [0,6,0.8)	-0.01 -0.021 0.006 -0.027	0.025 0.055** 0.005 0.018	0.074** 0.058* 0.015 -0.023	0.03 0.025** 0 0.004	1.284 0.53 -0.089 -0.084	-0.018 0.021 -0.001 0.038*	0.007 -0.019 -0.018 -0.007	0.021 -0.021 -0.002 0.028
Transition	[0,0,0.2) [0,2,0.4) [0,4,0.6) [0,6,0.8)	-0.048 -0.038 -0.048 -0.03	-0.01 0.023 -0.004 0	-0.007 -0.004 -0.049 -0.06**	0.005 0.006 0.007 -0.013	1.273 0.239 0.239 -0.5	-0.015 -0.025 -0.005 0.019	0.011 -0.046** -0.029 -0.02	0.003 -0.008 -0.008 -0.024
Post-Merger	[0,0,0.2) [0,2,0.4) [0,4,0.6) [0,6,0.8)	0.016 -0.03 0.023 0.01	-0.026 -0.019 -0.015 -0.014	0.006 -0.037 0.013 -0.034	-0.013 -0.008 -0.009 -0.014	0.129 0.524 -0.25 0.368	0.037 0.014 0.027 0.045**	0.023 -0.012 -0.003 -0.005	-0.023 -0.026 -0.002 0.005

Note:

This table is the same as Table B.1, except the outcomes are for Rover only. These results are analogous to Figure 6a.

* p<0.1; ** p<0.05; *** p<0.01

Table B.4: Estimates of Merger Effects - Rover Users

Period	Rover Share	Buyers (log)	Sitters (log)	Stays (log)	Match Rate	Price	Pr(Request Again)	Pr(Repeat Stay)	Pr(5 Star)
3 Mons Before Baseline	[0,0,0.2]	0.066	-0.051*	0.114***	-0.034	-0.446	-0.003	-0.039	0.029
	[0.2,0.4]	-0.058*	-0.09***	-0.034	-0.014	0.786	0.051*	-0.042	0.057
	[0.4,0.6]	0.006	-0.041**	-0.02	-0.035**	0.25	0.011	0.011	-0.019
	[0.6,0.8]	-0.002	-0.02	-0.037	-0.037***	1.157*	0.022	0.054	-0.019
Transition	[0,0,0.2]	0.047	0.122***	-0.053	-0.005	-1.356	0.01	0.022	-0.02
	[0.2,0.4]	0.072**	0.084***	0.025	-0.001	0.588	0.01	-0.053	0.026
	[0.4,0.6]	0.088***	0.08***	0.067**	0	-0.41	-0.004	-0.035	-0.02
	[0.6,0.8]	0.044**	0.057***	0.007	-0.023**	0.684	0.008	0.024	-0.002
Post-Merger	[0,0,0.2]	0.358***	0.257***	0.263***	0.041*	0.17	0.016	0.018	-0.042
	[0.2,0.4]	0.171***	0.116***	0.174***	0.039**	0.538	0.018	-0.005	0.055
	[0.4,0.6]	0.18***	0.125***	0.167***	0.013	0.053	-0.004	0.032	-0.024
	[0.6,0.8]	0.075***	0.081***	0.028	-0.024*	1.013*	-0.007	0.008	-0.022

Note:
This table displays the estimates of Equation (4) for users who engaged in a booking inquiry on Rover only in 2016. This table is analogous to Figure 6b.

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

Period	Rover Share	Buyers (log)	Sitters (log)	Stays (log)	Match Rate	Price	Pr(Request Again)	Pr(Repeat Stay)	Pr(5 Star)
3 Mons Before Baseline	[0,0,0.2]	0.008	0.057**	-0.044	-0.014	-3.375	0.043	-0.06	0.087
	[0.2,0.4]	0.03	0.062**	-0.006	0.012	-2.336	-0.006	0.157*	-0.043
	[0.4,0.6]	0.02	0.045**	-0.05*	-0.022	1.133	-0.018	0.038	-0.068
	[0.6,0.8]	-0.06**	-0.037	-0.073***	0	-2.234	0.04	0.134*	0.003
Transition	[0,0,0.2]	-0.001	-0.093***	0.074***	0.009	-0.327	-0.064	-0.144**	-0.006
	[0.2,0.4]	-0.008	-0.075***	0.077***	0.019	0.964	-0.029	-0.07	-0.052
	[0.4,0.6]	-0.032	-0.066***	0.038	-0.01	-0.279	-0.034	-0.016	0.057
	[0.6,0.8]	-0.01	-0.051**	0.043*	0.006	-1.053	0.057	0.041	-0.036
Post-Merger	[0,0,0.2]	-0.362***	-0.255***	-0.332***	-0.072**	-0.485	-0.085*	-0.126*	0.026
	[0.2,0.4]	-0.366***	-0.254***	-0.322***	-0.057**	1.037	-0.044	-0.106**	0.008
	[0.4,0.6]	-0.245***	-0.171***	-0.21***	-0.051**	-0.011	-0.032	-0.003	0.022
	[0.6,0.8)	-0.176***	-0.13***	-0.113***	-0.01	-1.346	0.04	-0.011	0.055

Note:
This table displays the estimates of Equation (4) for users who engaged in a booking inquiry on Rover only in 2016. This table is analogous to Figure 6c.

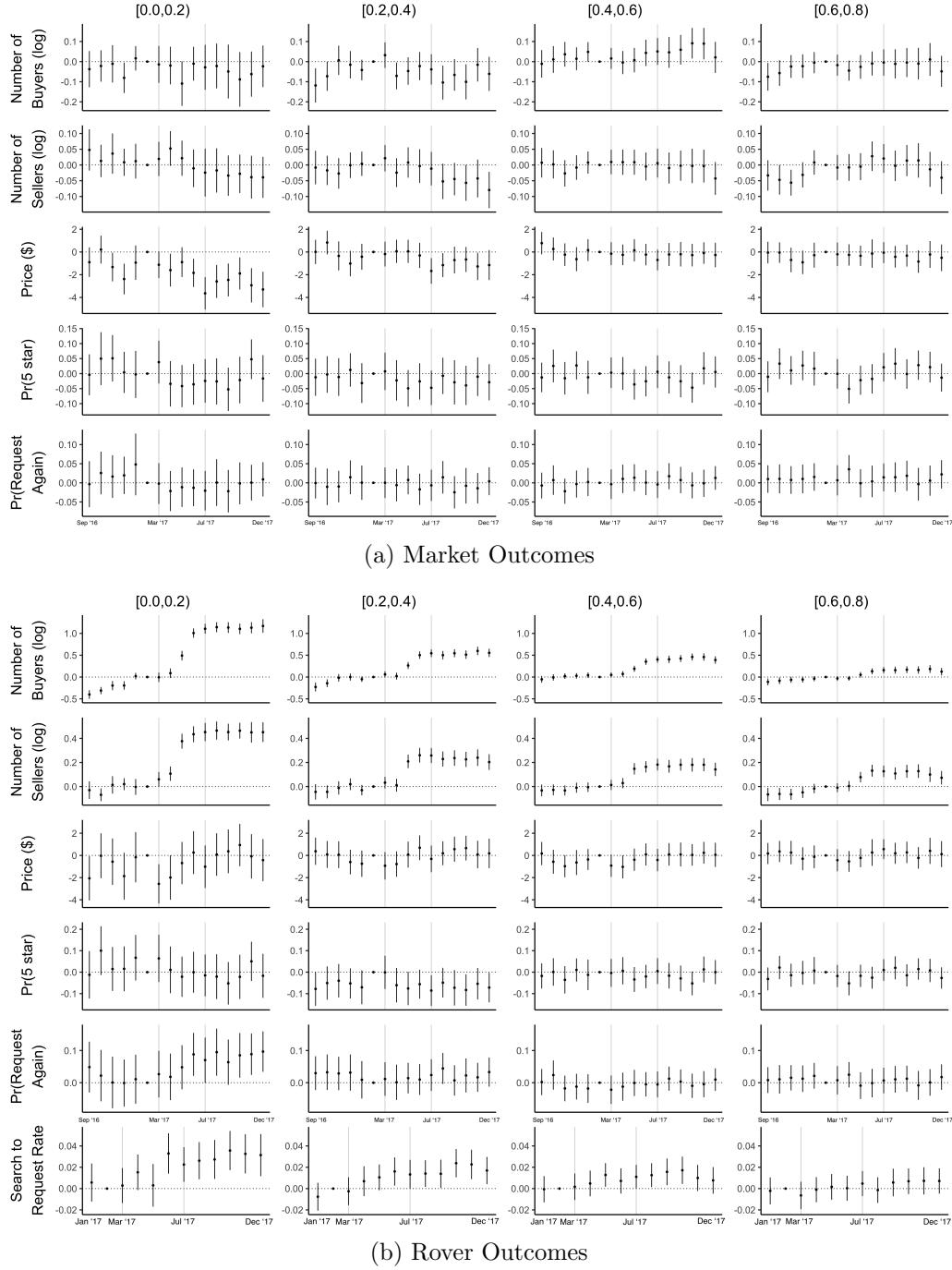
Table B.6: Estimates of Merger Effects for Conversion from Search to Request

Period	Rover Share	All	New	Rover	DogVacay
Transition	[0,0,0.2) [0,2,0.4) [0,4,0.6) [0,6,0.8)	0.011* 0.012** 0.007* 0	0.003 0.006 0.001 0.001	-0.017 -0.02 -0.007 -0.011	0.015 -0.137 -0.054 0.024
Post-Merger	[0,0,0.2) [0,2,0.4) [0,4,0.6) [0,6,0.8)	0.026*** 0.021*** 0.013*** 0.006	0.005 0.006 0.001 0	0 -0.015 -0.01 -0.001	0.049 -0.109 -0.05 0.017

Note:

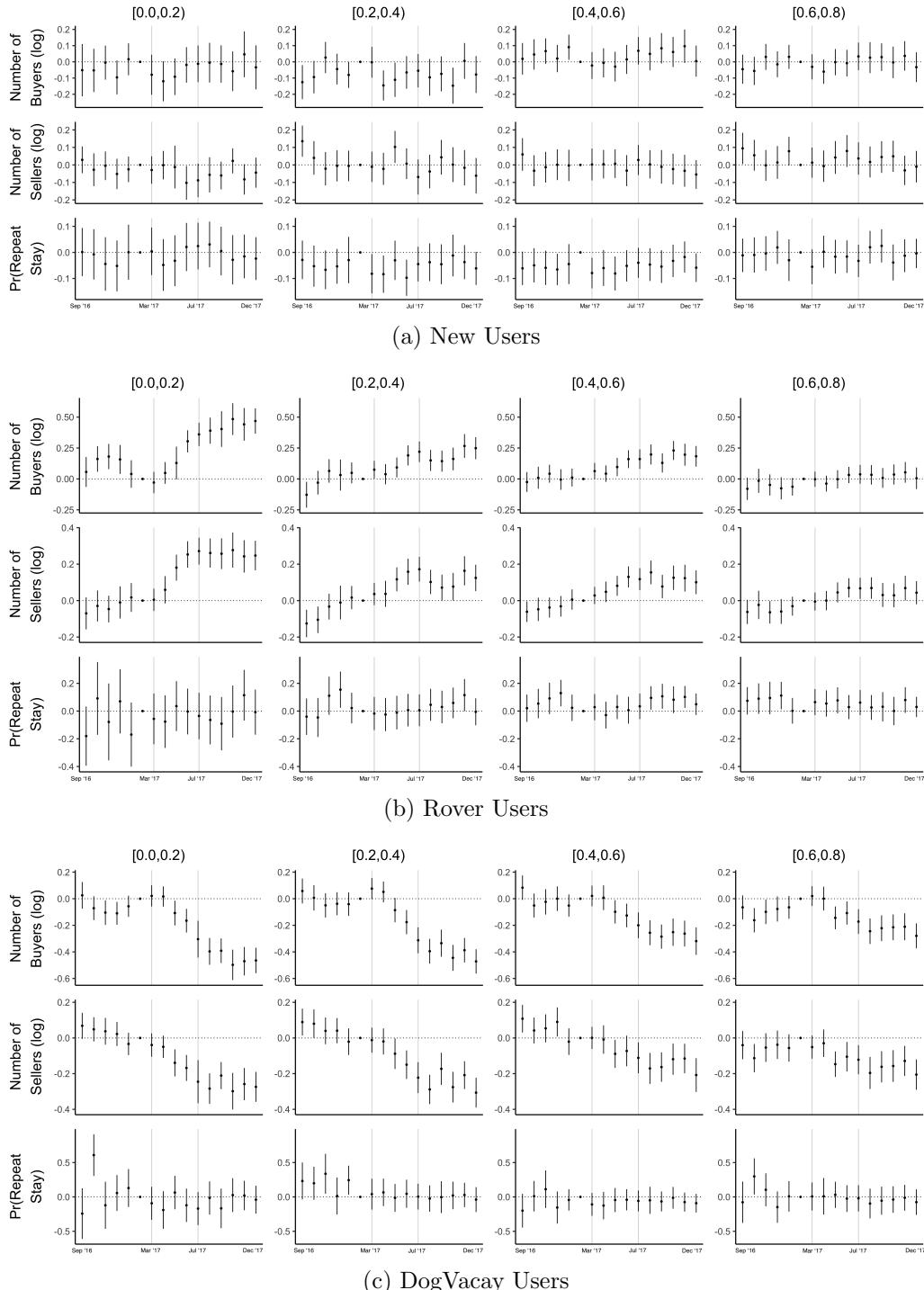
This table displays the estimates of Equation (4). The outcome variables are the search to request rate for various types of users. This table is analogous to Figure C.1.

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



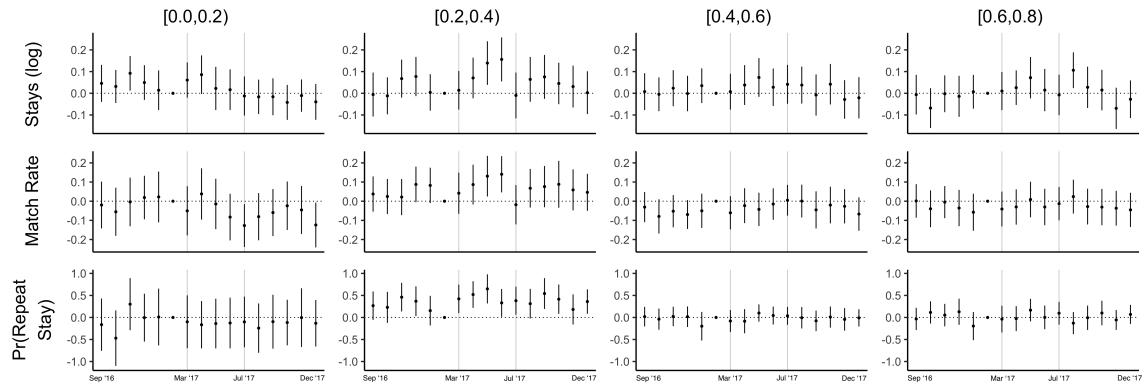
Regression estimates of Equation (3) for additional outcomes. Otherwise the figure is identical to Figure 5. Due to data limitations, we are not able to identify buyer and seller location precisely for DogVacay users, which limits our ability to use geographic distance between buyers and sellers as a proxy for match quality.

Figure B.2: Estimates of Merger Effects By User Type – Other Outcomes



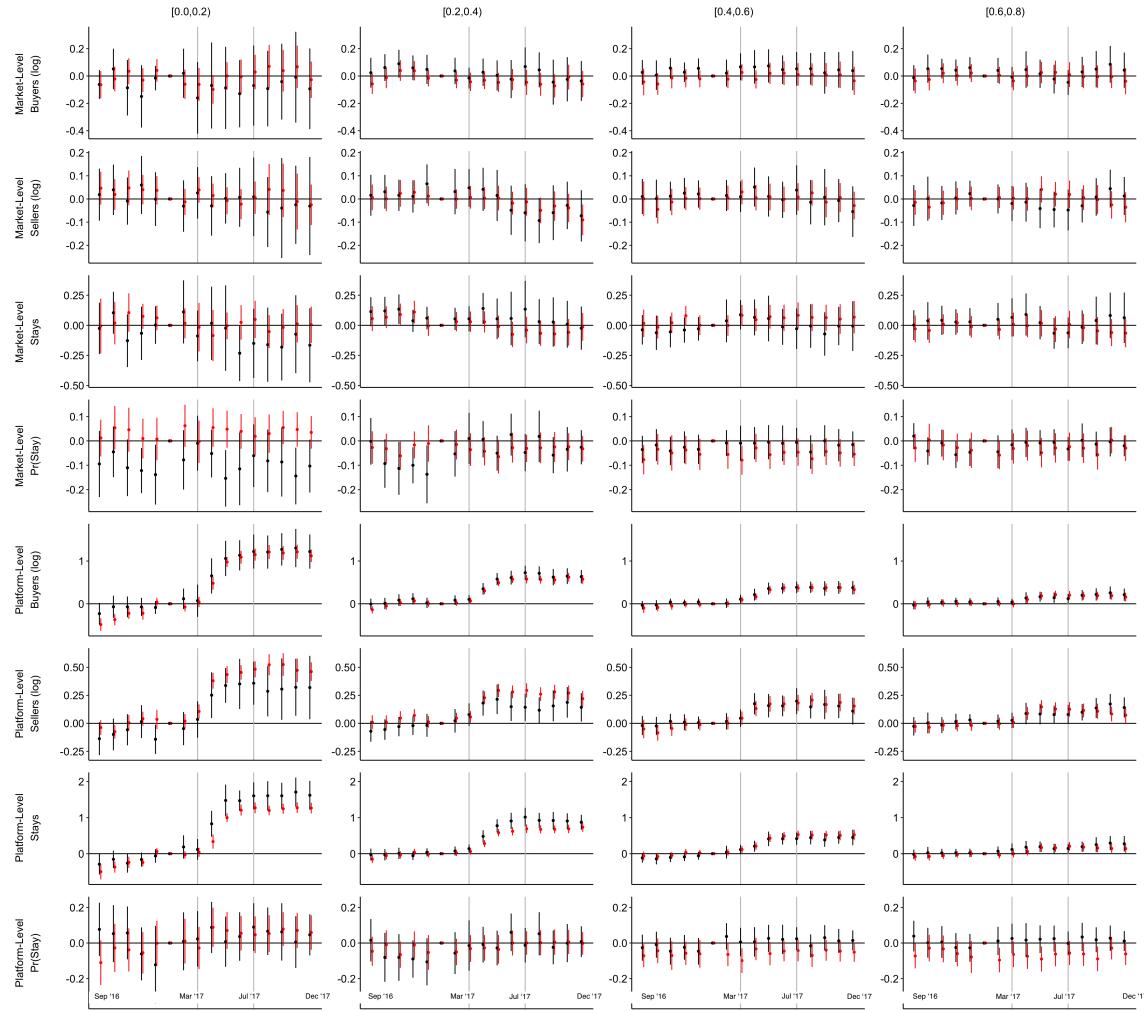
This figure displays results on additional outcomes for new users, Rover users, and DogVacay users. Otherwise the figure is identical to Figure 6. Outcomes for multi-homing users are in Appendix Figure B.3.

Figure B.3: Estimates of Merger Effects By User Type – Multihoming Users



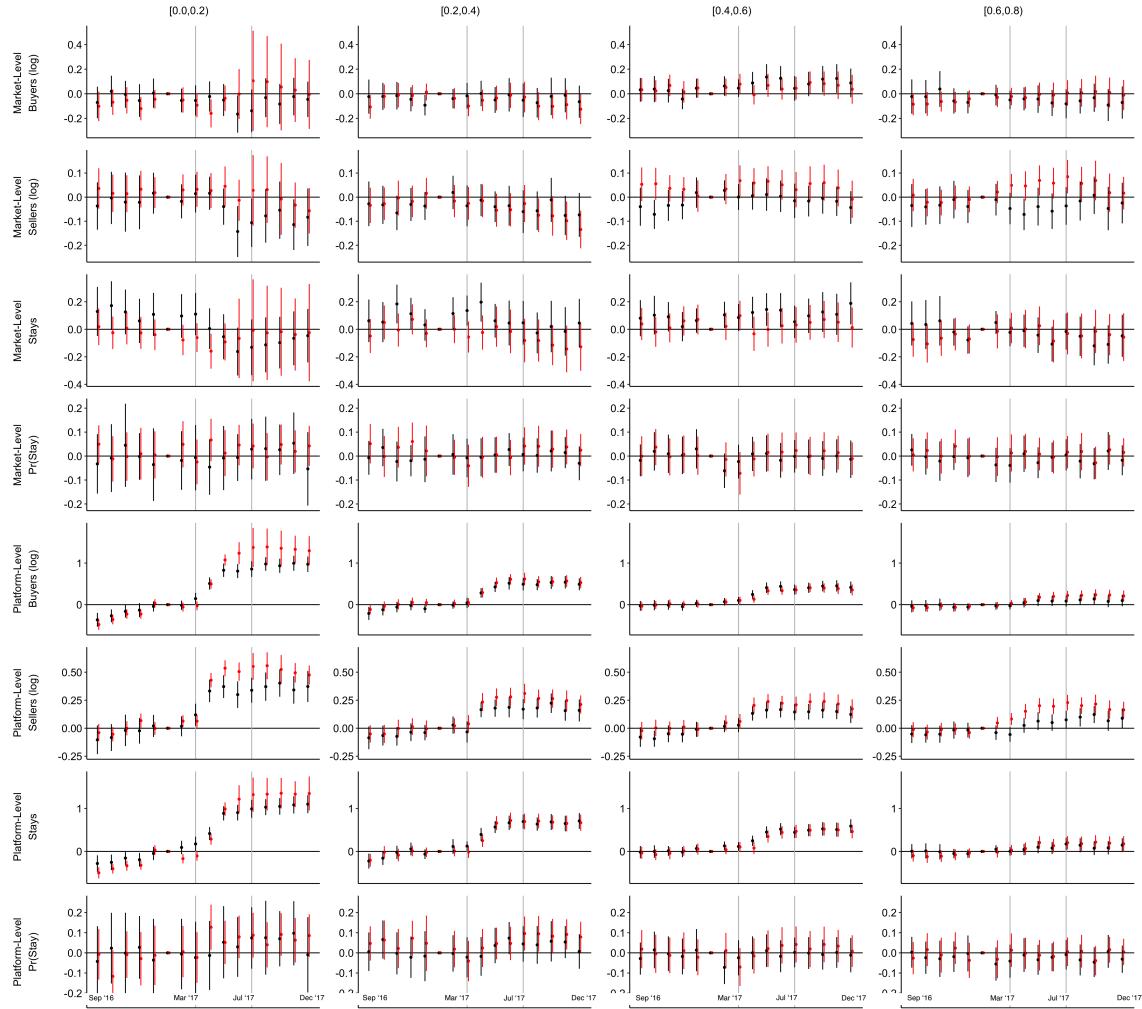
This figure displays results for multi-homing users. Multi-homing users are defined as those who engaged in booking inquiries on both Rover and DogVacay in the previous year. Otherwise the figure is identical to Figure 6 and Appendix Figure B.2.

Figure B.4: Estimates of Merger Effects – Heterogeneity by Market Size, Other Outcomes



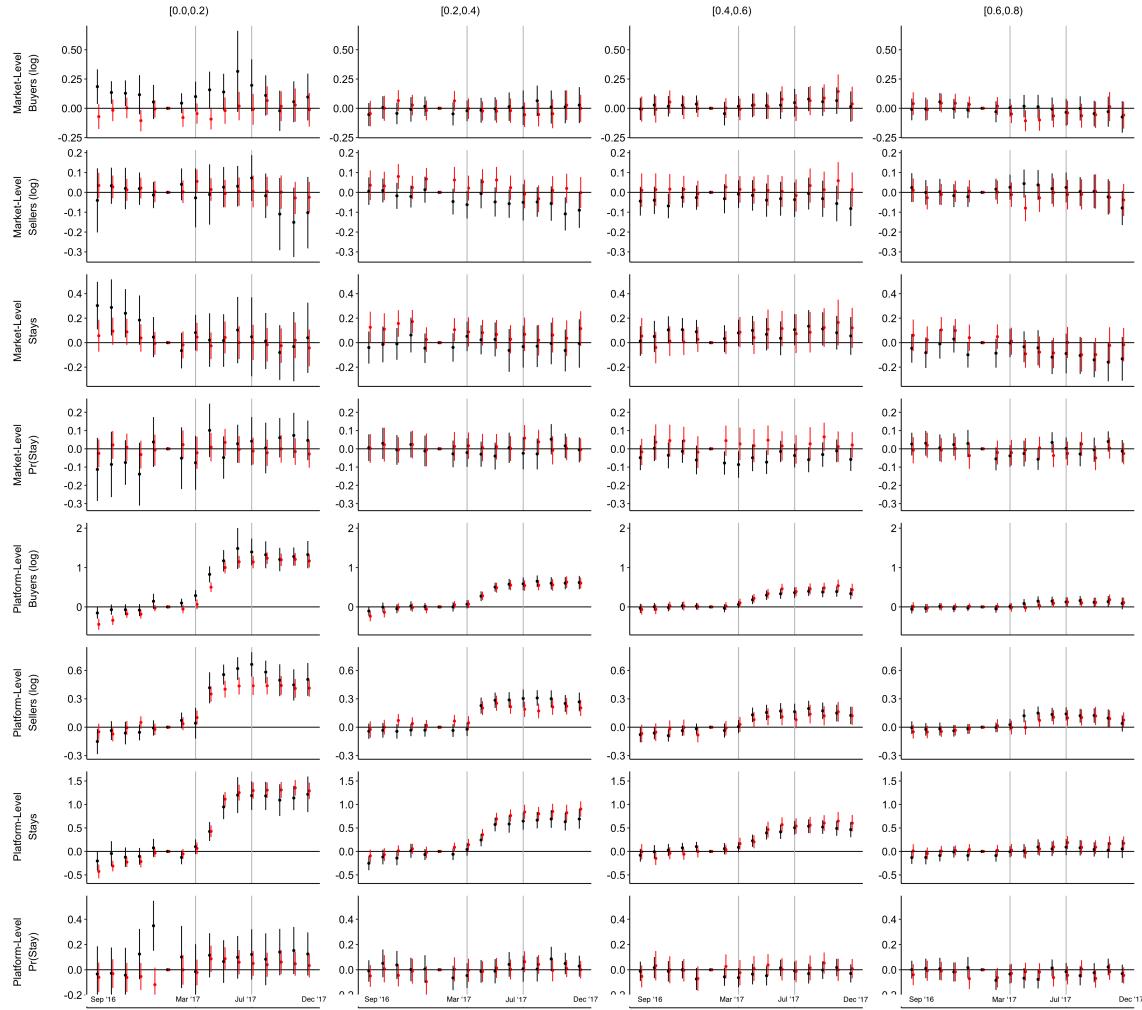
The figure is identical to Panel (a) of Figure 7 for *small* versus large markets, except that it provides results for additional outcomes.

Figure B.5: Estimates of Merger Effects – Heterogeneity by Multihoming Propensity, Other Outcomes



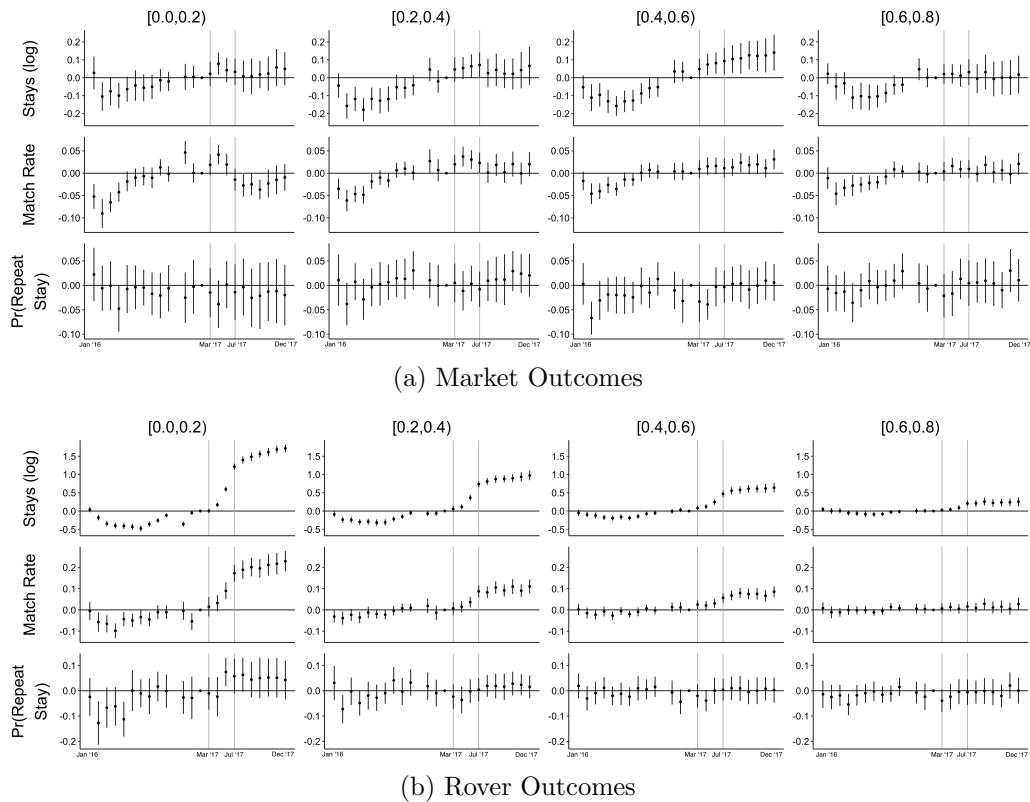
The figure is identical to Panel (b) of Figure 7 for markets with *little* versus substantial multihoming, except that it provides results for additional outcomes.

Figure B.6: Estimates of Merger Effects – Heterogeneity by Buyer to Seller Ratio, Other Outcomes



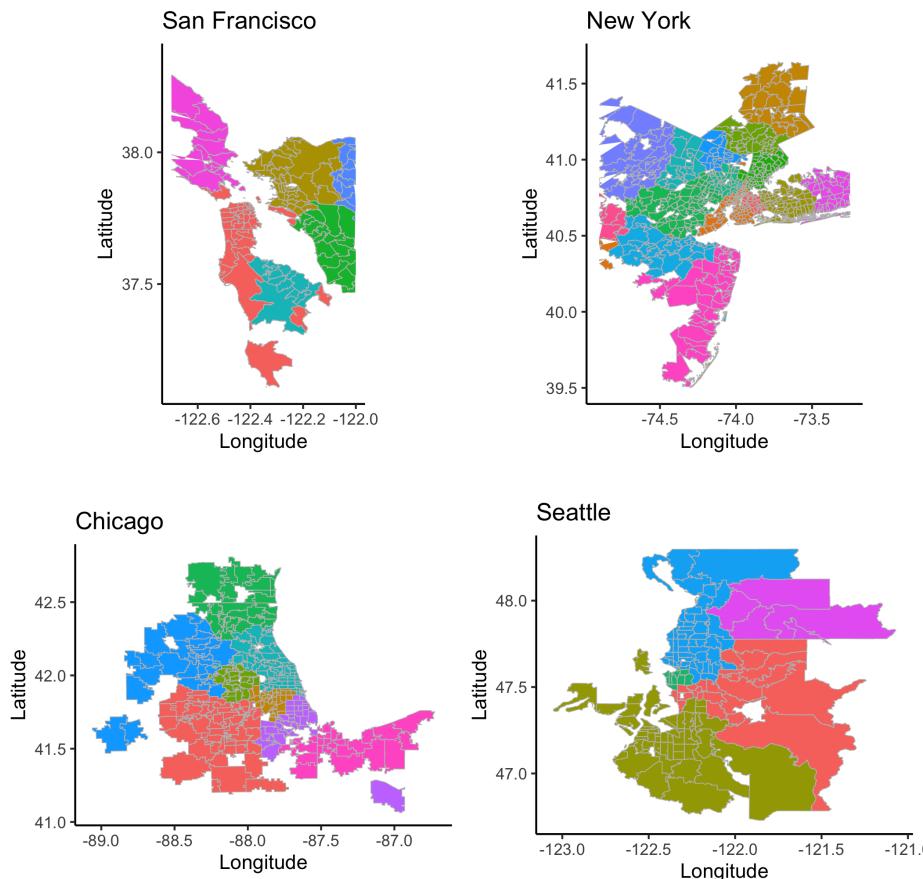
The figure is identical to Panel (c) of Figure 7 for markets with *large* versus *small* differences between Rover and DogVacay in the number of buyers relative to sellers, except that it provides results for additional outcomes.

Figure B.7: Estimates of Merger Effects – Unmatched



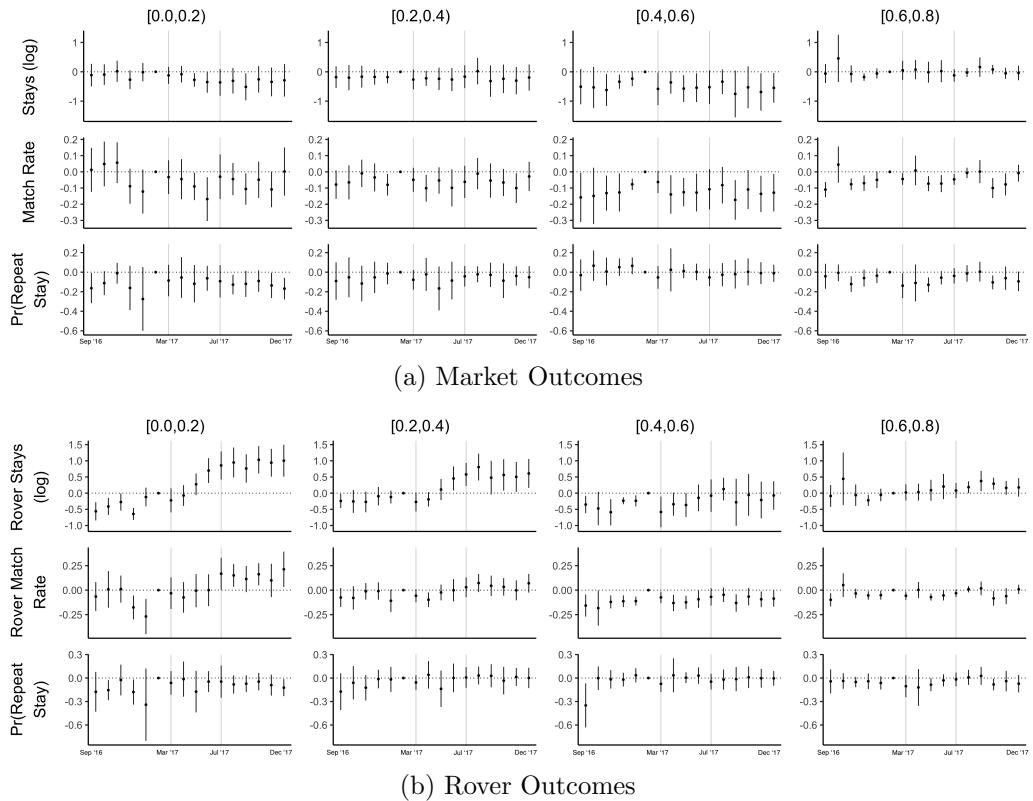
Regression estimates of Equation (5). Otherwise the table is identical to Figure 5.

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



Regression estimates of Equation (3) with geographic clusters as markets instead of zip codes. Otherwise the table is identical to Figure 5.

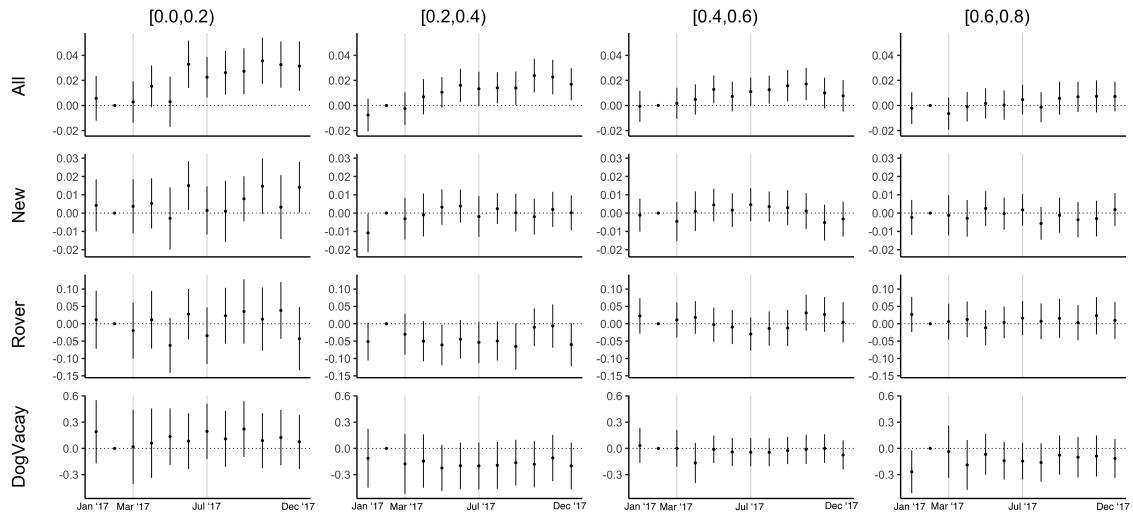
C Additional Results Based on Search Data

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). This is a large effect relative to the baseline conversion rate across year-month-zip codes in 2017 and confirms the finding in Figure 5b in the main paper. The increase is mostly driven by compositional changes—DogVacay users migrating to Rover—given that we do not see differences post-acquisition in conversion rates for existing or new users (last three rows of Figure C.1).

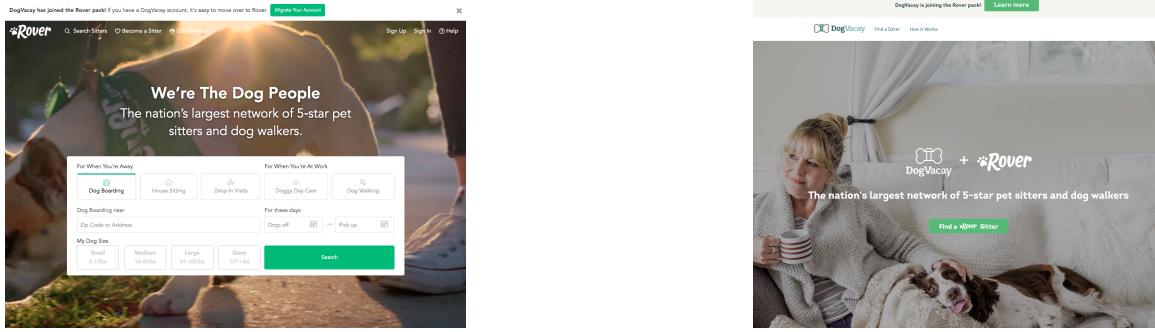
Figure C.1: Merger Effects for Conversion from Search to Booking Inquiry



Regression estimates of Equation (3). 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.

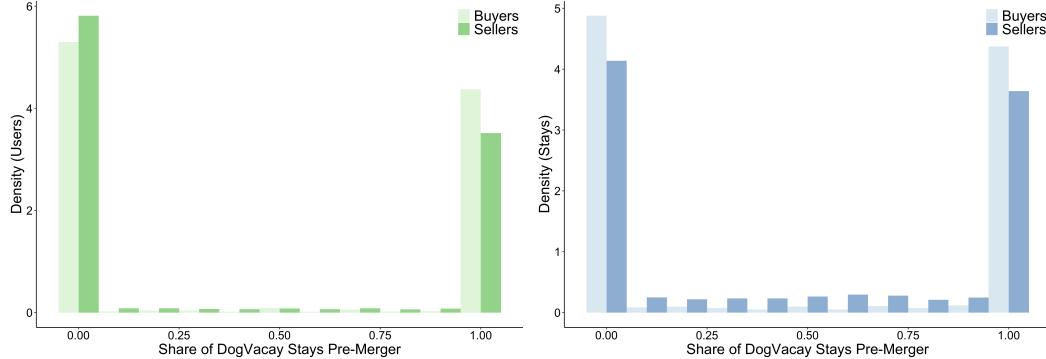
D Additional Figures and Tables

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



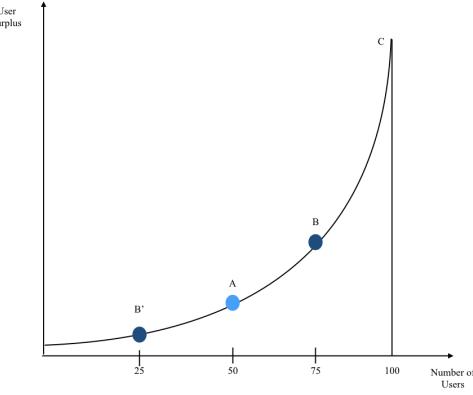
The figures show the landing page of Rover and DogVacay after the merger of the two platforms was completed. The screenshots are accessible on Wayback Machine (<https://web.archive.org/web/20170714115852/> <https://www.rover.com/> and <https://web.archive.org/web/20170704144306/> <https://dogvacay.com/>). 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



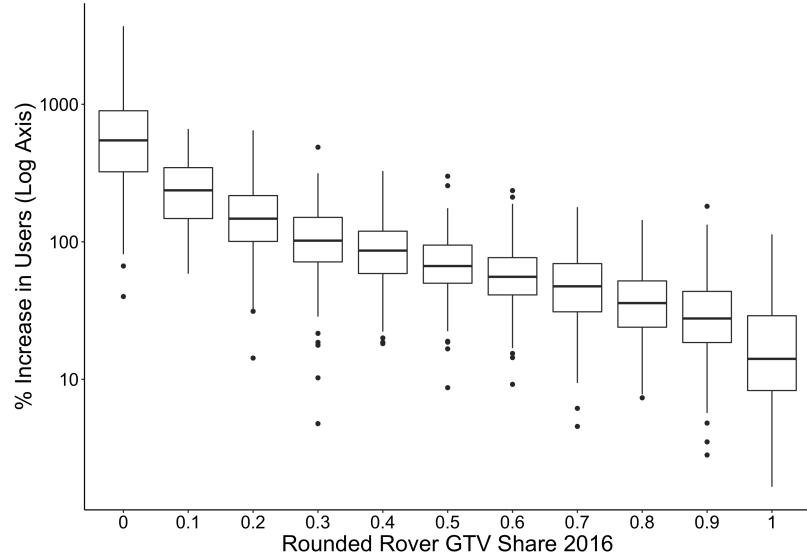
The figures plot the distribution of transactions between Rover and DogVacay for users active before the acquisition. On the left panel, an observation is a user (buyer in light, seller in dark). The histogram plots the share of users' transactions occurring on DogVacay. Users at 1 are those who only transacted on DogVacay prior to the acquisition, while those at 0 only transacted on Rover. Those in between multi-homed, 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: Network Effects and Aggregate Surplus



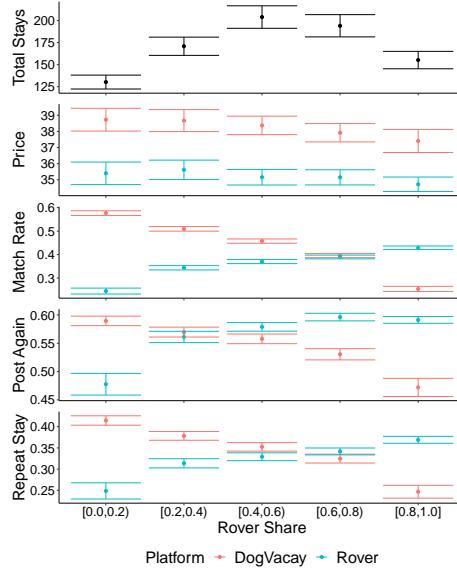
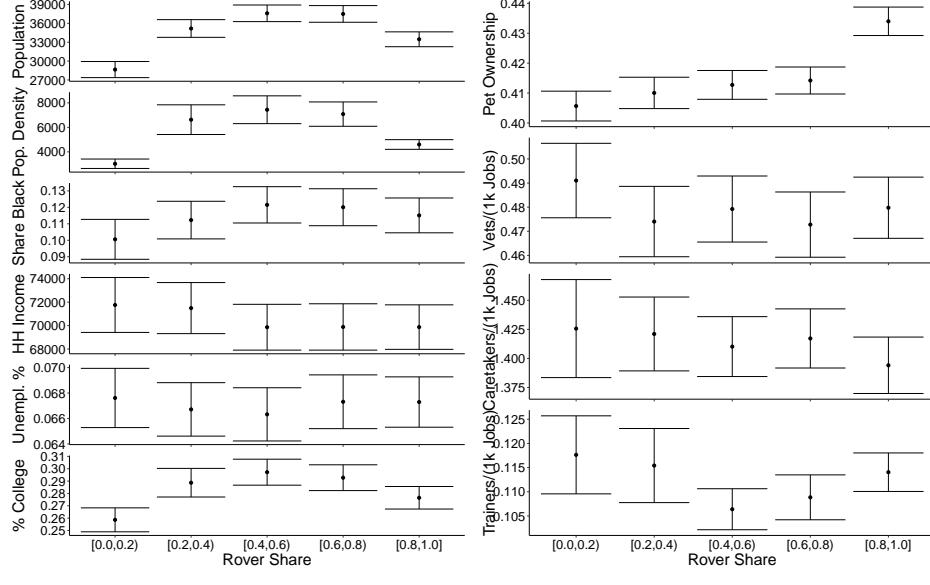
The figure plots user surplus as a function of market size, in a setting with network effects. Network effects imply that the surplus curve is increasing and convex. Point A denotes a city where Rover has 50 users, while point B denotes a city where Rover has 75 users. Both cities have a total of 100 users, so in city A DogVacay also has 50 users, while in city B DogVacay has 25 users (point B'). The merger leads Rover to have 100 users in both cities (point C), but the change in aggregate surplus is bigger in city A than in city B. Let y denote surplus. Because of network effects we have that $y_{B'} + y_B > 2y_A$, i.e. the sum of the surplus generated by DogVacay and Rover pre-merger is bigger in city B than in city A. So $y_C - 2y_A > y_C - y_{B'} - y_B$.

Figure D.4: Transactions from DogVacay Users as Share of Prior Rover Users



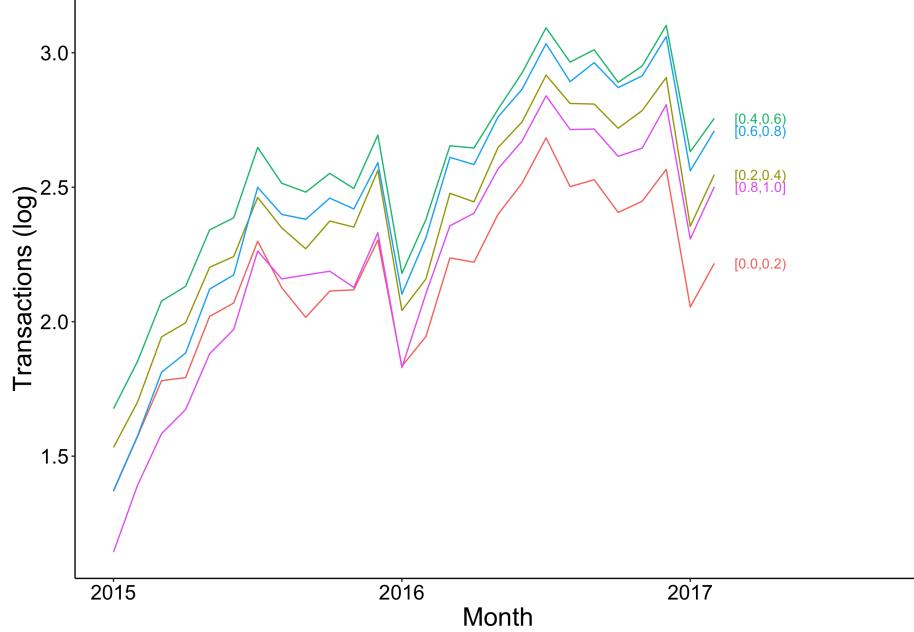
Box plot of the percentage change in the number of transacting users post-acquisition due to DogVacay users switching to Rover as a function of Rover market shares in 2016. Specifically, the percentage change in users is the number of DogVacay users who migrated their profiles to Rover and transacted 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.

Figure D.5: Differences Across Zip Codes



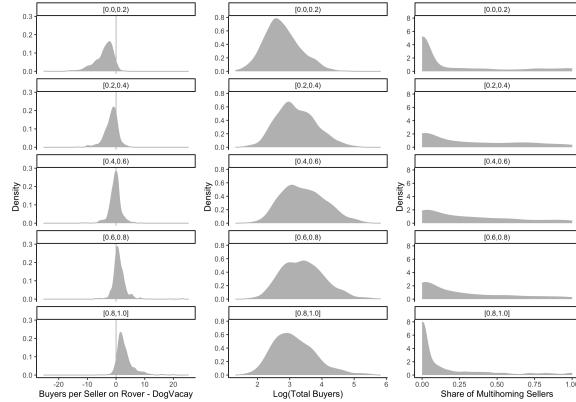
Differences across zip codes in population demographics (left), pet ownership and services (right), and Rover and DogVacay's performance (bottom). Each zip code is grouped by market share – the groupings are defined in Figure 4. The plot on the left shows average population demographics within each market 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.

Figure D.6: Matches over Time



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

Figure D.7: Heterogeneity Across Market Share Groups



The figure plots the density of three 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 2016 monthly average difference in the number of active buyers per seller on Rover compared to DogVacay in a zip code. The center column plots the monthly average number of (Rover + DogVacay) buyers in a zip code. The right column plots the share of sellers in a zipcode who transacted on both platforms in 2016.

Table D.1: 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.