Dog Eat Dog: Balancing Network Effects and Differentiation in a Digital Platform Merger*

Chiara Farronato† Jessica Fong‡ Andrey Fradkin§

April 8, 2022

Abstract

Network effects are often used to justify platform strategies such as acquisitions and subsidies that aggregate users to a single dominant platform. However, when users have heterogeneous preferences, a single platform may be worse than multiple platforms, both from a strategic and antitrust perspective. We study the role of network effects and platform differentiation in the context of the merger between the two largest platforms for pet-sitting services. To obtain causal estimates of network effects, we leverage geographic variation in pre-merger market shares and a difference-in-differences approach. We find that users of the acquiring platform benefit from the merger because of network effects, but users of the acquired platform are hurt because their preferred option is removed. Network effects and differentiation offset each other such that at the market level, users are not substantially better off with a combined platform rather than two separate platforms. Our results have strategic and regulatory implications, and highlight the importance of platform differentiation even in the presence of network effects.

*We thank Ian Meeker and Hirotaka Miura for outstanding research assistance. We thank the company employees for sharing data and insights, and participants at INFORMS, the Marketplace Innovation Workshop, Marketing Science, the Platform Strategy Research Symposium, the Workshop in Information Systems and Economics, the Simons Institute, the QME conference, and the NBER Summer Institute for valuable comments. We also thank seminar participants at Boston University, Harvard University, University of Maryland, University of Michigan, Toulouse School of Economics, the Bank of Italy, DIW Berlin, the Online Economics of Platforms Seminar, Louvain and Paris Economics of Digitization Seminar, the NYU Strategy Economics Workshop, University of Chicago, CU Boulder, and the CEPR Virtual IO seminar for very helpful feedback. Rover reviewed the paper to make sure that required confidential information was reported accurately. None of the authors have any material financial relationship with entities related to this research.

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

‡University of Michigan, jyfong@umich.edu

§Boston University, fradkin@bu.edu

1 Introduction

Companies face many strategic choices when pursuing growth, including how to innovate and attract new customers, whether to acquire competitors, and if so, how to integrate their processes into the merged company. These strategic choices become more complex with network effects, which occur when the value per user from a product or service increases with the number of other users (Katz and Shapiro (1985)). Network effects are often considered a defining characteristic of platforms (Rochet and Tirole (2003)) and a main driver of their growth (Dubé et al. (2010)). Network effects are also used to justify first-mover advantages or equilibria where a single winner eventually dominates the market (Lieberman and Montgomery (1988)). In practice however, the mere presence of network effects is not enough to draw these conclusions, because other countervailing forces may push in opposite directions.

We consider the role of platform differentiation in countervailing network effects in the context of digital transaction platforms (Cusumano et al. (2019), *platforms* henceforth). These platforms help buyers and sellers find each other and safely transact. Examples include Airbnb, Amazon Marketplace, and Uber. Sometimes, platforms are designed to cater to subsets of users with specific preferences, for example by emphasizing original and unique items (e.g., Etsy) versus delivery speed and convenience (e.g., Amazon). Even platforms that offer very similar services can attract different types of users due to subtle differences in design (Jia et al. (2021)). When platforms are differentiated and network effects are not too large, strategies designed to drive all users on a single platform may not be justified, for platform managers and regulators alike.

We study the relative importance of network effects and platform differentiation in a merger between two platforms competing in the local services industry, in which the largest platform acquired and then shut down its largest competitor. We find that buyers of the acquiring platform engaged in more transactions after users of the acquired platform joined. This first result confirms that some buyers benefited from the merger because of network effects. However, many buyers of the acquired platform left by choosing not to switch to the acquiring platform. This second result suggests that some buyers were hurt by the removal of their preferred platform. Network effect benefits and the loss of platform differentiation offset each other so that on average buyers are not significantly better off with a single platform compared to two competitors. Even though our focus is on buyer outcomes, we find similar results for platform and seller revenues, which remain constant after the merger compared to the sum of revenues from the two competing platforms before the merger.

Our findings on the role of network effects and platform differentiation provide insights on two key decisions that managers face when considering acquisitions. First, the net result that users are not better off with one compared to two platforms makes it more difficult for regulators and managers to justify platform acquisitions solely on the basis of network effects. Second, even if an acquisition is approved, it may be beneficial for a company to operate multiple platforms rather than merge them. More generally, our findings call into question growth strategies based on first-mover advantage and winner-take-all equilibria.

Measuring network effects on platforms is generally difficult since changes in the number of users are typically endogenous. For our identification strategy, we use the sudden increase in the number of buyers and sellers induced by a platform merger. In March 2017, Rover, the largest US platform for pet-sitting services, acquired DogVacay, their closest and largest competitor. A single platform emerged from this acquisition since DogVacay was shut down within four months and no other platform gained a sizable market share in the months following the acquisition. The setting is unique in that we observe data from *both* platforms.

This acquisition provides an excellent natural experiment to not only measure network effects but also evaluate whether network effects are large enough to offset the loss of platform differentiation. First, the local nature of services exchanged means that we can treat each geography as a separate market. Second, the two platforms appeared to be close substitutes and were active in the same geographies, making it more likely that combining users could lead to more and better matches. Third, prior to the acquisition, the platforms varied in their market shares across geographies, which means that some locations experienced bigger increases in the number of users interacting with each other compared to other locations. Finally, the acquiring platform did not increase its nominal or actual commission fees, a potential confound that may offset the benefits of the merger to platform users.

Our first question is whether network effects exist in platforms like ours. Answering this question is important because platform businesses like the ones we study have taken network effect benefits for granted despite recent evidence putting them into question (Cullen and Farronato (2021), Fradkin (2018), and Fong (2019)). To answer this question, we study the *effect of the merger on the buyers of the acquiring platform*, exploiting variation in pre-merger market shares that are at least in part explained by differences in early-stage growth efforts. In our setting, network effects arise because more sellers improve buyer outcomes by providing more and higher quality matches, and the same holds true for sellers when there are more buyers. The combination of the network effect benefits that each user group creates for the other group implies that increasing both buyers and sellers *at the same rate* benefits both user groups. We can test this implication in our context: the buyers of the acquiring platform should benefit more in geographies receiving a bigger influx of buyers and sellers from the acquired platform. In practice, the influx of buyers and sellers is not guaranteed to increase both user groups at the same rate, although our results are not driven by changes in the number of buyers *relative to* sellers.

Our second question is whether network effects are large enough to offset the reduction in platform variety and thus justify a single platform over two. This is both a managerial and policy-relevant question. From a managerial perspective, the acquiring firm has the opportunity to continue operating the two platforms separately, or to shut down one platform and invite its users to join the other. From a policy perspective, the antitrust regulator has the authority to allow or block a merger altogether, or even to stipulate that the acquiring firm continues operating both platforms separately. These strategic and policy decisions are made based on expectations regarding the effects of the merger on platform revenues and consumer welfare respectively, which are proxied for by the outcomes we analyze.

To evaluate whether network effects are large enough to justify a single platform, we study the *effects of the merger on the market*, aggregating data from both platforms.[1] If network effects were large enough, combining the two platforms would lead to larger user benefits in geographies where both platforms were equally large before the merger compared to geographies where one platform was already dominant. This is because in

[1] When we say "we study the effects of the merger on the market," we can actually only measure the effects on buyers who used one of the two platforms for which we have data, which represent the vast majority of online pet-sitting. Our assumptions on the value of the outside option (Section 3) imply that the value enjoyed by consumers who choose the outside option after the merger is either constant or lower compared to before.

split geographies, the merger effectively doubles the number of users who can interact.

We use a difference-in-differences strategy to measure the effects of the merger, comparing outcomes before and after the acquisition, and across zip codes with different market shares. We explicitly address selection into market shares with matching. We find that after the merger, existing Rover buyers increased platform usage more in geographies where Rover received a bigger influx of users from DogVacay. Existing DogVacay buyers similarly benefited from network effects, but, *relative to* existing Rover buyers, they decreased their platform usage after the merger. Many of these buyers chose not to switch to Rover, and those who switched transacted less frequently and matched at lower rates than comparable Rover buyers. We find support for two related mechanisms that partially explain these effects: a coordination failure and disintermediation, whereby DogVacay buyers have a harder time finding their previous providers on Rover and may be led to transact with those same providers off the platform.

Attrition by Dogvacay buyers almost perfectly offsets the increased usage of Rover buyers so that at the *market* level, we find no evidence that the combined platform substantially improves market outcomes compared to 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. Although we predominantly focus on buyer outcomes, we confirm that our results are not simply due to a redistribution of value across buyers, sellers, and the platform.

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

The rest of the paper is structured as follows. In Section 2, we present the relevant literature. Section 3 presents a stylized model motivating our empirical analysis. Section 4 describes the context and relevant data while Section 5 presents our empirical specification. Results are in Section 6. In Section 7, we conclude by discussing implications for platform strategy and antitrust regulation.

2 Literature Review

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

Early theoretical work focuses on competition and product compatibility in the presence of network externalities (Katz and Shapiro (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). In their models, platform businesses are characterized by multiple user groups and the presence of positive cross-side network effects, where each user benefits from having more users in other groups. The early papers focused on platform pricing strategies (Weyl (2010)). Other strategic choices, such as entry, vertical integration, and degree of openness are the focus of Hagiu and Wright (2014), Suarez et al. (2015), Zhu and Iansiti (2012), Eisenmann et al. (2011), and Boudreau (2010), among others. More recently, Bakos and Halaburda (2019), Jeitschko and Tremblay (2020), and Park et al. (2021) explore how platform strategies change as a function of multi-homing, i.e., the propensity of users to join multiple platforms.

In the theoretical literature on platforms, the presence of network effects has led to several strategic implications. Platforms entering first have an advantage (Lieberman and Montgomery (1988)), markets with multiple competitors tend to tip towards a single platform (Dubé et al. (2010)), and that single platform will eventually control the entire market (Cennamo and Santalo (2013)). In such cases when a dominant platform emerges, Tan and Zhou (2020) and Nikzad (2020) predict that the interaction of network effects, product variety, and pricing power lead to theoretically ambiguous effects of platform dominance on consumer surplus. Argenziano (2008) even theorizes that the competitive outcome is inefficient when platforms are differentiated. Our work adds empirical evidence to this literature by emphasizing the importance of platform variety in counterbalancing network effect benefits. Our insights challenge unconditional tipping by estimating network effects that are too weak to naturally lead to winner-take-all equilibria. We also provide some unique empirical evidence on the extent of multi-homing, finding that albeit limited, multi-homing is predominantly concentrated on the supply side among the largest sellers.

The empirical literature on network effects dates back to Greenstein (1993), Gandal

(1994), Saloner and Shepard (1995), and more recently Gowrisankaran and Stavins (2004) and Tucker (2008), who show early evidence that network effects are present in the adoption of a broad range of technologies, from banks' ATMs to video-messaging software. One of the first to empirically study and find evidence of positive cross-side network externalities is Rysman (2004) in the market for Yellow Pages, while Chu and Manchanda (2016) find similar evidence on e-commerce platforms. Unlike our work, these papers often focus on the extensive margins of user participation, ignoring usage intensity and match quality.

Data on how users interact with each other on digital platforms have allowed recent studies to become more granular and 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. With the exception of Kabra et al. (2017), most studies of digital markets have failed to find evidence of increasing returns to scale in matching (Cullen and Farronato (2021), Fradkin (2018), Fong (2019), and Li and Netessine (2020)), possibly due to a lack of exogenous shocks to the number of users or an inability to control for user selection. We address these limitation by observing users on two competing platforms before and after they merge. This degree of visibility allows us to evaluate the effects of merging two platforms not only at the level of the acquiring platform, but also at the market level, accounting for differences in user composition. It is the market-level analysis that allows us to derive implications for platform managers and regulators that weigh network effect benefits against the costs of reducing platform differentiation.

In addition to measuring network effects, our work relates to existing empirical work on platform competition. Many papers have studied platform competition predominantly in a non-digital setting or focusing on competition between digital platforms and more traditional service providers (Seamans and Zhu (2014), Farronato and Fradkin (Forthcoming), and Lam et al. (2021)). When comparing platform monopoly versus competition, the literature has traditionally focused on the trade-off between pricing power and network effect benefits (Song (2021), Filistrucchi and Klein (2013), Filistrucchi et al. (2012), Chandra and Collard-Wexler (2009), and Rysman (2004)). A handful of papers have looked at the interactions between quality and network effects (Zhu and Iansiti (2012), Fan (2013), Sweeting (2010), Berry and Waldfogel (1999), Jeziorski (2014)). Our paper confirms that the trade-off between quality and network effects is empirically important, by showing that rather than higher prices, market dominance leads to a reduction in platform differentiation, which hurts a subset of users.

Because concentration in the industry we study happens through acquisitions, we relate to the broad literature on strategic acquisitions to reconfigure businesses (Karim and Mitchell (2000)), to acquire new assets (Kaul and Wu (2016)), to remove competitive threats (Cunningham et al. (2021)), or to vertically integrate (He et al. (2021) and Li and Agarwal (2017)). Our results have implications for how to integrate the activities of acquired competitors, a topic that is ripe for further research because the divers of acquisition outcomes remain poorly understood (Graebner et al. (2017) and Zaheer et al. (2013)).

3 Theoretical Framework

This section presents a model that highlights the key trade-off between network effects and platform differentiation. The model gives us expressions for buyers' utilities before and after a merger of two competitors to guide our empirical analysis.

Our model, like our later analysis, focuses on buyers, implicitly assuming away any redistribution of merger gains between buyers, sellers, and the platform. In practice, this means that if buyers captured, say, 20%, of value before the merger, they still capture 20% after the merger.[2] This simplification, which is supported by the data, makes the model more tractable and intuitive. Our model also does not capture the separate effect of increasing the number of buyers versus sellers. In a two-sided platform, doubling buyers hurts each individual buyer due to a crowding out effect while doubling sellers benefits them because of cross-side network effects. However, the combination of cross-side network effects from each user group to the other implies that doubling both buyers and sellers should benefit each individual buyer. It is this combination of cross-side network effects that we focus on, so we assume that the number of buyers relative to sellers is fixed, equal to 1 for simplicity, so that doubling the number of users means increasing the number of buyers and sellers at the same rate.

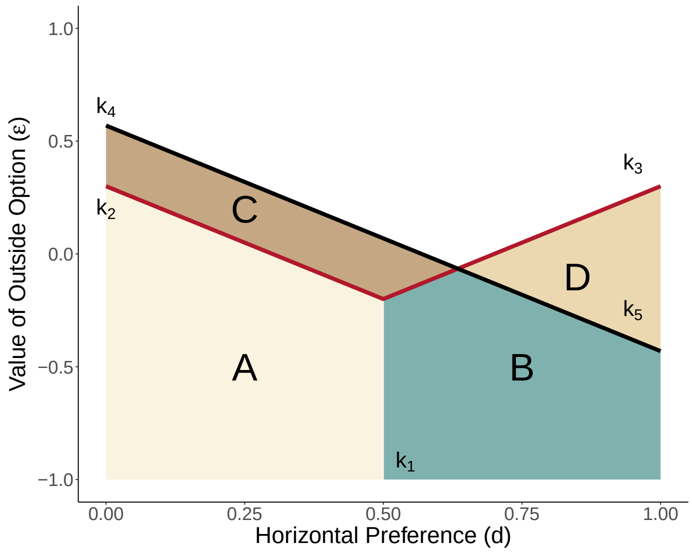
[2]This assumption ignores cost efficiencies that the platform may enjoy as a result of the merger or changes to sellers' service costs.

In our model, there are two platforms — platform α, the acquiring platform, and platform β, the acquired platform — and a unit-mass of buyers that are located on a Hotelling line. Platform α is located at 0 while platform β is located at 1. Each buyer also has a value for the outside option. Buyer types are identified by their location on the Hotelling line, $d_i \sim U(0,1)$, and their value for the outside option, $\epsilon_i \sim U(-1,1)$. A buyer i located at point d_i on the Hotelling line has utility for platform α equal to $u_{i\alpha}(n_\alpha) = v(n_\alpha) - d_i$, where n_α is the mass of buyers using platform α. Horizontal preferences are given by the parameter d_i. Network effects exist whenever $v()$ is increasing in its argument. We assume that $v()$ is not too small nor too large so that the share of buyers located at d_i who choose the outside option is strictly between 0 and 1 along the entire Hotelling line.

We have two periods, the pre-merger period in which both platforms α and β are available but each user is only aware of one of them, and the post-merger period in which only platform α is available and everyone is aware of platform α. Buyers do not expect the merger to occur. Pre-merger, when both platforms are available, we assume that advertising and customer acquisition efforts effectively split buyers in two groups, each of which is only aware of a single platform. We posit that there is an exogenous cutoff, k_1, such that buyers to the left of the cutoff ($d_i \leq k_1$) consider only platform α and the outside option, while to the right of k_1 buyers only consider platform β and the outside option. Buyers have rational expectations over the equilibrium number of buyers choosing the various options. They select the option of which they are aware that gives them the highest utility given their type (d_i, ϵ_i). In particular, buyer i for whom $d_i \leq k_1$ joins platform α if and only if $u_{i\alpha}(n_\alpha) \geq \epsilon_i$. Similarly, buyer i for whom $d_i > k_1$ joins platform β if and only if $u_{i\beta}(n_\beta) \geq \epsilon_i$.

Buyer choices result in two indifference conditions, depicted in Figure 1. The first condition is the point along the vertical axis, k_2, where buyers are indifferent between the outside option and platform α: $v(n_\alpha) = k_2$. Similarly, the second condition determines the point of indifference, k_3, between platform β and the outside option: $v(n_\beta) = k_3$. The two indifference conditions and the exogenous cutoff, k_1, allow us to find an equilibrium in (k_1, k_2, k_3). The two market shares n_α and n_β can be derived from k_1, k_2, and k_3. They are graphically depicted as the A area (for n_α) and the B+D area (for n_β) in Figure 1. Note that this model could in principle have multiple equilibria, although for our purposes

Figure 1: Buyer Types



This figure divides the space of buyer types according to an exogenous cutoff, k_1, and their optimal choices conditional on that cutoff. A denotes buyers who choose platform α both before and after the merger. B denotes buyers who switch from platform β to α. C denotes buyers who switch from the outside option to platform α. D denotes buyers who switch from platform β to the outside option.

equilibrium selection is not important.

At the realized equilibrium, the average per-buyer utility on platform α is equal to:

$$\bar{u}_\alpha = v(n_\alpha) - \int_0^{k_1} d_i g(d_i)\partial d_i, \tag{1}$$

where $g(d_i) = \frac{1}{2n_\alpha}[v(n_\alpha) + 1 - d_i]$ is the distribution of buyers' types along the Hotelling line (determined by the left trapezoid on Figure 1). Note that the utility has two components. The first, $v(n_\alpha)$, is the network effect component; the second, $\int_0^{k_1} d_i g(d_i)\partial d_i$, is the average distance from platform α among the buyers who choose it. The average per-buyer utility from platform β is similarly determined:

$$v(n_\beta) - \int_{k_1}^{1}(1 - d_i)h(d_i)\partial d_i, \tag{2}$$

where $h(d_i) = \frac{1}{2n_\beta}[v(n_\beta) + d_i]$.

After the merger, platform β is removed and every buyer becomes aware of platform α. The new equilibrium is determined by a single indifference condition: $v(n^*) = k_4$, where n^*

denotes platform α's market share post merger and k_4 is the utility for the outside option of the buyer located at $d_i = 0$ who is indifferent between platform α and the outside option. In Figure 1, the slope of the line between k_4 and k_5 is determined by the distribution of ϵ_i. Even if k_5 could be along the vertical line at $d_i = 1$ (where the share of buyers choosing platform α post-merger is strictly positive for all $d_i \in (0, 1)$) or along the horizontal line before $d_i = 1$, that line is parallel to the line separating platform α and the outside option pre-merger. It is also worth noting that, regardless of the initial pre-merger market shares induced by the exogenously-given k_1, the equilibrium post-merger always leads to the same split of buyers between platform α and the outside option, and thus the same n^*. The model assumptions imply that $n^* > n_\alpha$, i.e., the number of buyers on platform α increases post-merger, and similarly, $n^* > n_\beta$.

There are four groups of buyers whose utility change. The four groups are displayed in Figure 1. Buyers in the A area (stayers) are those who remain on platform α. Buyers in the B area (switchers) are those who migrate from platform β to α. Buyers in C (joiners) are those who join platform α from the outside option. Finally, buyers in D (leavers) are those who switch from platform β to the outside option.

To compare how utilities change after the merger, we start with buyers who remain on platform α. Their horizontal preferences remain constant (Equation (1)), while the value from a larger platform changes, so their per-buyer utility changes by:

$$v(n^*) - v(n_\alpha). \tag{3}$$

If network effects exist, this difference is positive and platform α's buyers are better off. Furthermore, the smaller n_α, the larger the influx of users post-merger and the larger the benefit to existing platform α's buyers. This is a testable hypothesis.

Hypothesis 1: The benefits of the merger to existing buyers of platform α is decreasing in n_α (or, equivalently, increasing in n_β).

The hypothesis states that with network effects, the increase in average value for existing buyers of platform α is bigger in geographies where platform α was smaller before the merger.

To evaluate the role of horizontal preferences, we compare the post- and pre-merger utility of buyers who switch from platform β to platform α (switchers). The change in utility is equal to

$$[v(n^*) - v(n_\beta)] - \left[\int_{k_1}^{1} (d_i + k_1 - 1) f(d_i) \partial d_i\right], \tag{4}$$

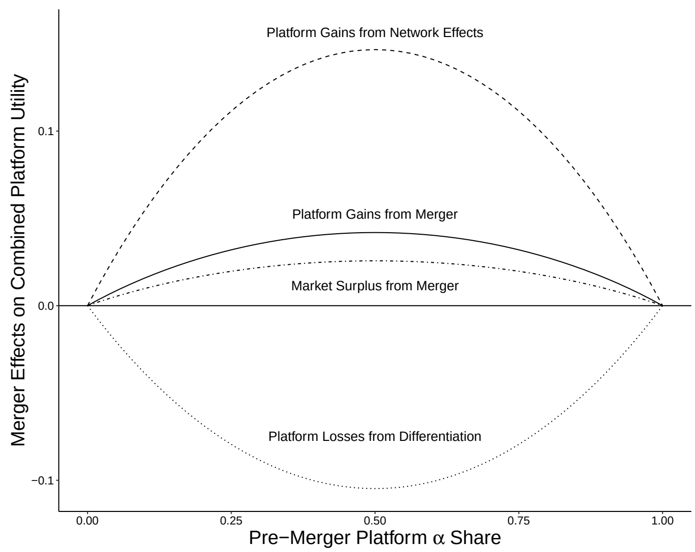
where $f(d_i)$ is the distribution of switchers along the Hotelling line (area B in Figure 1). Switchers benefit from network effects because $n^* > n_\beta$, but are also on average farther from their platform of choice.

Our model results does not yield a sharp prediction about how utility changes after the merger for switchers. Depending on whether network effects dominate over horizontal preferences, switchers may be better or worse off after the merger. We note, however, that there is a close relationship between the gains of buyers from platform α and platform β. In particular, suppose we compare the benefits to platform α's buyers of a merger in a geography where platform α had $\bar{n}$ buyers pre-merger and the benefits to platform β's buyers in a geography where platform β had $\bar{n}$ buyers. The benefits to platform α's buyers from the merger are greater than the benefits to platform β's buyers from the symmetric merger and the difference is solely due to the role of platform differentiation. That is because in both Equation (3) and Equation (4), the network effect benefits are $v(n^*) - v(\bar{n})$, while the reduction in platform differentiation only hurts switchers (the integral in Equation (4)). If users have horizontal preferences over different platforms, the difference between Equation (3) and Equation (4) when $n_\alpha = n_\beta = \bar{n}$ is negative. This is another testable implication.

Hypothesis 2: Consider two geographies, one where platform α has $\bar{n}$ number of buyers and the other where platform β has $\bar{n}$ buyers. If buyers have horizontal preferences over platforms, switchers in the second geography benefit less from the merger than stayers in the first geography.

Are network effects large enough for a single platform to create more value for buyers than two separate platforms? For this to be true, network effects need to dominate over horizontal preferences. We have already argued that stayers should benefit and switchers may or may not benefit. Joiners (area C) are definitely better off by switching to the now larger platform α from the outside option. Leavers (area D in Figure 1) are definitely worse off by switching to the outside option, which was already available pre-merger.

Figure 2: Change in Buyer Utility



The figure plots the change in aggregate utility experienced by platform buyers after the merger as a function of platform α's pre-merger market share. Market share is computed as $\frac{n_1}{n_1+n_2}$. The solid line represents the total gains by the platform from the merger. The top line represents the platform's benefits of the merger due to network effects. The bottom line represents the platform's costs from the loss of platform differentiation. The dot-dash line represents the total change in utility for all buyers, which includes the outside option.

Instead of providing the algebraically-complicated equations determining the change in buyer values, we provide graphical intuitions from Figure 1. Platform managers care about how the merger affects their users, regardless of the alternative choices those users have at their disposal. This implies that platform managers care about the change in utility of buyers in areas A and B, to which they add the post-merger utility for buyers in C and subtract the pre-merger utility for buyers in D. This comparison is displayed in Figure 2, which plots the change in aggregate utility created by the platform as a solid line. The figure also separates the net change into its two components: the gains from network effects (dashed) and the losses from the removal of platform β (dotted). To more closely map the model to our empirical strategy, we plot the change in buyer utility as a function of market shares that we can compute in our data, $\frac{n_\alpha}{n_\alpha+n_\beta}$. Network effect gains are maximized in geographies where platform α's pre-merger market share is 0.5. Similarly, the losses from platform differentiation are largest at the same point. If network effects dominate, as in Figure 2, the benefits from the merger are maximized in more competitive geographies, where the two platforms have similar market shares. This is our last testable hypothesis.

Hypothesis 3: If network effect benefits dominate the losses from the reduction in platform differentiation, then buyers in geographies with intermediate market shares for the two platforms will benefit the most from the merger.[3]

This latter hypothesis informs the strategic considerations of platform managers. Our theory highlights the tension between network effects and platform differentiation. Depending on the relative importance of these two forces, eliminating an acquired platform may or may not be beneficial to the acquirer. To make a correct decision about whether to combine platforms, managers need to understand the magnitude of these two forces.

Note from Figure 2 that the net gains from the merger are the smallest where platform α's pre-merger market share approaches 1. This rationalizes our use of such geographies as a control group in our empirical analysis. Before describing our setting and empirical results, we discuss how this model partially informs antitrust. Regulators care about the change in utility of all buyers, considering their alternative options with or without platform β. This means that, in addition to what platform managers focus on, regulators also take into account the value from the outside option that joiners enjoyed before the merger and the value from the outside option that leavers enjoy after the merger. Our theory assumes

[3]The benefits are maximized exactly where platforms α and β each have 50% market share under two additional conditions that need to jointly hold. The first is the uniform distribution of buyer types d_i and ϵ_i, which leads to balancing joiners and switchers such that network effect benefits and losses from platform differentiation are both maximized at 50% market shares. The second condition is that the absolute value of the two first derivatives for the platform gains from network effects and the losses from differentiation (dashed and dotted lines in Figure 2) cannot cross. If the marginal benefit from network effect is always higher than the marginal loss from differentiation, the change in market level average utility reaches a maximum at 0.5. If the marginal benefit from network effects is always lower, there is a minimum at 0.5. In the intermediate cases (where the order of the first derivatives flip) there can be maxima and minima away from 0.5. Our empirical analysis in Section 5 does not constrain the net benefits to be maximized at 0.5.

that the value of the outside option is constant before and after the merger. Under this assumption, although we cannot measure it in our empirical analysis, the value that a regulator considers when evaluating a platform merger (dot-dash line in Figure 2) will tend to be below the value that platform managers take into account when choosing whether to operate two versus one platform (solid line in Figure 2).

4 Setting and Data

We have proprietary data from "A Place for Rover, Inc." (Rover). Founded in 2012 in Seattle, Rover was the largest online platform for pet care services in the US, with a valuation of $970 million as of 2018.[4] At the time, Rover processed roughly one million bookings per month. DogVacay was a nearly identical platform, founded in 2012 in Santa Monica.

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. Before the acquisition, Rover and DogVacay were the largest players in the online dog boarding market. At the time, the next largest competitor was Wag Labs (Wag). Wag, which mainly offered dog-walking services, started offering overnight boarding only in 2016,[7] although it never grew to become their largest service category. In 2017, Rover earned five times higher revenues than Wag.[8]

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

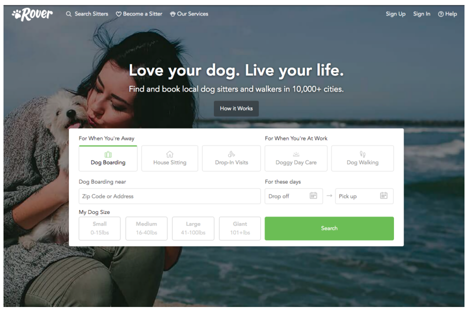
[5] `https://www.americanpetproducts.org/pr` (accessed April 2020).

[6] It is fairly easy to join the platform as a pet sitter. One of us signed up on Rover by creating a sitter profile. Platform approval was quickly granted after a general background check. Additional background checks can be performed at the sitter's will (`https://www.rover.com/background-checks/`, accessed July 2020).

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

[8] `https://secondmeasure.com/datapoints/wag-rover-dog-walking-sales/`, accessed December 2020.

Figure 3: 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/`)

Offline competitors include more traditional businesses like kennels and dog hotels, and more informal alternatives such as friends and family. Although we do not have data on these alternatives, our theoretical model rules out that kennels change the prices or quality of their offerings in response to the acquisition.

On the surface, Rover and DogVacay appear to be close substitutes, especially in comparison to competing platforms in other industries. In particular, Rover and DogVacay had similar interfaces (Figure 3) and transaction flows, which remained constant at least until the end of our study. When buyers need pet care services, they initiate a search for sellers available in the preferred category,[9] for a given location, and for the dates needed. As is typical in online platforms for local services, buyers then see a list of search results for available sellers ranked by the companies' proprietary algorithms. For each seller, 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. Transactions come with reservation protection, trust and safety support, and a secure payment system provided by the platform.

A deeper comparison uncovers a number of differences between Rover and DogVacay. Platforms use proprietary algorithms to rank sitters in search results, weighing sitter char-

Note that this figure includes total sales, not just from dog boarding.

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

acteristics differently.[10] DogVacay used to offer a 'meet and greet' option before finalizing a match whereas Rover did not. Lastly, user sorting across the platforms could create differences in the user experience, either due to path-dependence or due to strategic decisions by the platforms regarding which types of users to attract (Halaburda et al. (2018)).

Just before the acquisition, both Rover and DogVacay took about 20% of gross transaction volume in commission fees, up from 15% when they first started. Sellers would set the prices for their services.[11] As of 2018, fees are divided into a provider (seller) fee and a owner (buyer) fee. The provider fee is 15% for providers who joined before March 2016, and 20% for providers who joined after March 2016. The owner fee is zero if the owner joined before September 2015, while it varies but is never more than $50 per booking for owners who joined after September 2015.[12] DogVacay had a very similar fee structure and its commissions closely tracked those of Rover throughout the period between 2012 and 2017 (Figure 4).

4.1 The Acquisition

On March 29, 2017, Rover announced it would buy DogVacay.[13] DogVacay was reportedly struggling to keep up with the recent cash injections that Rover had received from venture capitalists,[14] and Rover acquired DogVacay in an all-stock deal.[15] Additional terms were not disclosed, but it is unlikely that the merger was subject to review by the Federal Trade Commission or the Department of Justice since the Hart-Scott-Rodino threshold for mandatory reporting was $80.8 million in 2017. Neither the Federal Trade Commission nor the Department of Justice have a publicly available case involving Rover.[16]

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

[11]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.

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

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

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

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

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

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.

First, it is rare for the acquired platform to merge with the acquiring platform. For example, even though Zillow acquired Trulia in 2015, the two platforms are still both active. The same is true for Google Maps and Waze, and for many online travel booking sites jointly owned by Booking Holdings. As Aaron Easterly, the CEO of Rover, confirms in a public interview,[17] the decision to fully absorb DogVacay into the Rover brand was a consequence of the rapid growth that Rover was experiencing during the acquisition rather than a direct consequence of network effects or the differentiation between Rover and DogVacay.

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.[18] By early July, DogVacay ceased operations.

Third, as DogVacay users migrated to Rover, Rover allowed users to link their DogVacay account to their Rover account, thus transferring all their transactions and online rating history on the Rover platform. Among those users who did not actively link their accounts, multi-homing users could still be identified from their email address. While matching users on email addresses can sometimes be inaccurate, we are confident that the similarity of services exchanged on the two platforms likely incentivizes people who are serious about using both platforms to use the same email address.[19]

[17] `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). At the time, Rover chose not to slow its growth to navigate the internal lobbying arising from two separate brands and the complexities of integrating the back-ends while keeping two separate front-ends.

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

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

4.2 Data

We observe all service requests, buyer-seller booking inquiries, matches, and reviews from *both* platforms before and after the acquisition. A *request* refers to a buyer's need for a sitter (e.g. dog boarding in Seattle from August 16^{th} until August 18^{th}) and is created when a buyer initiates a search or contacts a sitter directly. Contacts for the same request with different sellers are recorded as *booking inquiries.* A search leads to a recorded request only if a buyer sends at least one booking inquiry to a sitter. If a booking inquiry leads to a transaction, it is matched to a *stay.* Both DogVacay and Rover have multiple service categories, but we restrict attention to dog overnight boarding, which constitutes 70% of gross transaction volume on Rover and 91% on DogVacay before the acquisition.

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

We now describe the nature of competition between Rover and DogVacay before the acquisition, which suggests that a merger is likely to generate network effects if those exist in digital platforms like ours. First, the two platforms were of similar size in the dog overnight boarding category before the acquisition, with Rover transacting at a 25% higher volume compared to DogVacay in the quarter before the acquisition.[20] Second, 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 Core-Based Statistical Area (CBSA).[21] This means that we can measure competition between Rover and DogVacay at the local rather than aggregate level. Third,

[20]Across all service categories, Rover was 62% larger than DogVacay. Appendix Figure C.2 plots the number of monthly stays on DogVacay since January 2012, in log scale. Despite being founded after Rover, DogVacay immediately outgrew Rover in overnight boarding services, before being surpassed again around March 2015.

[21]CBSAs roughly coincide with metropolitan and micropolitan areas.

we investigate multi-homing. Few users, and fewer buyers than sellers, use both platforms. We define a user as multi-homing if they transact at least once on both platforms over the 5 years before the acquisition. 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 multi-homing sellers and 8% are made by multi-homing buyers.[22]

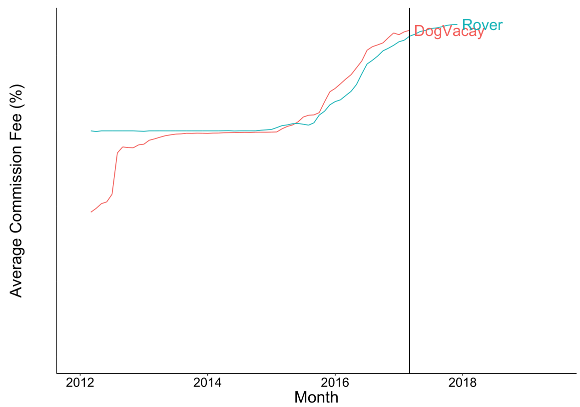
During the period before the acquisition, DogVacay sellers were expected to receive about \$3.50 more per night (13% more) than sellers on Rover.[23] After controlling for geographic and time observables, the price difference decreases to about 6% but it completely disappears once we compare prices of multi-homing sellers transacting on both Rover and DogVacay within the same month (Appendix Table C.1). This suggests that although sellers may have different qualities across platforms, which also may induce demand sorting, multi-homing sellers consider the two platforms as close substitutes.

Figure 4 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 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 increase prices.

[22] Appendix Figure C.3 plots the share of a user's transactions occurring on DogVacay prior to the acquisition, separately for buyers and sellers. On average, only 4.2% of users are both buyers and sellers of services on any given year. Buyers rarely act as service providers on the platforms. In the years before the acquisition, on average 4.8% of buyers also transacted as sellers on any given year. Sellers are more often buying pet-sitting services on the platforms. Indeed, 25.8% of sellers also transacted as buyers on any given year.

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

Figure 4: 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.

5 Empirical Strategy and Identification

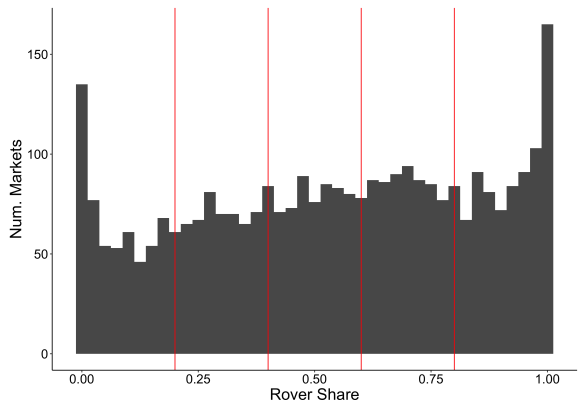
In this section, we describe how to test our theory. Our hypotheses in Section 3 rely on pre-merger variation in the number of platform users across geographies. There is a direct mapping from users to market shares, so we focus on empirical variation in market shares measured in terms of gross transaction volume (GTV, which is the total amount paid by buyers for platform and seller revenues). Figure 5 shows the distribution of Rover's market shares (equal to Rover GTV divided by the sum of Rover and DogVacay GTV) in 2016 across zip codes with at least 50 stays in that year. Because buyers and sellers' zip codes may differ, we use sellers' zip codes for our market definition. In the average zip code in 2016, Rover had about 53.6% market share, but there was substantial variation across zip codes. At least part of that variation can be explained by the different expansion strategies that Rover and DogVacay adopted years earlier when they just started out.[24]

We 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

[24]We find that part of the variation in 2016 market shares can be explained by which platform was the first mover in the market. Appendix Table C.2 shows that on average, Rover tends to have a 7% higher market share in zip codes where the first stay was booked on Rover rather than DogVacay. Due to confidentiality terms, we cannot disclose how the expansion strategies differed between Rover and DogVacay, although the two differed substantially in the way they targeted growth by expanding across geographies versus growing their user base within particular geographies.

80%. Merging the two platforms after the acquisition was effective in migrating DogVacay users to Rover. Zip codes with Rover market shares smaller than 10% experienced a median increase in users on Rover of 550% while markets above 90% had a median increase of 14% (Appendix Figure C.4).

Figure 5: Rover Market Shares Pre-Acquisition



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

To test our hypotheses, we cannot simply compare zip codes before and after the merger because aggregate shocks, e.g., due to seasonality or changes in business operations following the acquisition, may confound the results. Instead, we need a control group, which we expect to be relatively unaffected by network effects and platform differentiation. We create such a control group using the zip codes where Rover was already dominant pre-merger (i.e., Rover had more than 80% of the market share). We divide the remaining markets into four treatment groups, corresponding to the other market share groups displayed in Figure 5. It is important to allow for the treatment effects to vary across markets with differing market shares since our theory predicts non-monotonic effects across these markets.

Zip codes where either Rover or DogVacay were dominant before the acquisition tend to be more rural, have fewer residents, lower population densities, and lower shares of college graduates. Areas where Rover is particularly successful also tend to have higher pet ownership rates.[25] Given these differences, we may be concerned that the main assumption

[25] Appendix Figures C.5 and C.6, together with Appendix Table C.3, provide comparisons for a large set of observable demographics and platform performance metrics.

behind a difference-in-differences approach, that zip codes with different market shares have the same latent trends in platform performance, does not hold.

To ensure that zip codes in treated market share groups are as similar as possible to zip codes in the control group, we employ a matching estimator that accounts for covariate imbalance across groups (Imai et al., 2018). We match one zip code from the control group to each "treated" zip code using covariate balancing propensity score matching (CBPS), introduced by Imai and Ratkovic (2014). Distances are calculated on the total number of active sellers in each month up to a year before the acquisition, where an active seller is defined as a seller who was involved in at least one booking inquiry in the given month. We hold the matched control group constant as we measure the effects of combining the two platforms across different outcomes of interest. Matching on number of sellers ensures that treated and control groups have similar number of participants across the two platforms combined, but our results do not depend on whether we match on the number of buyers, the number of sellers, or a combination of both (Appendix A.2).

Appendix Table C.4, which provides descriptive statistics for the matched samples, shows that we are able to improve matching on a number of covariates that we do not explicitly use in the matching procedure.[26] However, platform performance metrics that are not explicitly considered in matching (e.g. prices, match rates, and share of repeat transactions) fail to balance across treatment and control group. Some of this imbalance is expected — for example we know that prices are higher on DogVacay and average prices will therefore be higher in markets with a higher DogVacay share. Other differences reflect the fact that platform performance metrics tend to positively correlate with a platform's market share. We should note however, that our empirical strategy, described below, does not require identical levels of pre-treatment outcomes, but rather parallel trends. The figures in Section 6 provide support for this assumption.

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

[26]Appendix Table C.3 presents descriptives for the unmatched zip codes.

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

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

where z is the treated zip code, and z' is the matched control zip code. The coefficients α_t should be interpreted as changes in the outcome variable relative to the control group, and relative to February 2017, the month before the acquisition announcement. Cluster-robust standard errors are calculated using the method from Aronow et al. (2015).[27]

Equation (5) allows us to test Hypothesis 1 and Hypothesis 3. Hypothesis 1 posits that, due to network effects, the coefficients α_t after the merger should be positive and increasing as Rover market share decreases. For Hypothesis 3, if network effects are large enough to justify a single combined platform, we would expect the largest benefits from network effects to arise in the zip codes with intermediate market shares.

To test Hypothesis 2 we need a different approach. Recall that in order to evaluate the role of platform differentiation, we need to estimate the extent to which DogVacay buyers are worse off *relative to* Rover buyers who experienced the same change in platform size. Rover buyers in markets with Rover's pre-merger market share of $\bar{n}$ experience a change in platform size similar to DogVacay buyers in markets with Rover's pre-merger market share of $1 - \bar{n}$. We attribute any difference in outcomes between Rover and DogVacay buyers of these symmetric markets to a reduction in platform differentiation.

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

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

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

[27] Each matched pair, or dyad, is no longer independently informative, as a single control market can impact the estimates of multiple dyads. The method proposed in Aronow et al. (2015) accounts for the correlation in error terms between each matched pair.

or the outcome of DogVacay buyers in zip code z and year-month t if $z \in [80\% - s, 100\% - s)$. The coefficients γ_t measure the difference in outcomes between DogVacay and Rover buyers in markets where both users experienced the same change in market size, and in month t relative to February 2017. We expect the γ to be negative due to the loss of platform differentiation.

In estimating Equations (5) and (6), we first use outcomes that proxy for buyer's utility: match rates, computed as the number of successful transactions in a given month and zip code divided by the number of posted requests; and total number of transactions in a month ans zip code. To ensure that results for buyers are not driven by a reallocation of value to the platform or sellers, we also use GTV and commission revenues as additional outcomes.

To test Hypotheses 1 and 2, we need to categorize buyers as Rover or DogVacay buyers pre-merger. We define buyers as Rover buyers if all their booking inquiries during a given calendar year were on Rover. We define DogVacay buyers similarly. We then measure the outcomes of those buyers – match rates and transactions – in any given month of the following calendar year. The small share of multi-homers, those with inquires on both platforms in a given year, are analyzed separately in Figure A.6.

To test Hypothesis 3 – are network effects large enough to justify a combined platform? – we compute market-level outcomes by aggregating Rover and DogVacay outcomes (after DogVacay was shut down this will coincide with just Rover outcomes). We also show that the results hold true for new buyers, by measuring outcomes for buyers who had never posted requests prior to the given month.

Appendix A presents additional outcomes proxying for other components of buyers' utility, as well as robustness to alternative matching strategies and synthetic difference-in-differences (Orchinik and Remer (2020) and Arkhangelsky et al. (2021)). Finally, our results are also similar for more aggregated market definitions based on zip code clusters, which are less prone to potential violations of the stable unit treatment value assumption, but give rise to noisier estimates.

6 Results

This section presents our results.[28] We start with tests of platform level network effects (Hypothesis 1). In this case, y_{zt} is the outcome of buyers in zip code z and year-month t for buyers who had posted booking inquiries only on Rover in the calendar year preceding t. Figure 6a plots the estimates of Equation (5) with log number of transactions and request match rates as the outcomes. As our theory predicts, the top row shows that Rover buyers benefit more from the merger when the influx of users from DogVacay is larger. The effects on the top row imply a 26% increase in transactions for the markets with 0-20% market shares (first plot from the left) and around 17% increase in transactions for markets with 20-40% or 40-60% market shares (second and third plots). This increase in transactions is consistent with the increased variety of sellers on the platform due to the migration of sitters from DogVacay, as opposed to other explanations such as relatively less competition from other buyers.[29] The increase in activity from Rover buyers comes from the extensive margins – more users posting requests – rather than match quality or match rates. Indeed the bottom row of Figure 6a shows that Rover buyers did not experience an improvement in match rates, and the appendix confirms that our proxies for match quality remain unchanged (Appendix Figure A.1).

The top row of Figure 6a is our evidence that network effects exist and provides a potential justification for why a company may want to integrate an acquired competitor into its existing platform. However, the presence of network effects is not sufficient to justify a dominant platform.

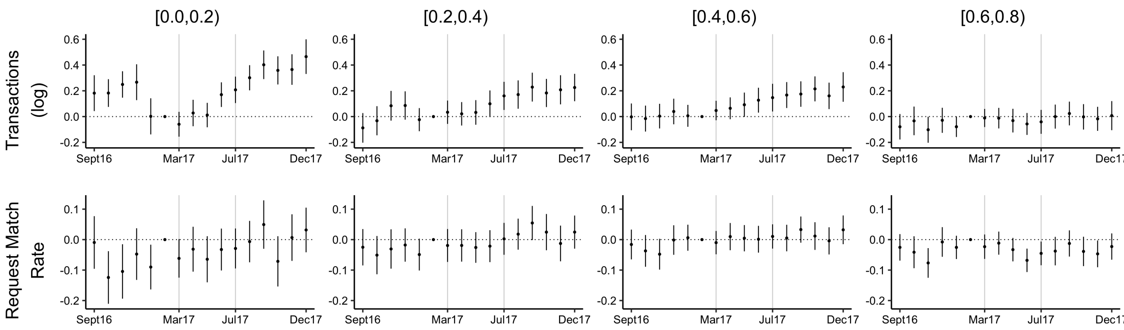
Next, we evaluate the effects of the merger on DogVacay users. We start with Figure 6b, which mirrors the previous analysis. Here, y_{zt} is the outcome in zip code z and year-month t for buyers who had posted booking inquiries only on DogVacay in the calendar year preced-

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

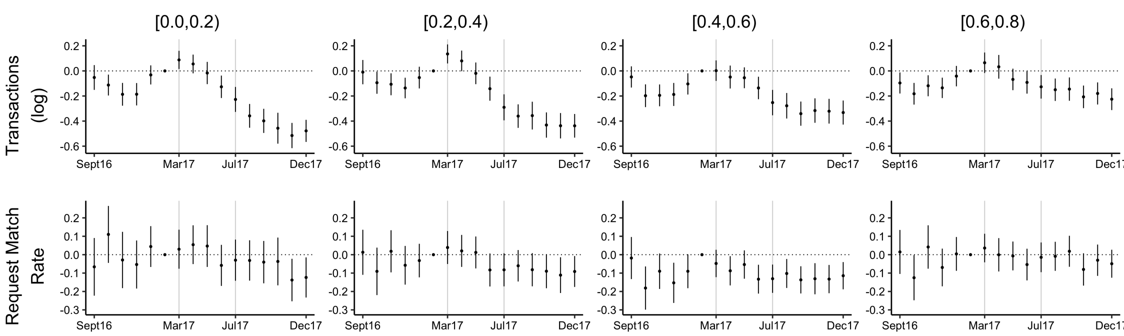
[29]Pre-merger, the larger platform in a geography tends to have more buyers for each seller relative to the smaller platform, as shown in Appendix Figure C.8a. As a result, Rover buyers in 0-20% markets receive a higher influx of buyers relative to sellers compared to the control group. This should make it relatively harder for Rover buyers to find sitters in these markets. Instead, these markets are where we find that Rover buyers benefit the most, making our results an underestimate of network effects if we could hold the shares of buyers and sellers constant.

ing t. The top row of Figure 6b shows that DogVacay buyers experience higher attrition and lower match rates compared to before the acquisition and compared to DogVacay buyers in the control zip-codes.[30]

Figure 6: Estimates of Merger Effects at the Platform Level



(a) Rover Users



(b) DogVacay Users

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

The negative coefficients in Figure 6b seem to suggest that DogVacay buyers are worse off after the merger. However, this figure is actually showing something more subtle. The

[30] Appendix Figure A.2 shows that the reduction in transactions is largely due to a reduction in the number of buyers rather than the frequency of transactions per transacting buyer.

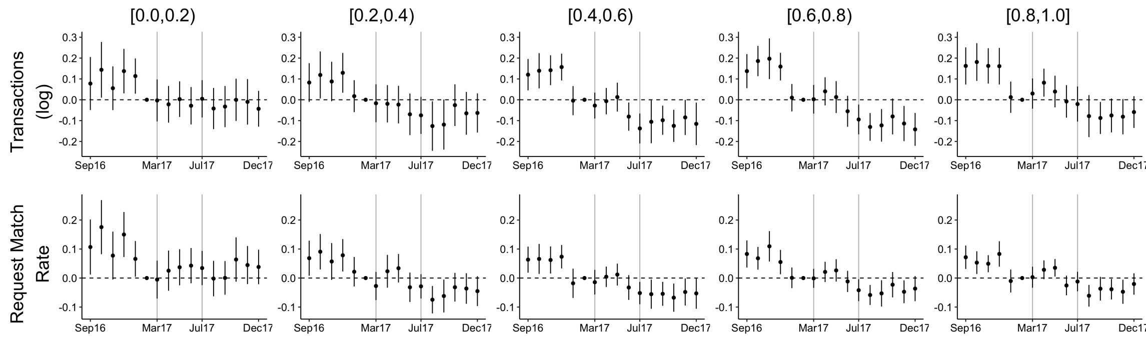
merger benefits are lower for DogVacay buyers in higher DogVacay share markets versus control markets. This pattern simply confirms that the network effect benefits of the merger for DogVacay buyers are largest in control markets.

To evaluate the role of platform differentiation, we need to estimate Equation (6). The γ_t coefficients in that equation represent to what extent DogVacay buyers are worse off *relative to* Rover buyers who experienced the same change in platform size. Figure 7 plots the estimated γ_t coefficients for each month leading up to and after the acquisition. Across all market share groups, it is clear that DogVacay buyers experienced a reduction in the number of transactions (top row) and request match rate (bottom row) relative to Rover buyers in symmetric markets. In fact, the decline in outcomes started occurring in January and February 2017, before the merger was announced but presumably during merger talks. This decline continued during the March-July 2017 period as DogVacay users started migrating to Rover. Outcomes drop more drastically after DogVacay was shut down and then stabilize. Overall, the reduction in transactions of DogVacay buyers relative to Rover is at least 10% across all market share groups, and the reduction in match rates is at least 4 percentage points (Appendix Table A.3).

The final step in our analysis is to test whether network effects are large enough that they more than offset the harm from the loss of platform differentiation (Hypothesis 3). Figure 8a plots the results of the test. The outcome in the first row is the (log) total number of transactions in a given zip code-month, regardless of whether they were intermediated by DogVacay or Rover. Like before, each column corresponds to a different treatment group. This time however, if network effects dominate the reduction in platform differentiation, we would expect the largest increase in the number of transactions to occur in zip codes with intermediate market shares, i.e., 40-60%.

The first row of Figure 8a shows that indeed, there seems to be an uptick in the number of transactions after merging the two platforms in the zip codes with 40-60% market shares, but the estimated effect is noisy and often is indistinguishable from a null effect. Pooling together the months after DogVacay's shutdown to estimate a single difference-in-differences coefficient for each treatment group (Appendix Table A.4) confirms that the effect is not statistically significant. Zip codes with market shares farther away from 40%-60% are indis-

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

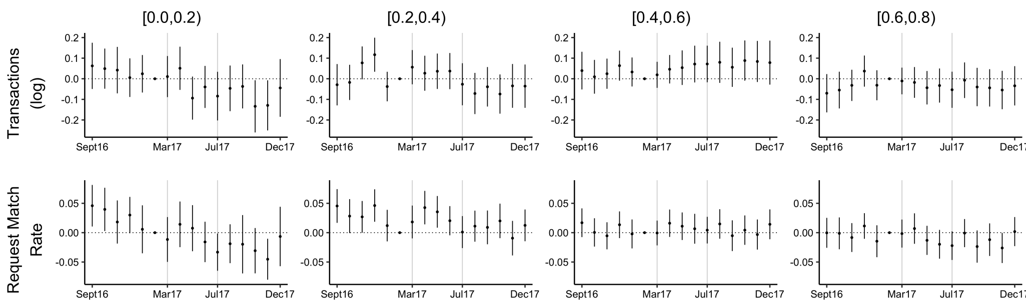


Regression estimates of Equation (6) *testing Hypothesis 2. The first row displays results where the outcome is the (log) number of transactions from buyers who, in the prior calendar year, had only engaged in booking inquiries on Rover or DogVacay. The second row displays results for the match rate of those same users, i.e., the number of stays divided by the number of requests submitted. Each column corresponds to a market share group* $(s, s + 20\%)$. *Given* $(s, s + 20\%)$ *the figure plots the estimated difference in outcomes between DogVacay users in markets with Rover market shares in* $(80\% - s, 100\% - s)$ *and Rover users in markets with Rover market shares in* $(s, s + 20\%)$. *So for example, the top-left plot compares the (log) number of transactions that DogVacay users exchanged in markets where Rover had pre-merger market shares above 80% and the number of transactions that Rover users exchanged in markets Rover had pre-merger market shares below 20%.*

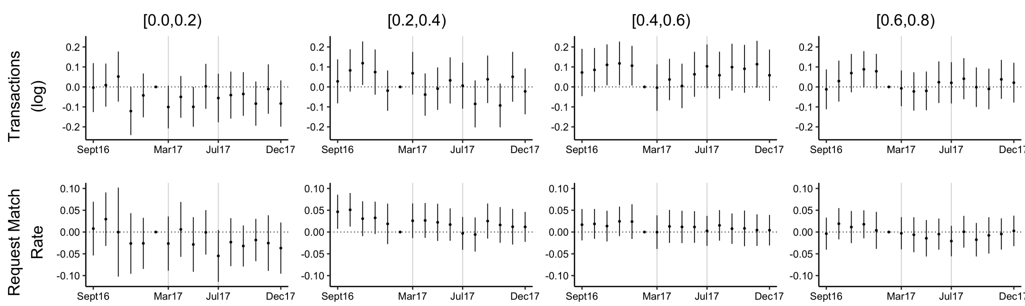
tinguishable from the control group and, if anything, the difference-in-differences coefficient for 0-20% and 20-40% market share groups implies a marginally significant 7.5% decrease in the number of transactions. Similarly for the request match rate (second row of Figure 8a), we do not find any positive effect of the merger across market share groups. For zip codes where Rover had less than 20% market share, we even find a significant reduction in match rates of 3.5 percentage points. These results and the results in Appendix Figure A.4 suggest that buyers do not find matches of higher quality or at higher rates with the single merged platform compared to when there were two competing platforms. These market-level results are not driven by differences in the mix of buyers and sellers across market shares; indeed post-merger, the number of buyers for each seller is similar in magnitude across market share groups (Appendix Figure C.8b).

The same conclusion rejecting the hypothesis that a single platform is better for buyers than two competitors is true when focusing on new buyers only. Figure 8b displays regression estimates of Equation (5) using transactions and match rates of new buyers, defined as those who never posted a request prior to the current month. The plots show surprisingly stable

Figure 8: Net Effects at the Market Level



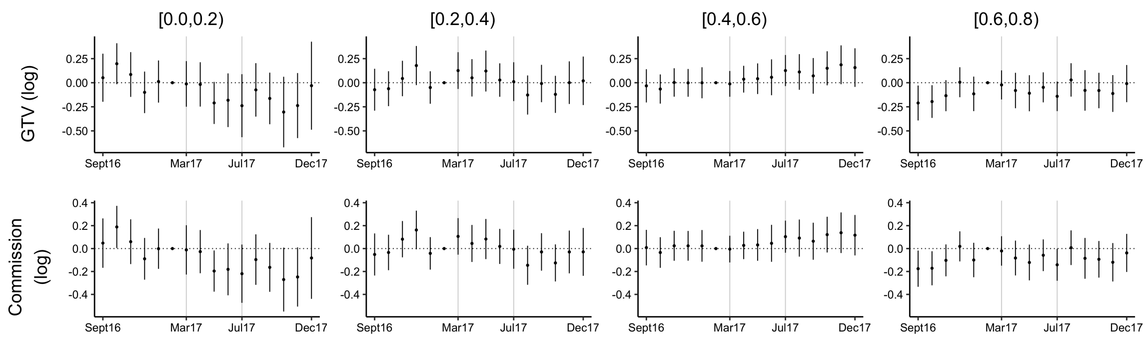
(a) Market Outcomes



(b) New Users

Regression estimates of Equation (5) *to test Hypothesis 3. Panel (a) presents market-level outcomes (log transactions and request match rate), while Panel (b) focuses on the same outcomes for new users, defined as users who never had a booking inquiry before the given month. Otherwise, the plots are identical to Figure 6. Extensions and robustness checks are in Appendix A.*

Figure 9: Net Effects on Platform and Seller Revenue



Regression estimates of Equation (5) *in which the outcomes are the logged gross transaction value (GTV) and logged commission fees (for Rover post-merger, and as the sum of Rover and DogVacay pre-merger). Otherwise, the plots are identical to Figure 8.*

transaction volumes and match rates after the merger across all treatment groups relative to the control group. This is a notable result, because it shows that horizontal preferences for platforms are not something that users develop *after* joining a particular platform, because if that were the case we would find a single dominant platform to be on average preferred by new buyers.

Lastly, we measure the effects of the merger on platform revenue as measured by the GTV and platform revenues from commission fees. The results are presented in Figure 9 and show that both GTV and commission fees post-merger are comparable to the sum of GTV and commission fees from the two competitors pre-merger. This confirms that the results that we find for buyers are not due to a redistribution of value to the platform or its sellers.

6.1 Predictors of User Attrition Post-Merger

In this subsection, we offer some evidence on the potential reasons why DogVacay buyers, despite benefiting from the increase in platform size, are worse off relative to Rover buyers. The same analysis for sellers provides similar results (Appendix Table C.5).

We match DogVacay buyers to similar Rover buyers and explore their activity after DogVacay was shut down. We consider buyers who had at least one transaction in 2016 and match them based on their activity throughout 2016. Each buyer is associated to a unique market corresponding to the modal zip code of the sellers with whom they communicated in 2016. We use coarsened exact matching on the number of transactions and booking inquiries, the month of the last transaction, whether they had at least two transactions in 2016 with the same seller, the average nightly price of all their 2016 transactions, and Rover's pre-merger market share in their market. For the latter, we match DogVacay buyers from market share group $[80\% - s, 100\% - s)$ with Rover users from market share group $[s, s + 20\%)$. We then conduct regression analyses using the matching weights we obtain and excluding users for whom there was no match (Hong (2010)). Our outcome of interest is a buyer's total number of transactions between August and December 2017, after DogVacay was shut down.

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

The first potential explanation is that dog owners prefer to engage in repeat transactions with prior sellers. On average, 50.8% of 2016 transactions are between a buyer and a seller who had already transacted with each other before. If buyers and sellers trust each other, then they may be willing to transact off the platform. The shutdown of DogVacay could thus lead some users to disintermediate rather than migrate to Rover.

If disintermediation occurs, then we would expect that DogVacay buyers with repeat transactions in 2016 would have fewer post-shutdown transactions relative to similar Rover buyers. Column (2) of Table 1 finds that this is the case, since the interaction term between DogVacay user and having repeat transactions has a statistically significant coefficient equal to -0.24. In fact, we find that DogVacay buyers with a prior repeat stay have 0.17 (0.24-0.07) fewer transactions post-shutdown relative to those without repeat stays, whereas Rover buyers have 0.07 more transactions, consistent with disintermediation.

Another explanation for why DogVacay buyers are worse off relative to Rover buyers is that DogVacay buyers may not be able to find each other on Rover. Both buyers and sellers

Table 1: Transactions of Buyers After DogVacay is Shut Down

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

This table displays coefficients of regressions where the outcome is the number of transactions of a user post-DogVacay shut-down. Each observation is a single-homing buyer who had at least one transaction in 2016. The control variables include whether the user was on DogVacay in 2016, the number of stays in 2016, the average nightly price, whether a stay in 2016 was a repeat stay with a sitter from a prior transaction, and whether the seller migrated their profile to Rover post-merger (only applies to DogVacay users). A similar analysis for sellers is presented in Appendix Table C.5.

need to migrate to the acquiring platform, but not all DogVacay sellers migrated to Rover. Buyers who did not find their prior sitter may have been induced to stop searching or send a request to a less preferred sitter. If this were true, then sellers' decisions to join Rover would help predict the post-merger transactions of the buyers with whom they interacted before the merger.

To study this coordination failure, we measure whether a DogVacay buyer's last seller in 2016 migrated their account on Rover post-merger. We add this dummy variable in column (3) of Table 1 . We see that DogVacay buyers have 0.06 more transactions on Rover if their most recent DogVacay seller migrated, and that having a prior repeat stay and a seller who migrated is associated with an additional 0.17 increase in the number of transactions. This result provides support for the presence of coordination failures.

Finally, we show that the attrition patterns are consistent with switching costs. In column (4) of Table 1, we add a predictor by interacting an indicator for whether a buyer was on DogVacay in 2016 with their number of transactions in 2016. We find a negative coefficient of 0.09, implying that the more active DogVacay buyers had fewer transactions after DogVacay was shut down relative to similar Rover users. However, this coefficient is not large enough to imply that more frequent DogVacay buyers transact less post-merger compared to less frequent DogVacay buyers. This results suggests that switching costs at least partially explain attrition since high value DogVacay buyers have the most incentives to switch platforms.

To summarize, we find that DogVacay buyers have 30% fewer transactions relative to similar Rover buyers after DogVacay was shut down. Although we find that switching costs partially explain this difference, we also find support for two alternative explanations. The first is that DogVacay buyers may continue transacting with prior providers off platform (disintermediation). The second is that there may be coordination failures, so that DogVacay buyers are not able to find previous providers on Rover, in part because those sellers do not switch platforms.

7 Discussion

Network effects are often assumed to be large enough to justify digital platforms' growth strategies that progressively concentrate activity on a single dominant platform. Even antitrust authorities have historically been hesitant to limit the acquisition efforts of platforms characterized by network effects. However, the simple presence of network effects is not enough to justify the dominance of a single platform, especially when consumers have differentiated preferences over competing platforms.

In this paper, we show that platform differentiation can be an important factor offsetting network effects even in industries where competing platforms appear to be very close substitutes. Using the merger of the two largest platforms for pet-sitting services into a single platform, we find that the acquiring platform experienced sizable network effects. Its existing buyers increased their platform activity, more so in locations experiencing a bigger influx of users from the acquired platform. Although network effects are often assumed to exist in digital platforms, we provide one of the few empirical confirmations of their existence.

We also find that while existing buyers of both platforms benefit from aggregating user participation on a single platform, buyers of the acquired platform are worse off. In particular, they match at lower rates and complete fewer transactions compared to buyers of the acquiring platform. We show that some of these differences are likely driven by the importance of repeat transactions, which may lead to disintermediation. However, we also find that new users do not prefer a single platform over two competitors, suggesting that horizontal preferences do not simply originate from experience gained while using a particular platform.

We confirm that the two distinct forces – network effects and horizontal preferences over platforms – offset each other such that on average at the market level, buyers are equally well off with one or two platforms. Combined with our evidence that platform commission rates did not increase post-acquisition, nor did aggregate platform or seller revenues, our results suggest that, on average, a single platform does not generate more value for its users than the sum of two competing platforms.

Our results have important implications for the strategy and regulation of platforms. We start with implications that are specific to mergers. From a strategic perspective, our work provides insights on two decisions that managers face when considering whether to acquire competitors and how to integrate them. The first decision is whether to shut down acquired platforms and merge their users into a single platform. We show that it may be beneficial for a company to operate multiple platforms rather than combine them, offering a novel rationale for the instances of platform acquisitions that kept acquired platforms in operation (e.g., Zillow and Trulia, or the many online travel sites within the Booking Holdings group). When platform differentiation is as valuable to consumers as the benefits of a larger network, managers can shut down acquired platforms while increasing users' incentives to switch to the surviving platform. For example, algorithms and notifications could be temporarily adjusted to further prioritize prior service providers when displaced buyers request services, or discounts on platform fees could be offered to migrate existing relationships to the new platform. Alternatively, managers can operate multiple platforms while facilitating multi-homing. For example, automatically cross-listing explicitly consenting users across platforms (Yan et al. (2021)) would allow users with strong preferences for one platform to stick with their preferred option without preventing exchanges with users who are indifferent between multiple platforms.

The second managerial decision is whether to acquire competitors in the first place. If network effects are not very large relative to the value of platform differentiation, then there may be little benefit to the merger beyond foreclosing competition. Indirectly, firms considering platform acquisitions are also facing increased antitrust scrutiny (The Economist (2017)) compared to the past (Gautier and Lamesch (2021) and Pérez-Pérez et al. (2021)).[31] Our results imply that antitrust regulators are unlikely to allow mergers solely on the basis of network effects (Farrell and Shapiro (2000)). Therefore, platform managers must now more carefully choose whether to engage in acquisitions in the first place, and be prepared to defend their acquisitions as beneficial for the market. In the context of pet sitting services, our results indicate that a merged platform may be better able to compete with a large fringe of non-platform incumbents (kennels and dog hotels) by reducing fixed and variable costs without imposing higher prices or fewer and lower quality matches to its users. These considerations would of course be different in a context where the acquiring platform were the only option to access pet-sitting services or where offline and online options were considered non-substitutable.[32]

Beyond mergers, our findings have implications for platforms' growth strategies more broadly. In particular, our results put into question the importance of a first-mover advantage and the likelihood of a winner-take-all equilibrium, which have historically pushed platforms to invest heavily to achieve scale fast and deter competitive entry. Our results also imply that despite network effects, entry and competition are likely in equilibrium, where multiple platforms can coexist and new platforms can successfully enter by identifying niche

[31] The appointment of Lina Khan as the Chair of the U.S. Federal Trade Commission was one step towards more regulatory oversight (`https://www.ftc.gov/about-ftc/biographies/lina-m-khan`, accessed February 2022.

[32] For example, H&R Block was stopped from acquiring rival TaxAct because, the government argued, they would have monopolized the digital tax preparation market, despite the availability of many offline alternatives (`https://www.wsj.com/articles/SB10001424052970203707504577010512495467038`, accessed March 2022).

consumer preferences.

Our study has focused on platforms that intermediate local and time-sensitive services. Other platforms with similar features include ride-sharing (Lyft), food delivery (Doordash), home-improvement (HomeAdvisor), and child care (Care.com). These platforms are well suited for a similar causal analysis of network effects because they are comprised of geographically separate markets exchanging services. Our analysis of user attrition post-merger shows that repeat transactions play an important role in counterbalancing network effects. As a result, platform differentiation may be even more important on child care platforms than in our setting, where repeat transactions are more frequent, and less important on ride-sharing platforms, where repeat transactions are rarer.

Our result that network effects are not large enough to justify a single platform is particularly informative for the many other contexts where platforms tend to be more differentiated. Indeed, the two platforms in our study are as similar as they can be in the way they intermediate services. In the majority of 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, preferences for platform differentiation are likely to more than offset network effect benefits, so it may be particularly important to ensure the existence of separate platforms.

Our paper has a number of limitations. We have focused on differentiation among platforms rather than differentiated offerings within a platform. While we find that some users prefer the acquired platform over the other, we cannot distinguish whether such preferences are due to the type of users that the platform attracts, or to platform-specific characteristics – such as user interfaces, customer support, or brand image – or a combination of both. If the differentiation among platforms is purely due to the type of users that platforms attract, it is conceivable to expect that in the long-run the remaining platform may differentiate its offerings enough to eliminate consumers' strong preferences for the acquired platform.

It is also possible for the remaining platform to increase or decrease the speed of innovation, which is a key driver of consumer value (Cabral (2021)). However, the effects on innovation are likely to take longer to realize than the few months of data available to us. Given the difficulty of causally linking a merger in 2017 to events occurring many months later, our evidence concerns just the short-run. Extending theories and empirical approaches to estimate the dynamic effects of mergers would be crucial to assess the costs and benefits of acquisitions of early stage competitors by incumbent platforms.

The merger was not investigated by antitrust authorities, so it is questionable whether our results based on a retrospective merger analysis would generalize to larger mergers (Carlton (2009)). Our results may nonetheless apply to the 95% of mergers that are not investigated by antitrust authorities because deemed too small to impact competition,[33] which may anyway result in significant consolidation of an entire industry (Wollmann (2019)).

We have also focused on local, as opposed to global effects. Many important platforms also enjoy global network effects across geographies, such as in the context of virtual work like Upwork, or mobile applications like iOS and Android. Our paper does not speak to whether it is better for consumers to have two platforms with non-overlapping geographic presence or a single platform active in all geographies (Zhu et al., 2019), nor are we able to measure cost efficiencies from the acquisition. The exploration of these topics is ripe for future research.

[33] `https://www.ftc.gov/tips-advice/competition-guidance/guide-antitrust-laws/mergers`, accessed January 2022.

References

ARGENZIANO, R. (2008): "Differentiated networks: Equilibrium and efficiency," The RAND Journal of Economics, 39, 747–769. 5

ARKHANGELSKY, D., S. ATHEY, D. A. HIRSHBERG, G. W. IMBENS, AND S. WAGER (2021): "Synthetic Difference-in-Differences," American Economic Review, 111, 4088–4118. 24, 62

ARMSTRONG, M. (2006): "Competition in two-sided markets," The RAND Journal of Economics, 37, 668–691. 5

ARONOW, P. M., C. SAMII, AND V. A. ASSENOVA (2015): "Cluster–robust variance estimation for dyadic data," Political Analysis, 564–577. 23

BAKOS, Y. AND H. HALABURDA (2019): "Platform competition with multihoming on both sides: Subsidize or not?" Working Paper. 5

BERRY, S. T. AND J. WALDFOGEL (1999): "Free entry and social inefficiency in radio broadcasting," RAND Journal of Economics, 30, 397–420. 6

BOUDREAU, K. (2010): "Open platform strategies and innovation: Granting access vs. devolving control," Management science, 56, 1849–1872. 5

CABRAL, L. (2021): "Merger policy in digital industries," Information Economics and Policy, 54, 100866. 36

CAILLAUD, B. AND B. JULLIEN (2003): "Chicken & egg: Competition among intermediation service providers," RAND journal of Economics, 309–328. 5

CARLTON, D. W. (2009): "Why We Need to Measure the Effect of Merger Policy and How to Do it," NBER Working Paper. 37

CENNAMO, C. AND J. SANTALO (2013): "Platform competition: Strategic trade-offs in platform markets," Strategic management journal, 34, 1331–1350. 5

Chandra, A. and A. Collard-Wexler (2009): "Mergers in two-sided markets: An application to the Canadian newspaper industry," Journal of Economics & Management Strategy, 18, 1045–1070. 6

Chavent, M., V. Kuentz-Simonet, A. Labenne, and J. Saracco (2018): "ClustGeo: an R package for hierarchical clustering with spatial constraints," Computational Statistics, 33, 1799–1822. 65, 66

Chu, J. and P. Manchanda (2016): "Quantifying cross and direct network effects in online consumer-to-consumer platforms," Marketing Science, 35, 870–893. 6

Cullen, Z. and C. Farronato (2021): "Outsourcing tasks online: Matching supply and demand on peer-to-peer internet platforms," Management Science, 67, 3985–4003. 3, 6

Cunningham, C., F. Ederer, and S. Ma (2021): "Killer acquisitions," Journal of Political Economy, 129, 649–702. 7

Cusumano, M. A., A. Gawer, and D. B. Yoffie (2019): The Business of Platforms: Strategy in the Age of Digital Competition, Innovation, and Power, HarperBusiness. 1

Dubé, J.-P. H., G. J. Hitsch, and P. K. Chintagunta (2010): "Tipping and concentration in markets with indirect network effects," Marketing Science, 29, 216–249. 1, 5

Eisenmann, T., G. Parker, and M. Van Alstyne (2011): "Platform envelopment," Strategic management journal, 32, 1270–1285. 5

Fan, Y. (2013): "Ownership consolidation and product characteristics: A study of the US daily newspaper market," American Economic Review, 103, 1598–1628. 6

Farrell, J. and G. Saloner (1985): "Standardization, compatibility, and innovation," Rand Journal of Economics, 16. 5

Farrell, J. and C. Shapiro (2000): "Scale economies and synergies in horizontal merger analysis," Antitrust LJ, 68, 685. 35

Farronato, C. and A. Fradkin (Forthcoming): "The Welfare Effects of Peer Entry: The Case of Airbnb and the Accommodation Industry," . 6

Filistrucchi, L. and T. J. Klein (2013): "Price competition in two-sided markets with heterogeneous consumers and network effects," Available at SSRN 2336411. 6

Filistrucchi, L., T. J. Klein, and T. O. Michielsen (2012): "Assessing unilateral merger effects in a two-sided market: an application to the Dutch daily newspaper market," Journal of Competition Law and Economics, 8, 297–329. 6

Fong, J. (2019): "Search, Selectivity, and Market Thickness in Two-Sided Markets: : Evidence from Online Dating," Working Paper. 3, 6

Fradkin, A. (2018): "Search, matching, and the role of digital marketplace design in enabling trade: evidence from Airbnb," Working Paper. 3, 6

Gandal, N. (1994): "Hedonic price indexes for spreadsheets and an empirical test for network externalities," the RAND Journal of Economics, 160–170. 5

Gautier, A. and J. Lamesch (2021): "Mergers in the digital economy," Information Economics and Policy, 54, 100890. 35

Gowrisankaran, G. and J. Stavins (2004): "Network externalities and technology adoption: lessons from electronic payments," RAND Journal of Economics, 35, 260–276. 6

Graebner, M. E., K. H. Heimeriks, Q. N. Huy, and E. Vaara (2017): "The process of postmerger integration: A review and agenda for future research," Academy of Management Annals, 11, 1–32. 7

Greenstein, S. M. (1993): "Did installed base give an incumbent any (measureable) advantages in federal computer procurement?" The RAND Journal of Economics, 19–39. 5

Hagiu, A. and J. Wright (2014): "Marketplace or reseller?" Management Science, 61, 184–203. 5

Halaburda, H., M. Jan Piskorski, and P. Yildirim (2018): "Competing by restricting choice: The case of matching platforms," Management Science, 64, 3574–3594. 16

He, L., I. Reimers, and B. Shiller (2021): "Does Amazon Exercise its Market Power? Evidence from Toys R Us," Working Paper. 7

Holtz, D. M. and S. Aral (2018): "Limiting Bias from Test-Control Interference in Online Marketplace Experiments," Working Paper. 65

Hong, G. (2010): "Marginal mean weighting through stratification: Adjustment for selection bias in multilevel data," Journal of Educational and Behavioral Statistics, 35, 499–531. 31

Imai, K., I. S. Kim, and E. Wang (2018): "Matching methods for causal inference with time-series cross-section data," Working Paper. 22

Imai, K. and M. Ratkovic (2014): "Covariate balancing propensity score," Journal of the Royal Statistical Society: Series B (Statistical Methodology), 76, 243–263. 22

Jeitschko, T. D. and M. J. Tremblay (2020): "Platform competition with endogenous homing," International Economic Review, 61, 1281–1305. 5

Jeziorski, P. (2014): "Effects of mergers in two-sided markets: The US radio industry," American Economic Journal: Microeconomics, 6, 35–73. 6

Jia, J., G. Z. Jin, and L. Wagman (2021): "Platform as a Rule Maker: Evidence from Airbnb's Cancellation Policies," . 1

Kabra, A., E. Belavina, and K. Girotra (2017): "Designing promotions to scale marketplaces," Working Paper. 6

Karim, S. and W. Mitchell (2000): "Path-dependent and path-breaking change: reconfiguring business resources following acquisitions in the US medical sector, 1978–1995," Strategic management journal, 21, 1061–1081. 7

Katz, M. L. and C. Shapiro (1985): "Network externalities, competition, and compatibility," American economic review, 75, 424–440. 1, 5

Kaul, A. and B. Wu (2016): "A capabilities-based perspective on target selection in acquisitions," Strategic Management Journal, 37, 1220–1239. 7

Lam, C. T., M. Liu, and X. Hui (2021): "The geography of ridesharing: A case study on New York City," Information Economics and Policy, 100941. 6

Li, H., G. Zhao, R. Johari, and G. Y. Weintraub (2021): "Interference, Bias, and Variance in Two-Sided Marketplace Experimentation: Guidance for Platforms," arXiv preprint arXiv:2104.12222. 65

Li, J. and S. Netessine (2020): "Higher market thickness reduces matching rate in online platforms: Evidence from a quasiexperiment," Management Science, 66, 271–289. 6

Li, Z. and A. Agarwal (2017): "Platform integration and demand spillovers in complementary markets: Evidence from Facebook's integration of Instagram," Management Science, 63, 3438–3458. 7

Lieberman, M. B. and D. B. Montgomery (1988): "First-mover advantages," Strategic management journal, 9, 41–58. 1, 5

Nikzad, A. (2020): "Thickness and Competition in On-demand Service Platforms," Working Paper. 5

Orchinik, R. and M. Remer (2020): "What's the Difference? Measuring the Effect of Mergers in the Airline Industry," Measuring the Effect of Mergers in the Airline Industry (May 15, 2020). 24, 62

Park, K. F., R. Seamans, and F. Zhu (2021): "Homing and platform responses to entry: Historical evidence from the US newspaper industry," Strategic Management Journal, 42, 684–709. 5

Parker, G. G. and M. W. Van Alstyne (2005): "Two-sided network effects: A theory of information product design," Management science, 51, 1494–1504. 5

Pérez-Pérez, C., D. Benito-Osorio, and S. M. García Moreno (2021): "Mergers and acquisitions within the sharing economy: Placing all the players on the board," Sustainability, 13, 743. 35

Rochet, J.-C. and J. Tirole (2003): "Platform competition in two-sided markets," Journal of the european economic association, 1, 990–1029. 1, 5

Rysman, M. (2004): "Competition between networks: A study of the market for yellow pages," The Review of Economic Studies, 71, 483–512. 6

Saloner, G. and A. Shepard (1995): "Adoption of technologies with network effects: an empirical examination of the adoption of automated teller machines," The RAND Journal of Economics, 26, 479–501. 6

Seamans, R. and F. Zhu (2014): "Responses to entry in multi-sided markets: The impact of Craigslist on local newspapers," Management Science, 60, 476–493. 6

Song, M. (2021): "Estimating platform market power in two-sided markets with an application to magazine advertising," American Economic Journal: Microeconomics, 13, 35–67. 6

Suarez, F. F., S. Grodal, and A. Gotsopoulos (2015): "Perfect timing? Dominant category, dominant design, and the window of opportunity for firm entry," Strategic management journal, 36, 437–448. 5

Sweeting, A. (2010): "The effects of mergers on product positioning: evidence from the music radio industry," The RAND Journal of Economics, 41, 372–397. 6

Tan, G. and J. Zhou (2020): "The Effects of Competition and Entry in Multi-sided Markets," The Review of Economic Studies. 5

The Economist (2017): "The University of Chicago worries about a lack of competition," Apr 15, 2017. 35

Tucker, C. (2008): "Identifying Formal and Informal Influence in Technology Adoption with Network Externalities," Management Science, 54, 2024–2038. 6

Weyl, E. G. (2010): "A price theory of multi-sided platforms," American Economic Review, 100, 1642–72. 5

Wollmann, T. G. (2019): "Stealth consolidation: Evidence from an amendment to the Hart-Scott-Rodino Act," American Economic Review: Insights, 1, 77–94. 37

Yan, Z., H. Yang, L. Jia, and Y. Tan (2021): "Asymmetric Network Effects in the Integration of Digital Platforms," Available at SSRN 3871279. 35

Zaheer, A., X. Castañer, and D. Souder (2013): "Synergy sources, target autonomy, and integration in acquisitions," Journal of Management, 39, 604–632. 7

Zhu, F. and M. Iansiti (2012): "Entry into platform-based markets," Strategic Management Journal, 33, 88–106. 5, 6

Zhu, F., X. Li, E. Valavi, and M. Iansiti (2019): "Network Interconnectivity and Entry into Platform Markets," Harvard Business School Working Paper, 19–06. 37

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

By Chiara Farronato, Jessica Fong, Andrey Fradkin

A Extensions to the Empirical Results

In this appendix, we provide additional results and robustness checks related to Section 6.

We start by providing estimates for additional outcomes. In addition to match rates and total transactions presented in the main paper, several other outcomes proxy for the various components of buyers' utility. Utility is a function of the probability to find a sitter to transact with, the quality of the transaction, the price of the transaction, and search costs affecting the propensity of buyers to even post a request in the first place. We compute the average nightly price of successful transactions as the total price that the buyer pays divided by the duration of the booking averaged over all transactions in a given month and zip code. We proxy for the average match quality with three metrics: the share of transactions in a given month and zip code whose buyer requests help again in the subsequent three months; the share of (non-repeat) transactions leading to a repeat stay in the future; and the share of transactions with a 5-star review submitted by the buyer. We also look at number of unique buyers posting requests as an additional aggregate metric. Finally, we consider the number of transactions by Rover and DogVacay sellers and the number of unique sellers engaging in inquiries in a given month and zip code.

First, we provide estimates for additional outcomes similar to Figure 6. Figure A.1 presents additional outcomes for users who were involved in booking inquiries only on Rover in the calendar year preceding the current month. Figure A.2 is analogous for existing DogVacay users.

Second, Figure A.3 provides estimates for additional outcomes similar to Figure 7.

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

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

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

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

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

Finally, the next three subsections present heterogeneous results by market size and degree of multi-homing (Appendix A.1), robustness checks to alternative estimators and matching approaches (Appendix A.2), and robustness to a coarser market definition (Appendix A.3).

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

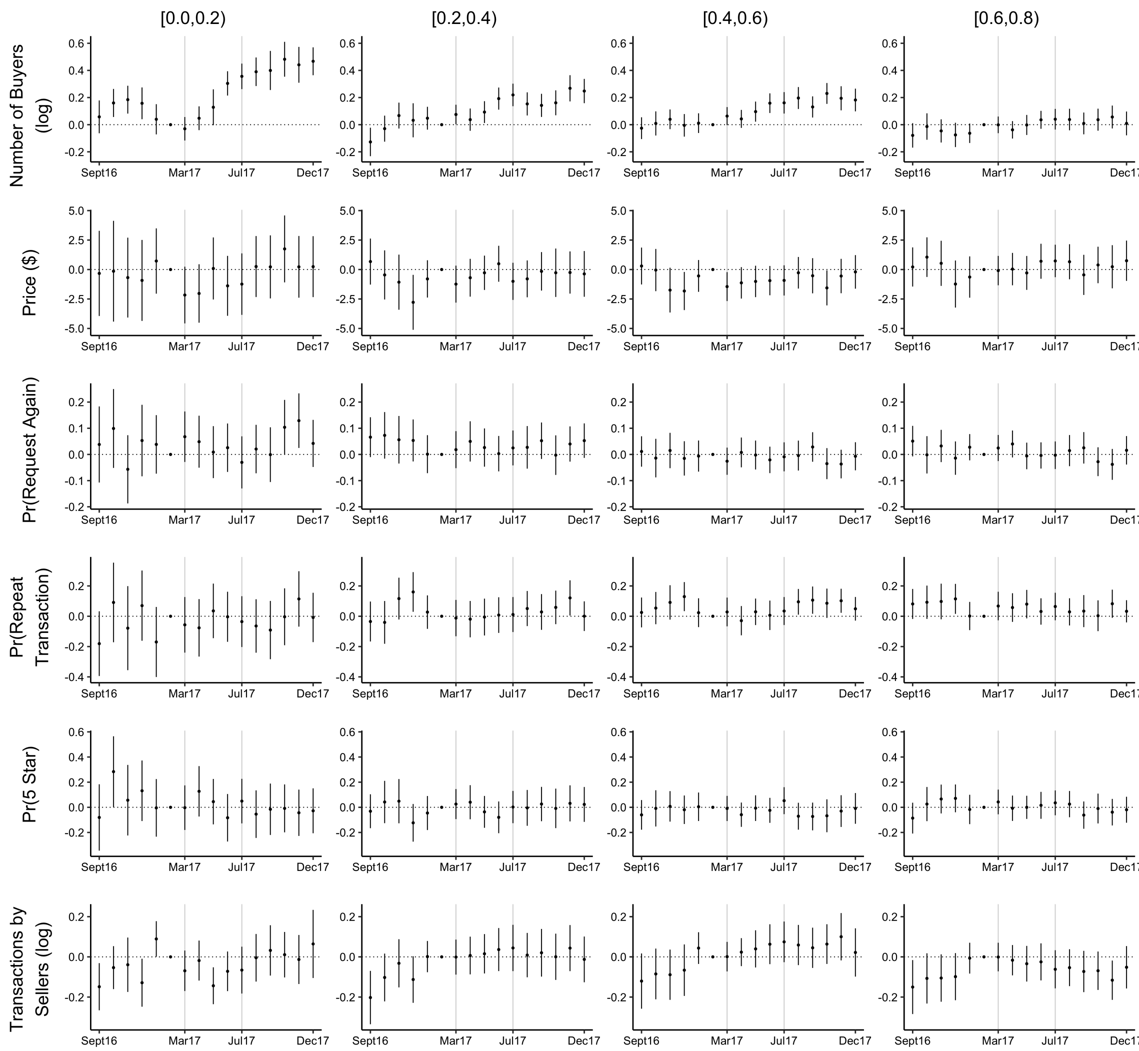
Table A.5: Estimates of Merger Effects - New Users

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

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

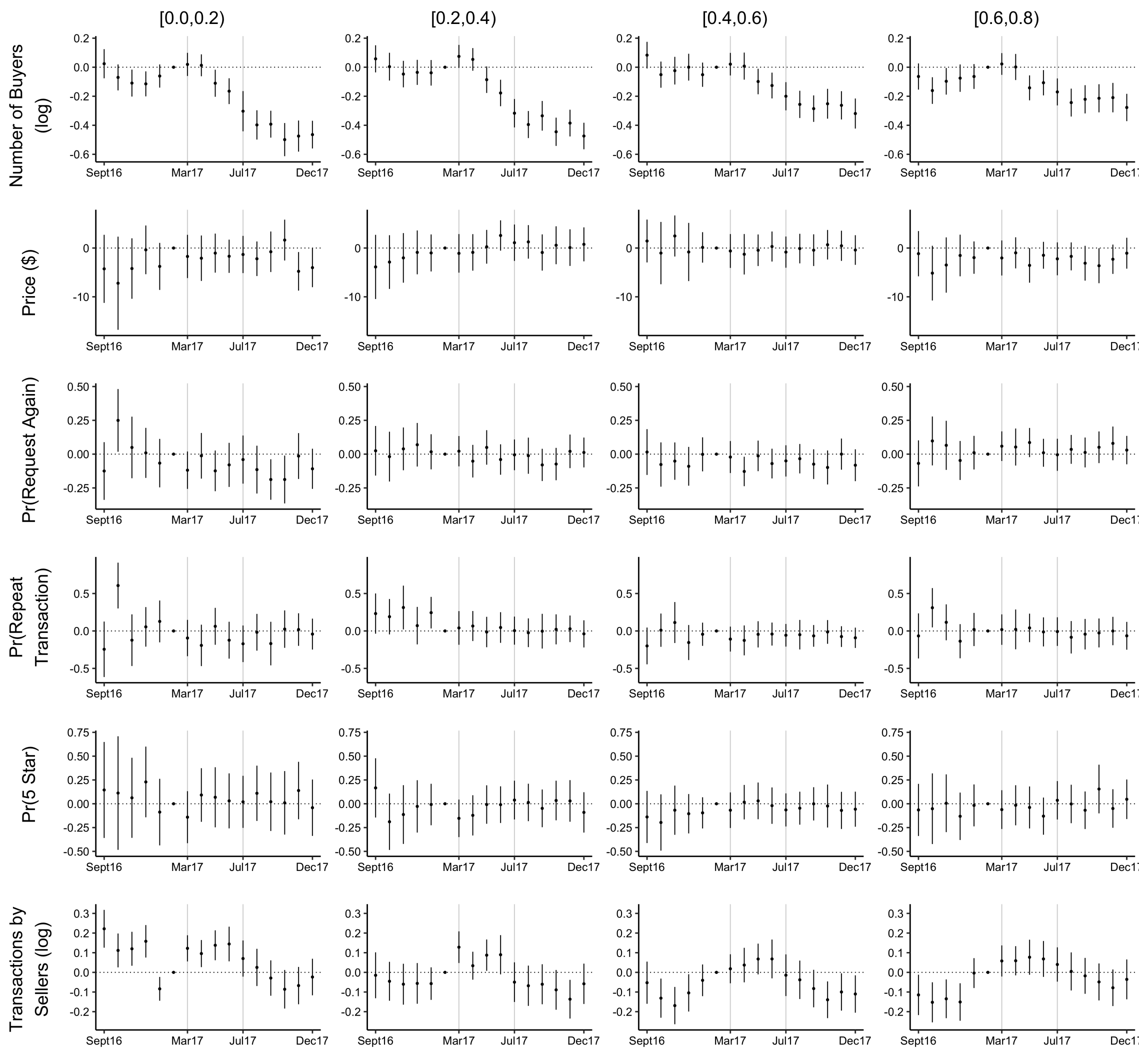
This table displays the estimates of Equation (7) for buyers who never posted a request or were involved in a booking inquiry on any platform prior to the current month and is analogous to Figure 8b. The baseline is the 3 months before the merger announcement (December 2016 - February 2017).

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



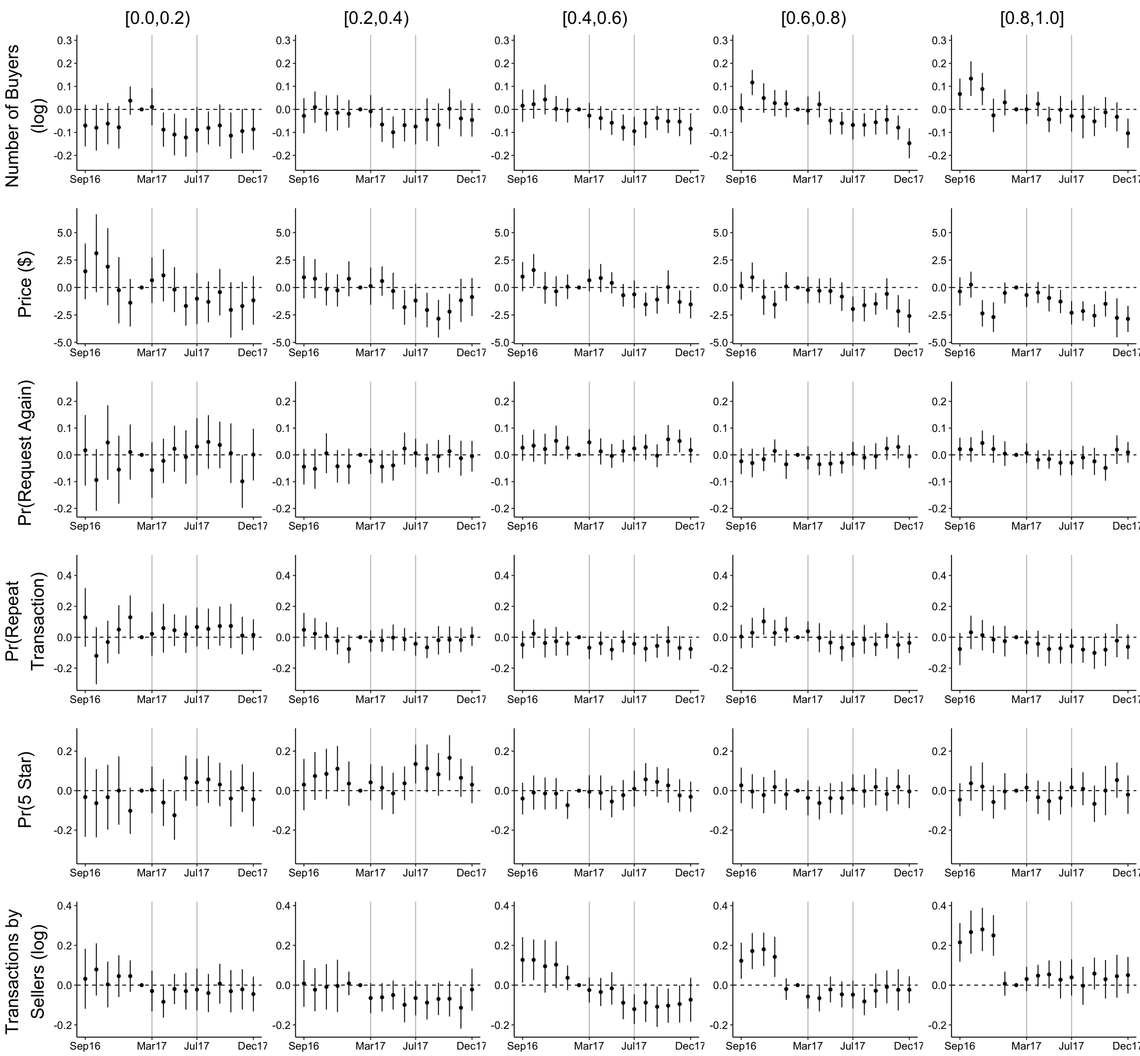
Regression estimates of Equation (5) *for additional outcomes of users who posted requests only on Rover in the previous calendar year. The first five rows focus on outcomes of existing Rover buyers, while the last row considers current transactions involving existing Rover sellers. Otherwise, the figure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

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



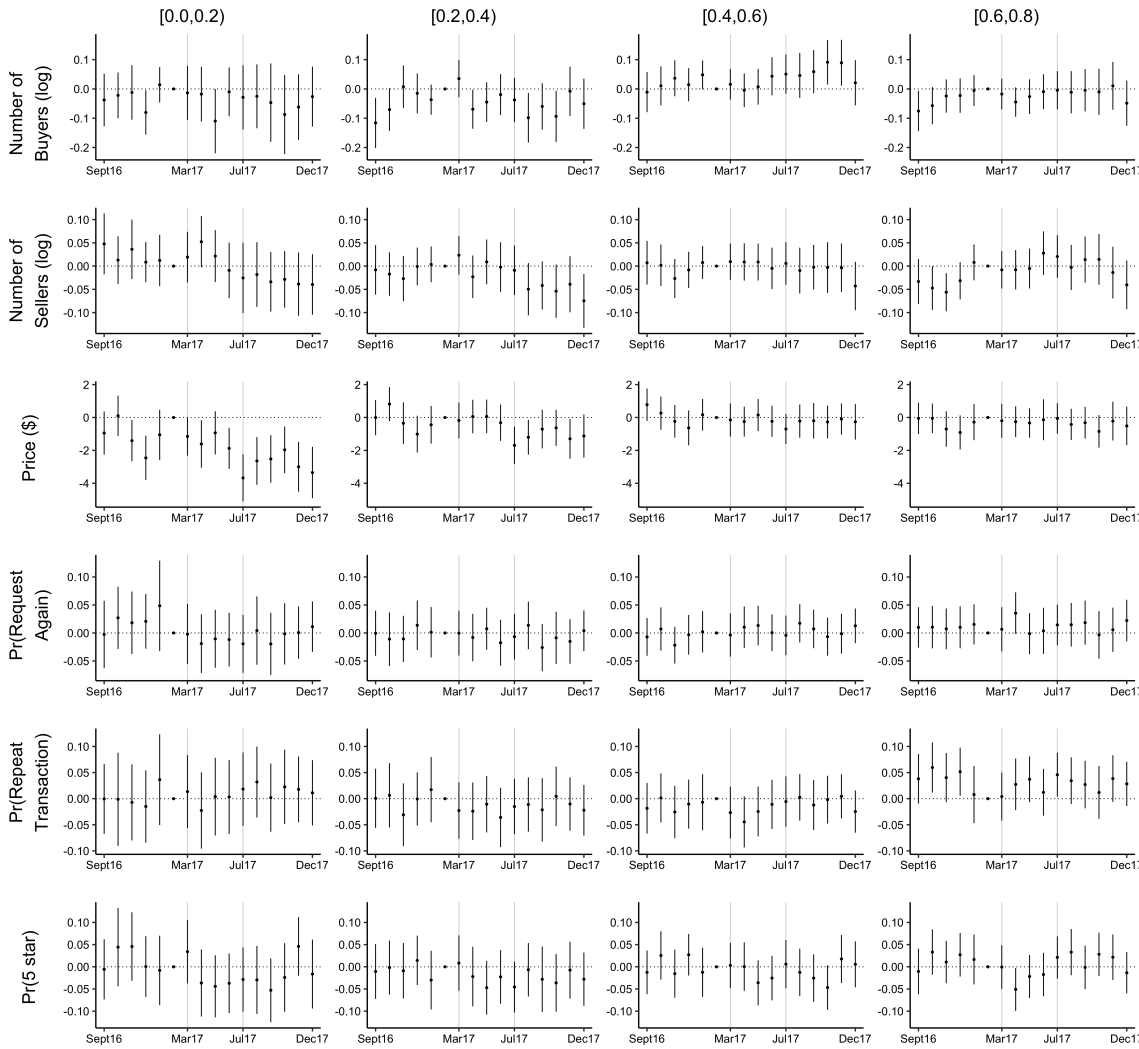
Regression estimates of Equation (5) *for additional outcomes of users who posted requests only on DogVacay in the previous calendar year. The first five rows focus on outcomes of existing DogVacay buyers, while the last row considers current transactions involving existing DogVacay sellers. Otherwise,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

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



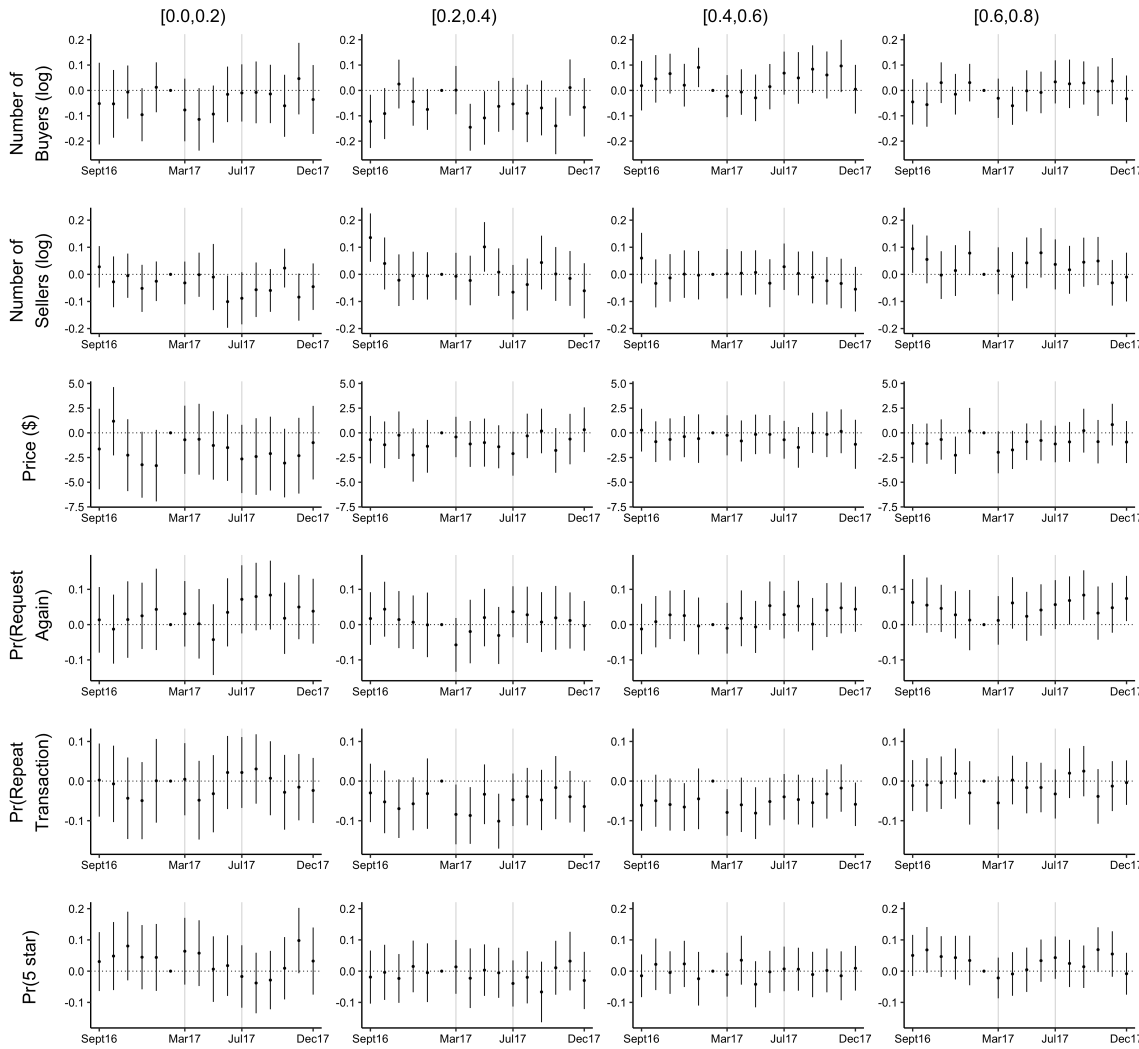
Regression estimates of Equation (6) for additional outcomes of users who posted requests only on DogVacay or Rover in the previous calendar year. The first five rows focus on outcomes of existing buyers, while the last row considers current transactions involving existing sellers. Otherwise, the figure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

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



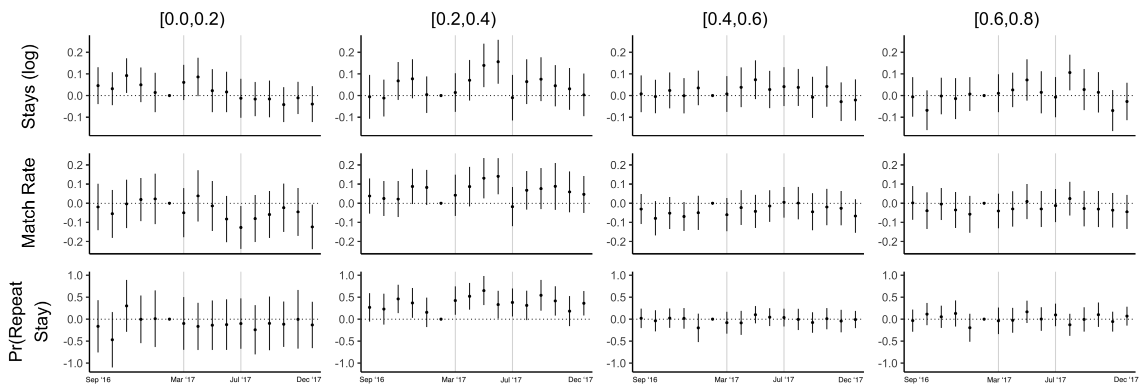
Regression estimates of Equation (5) *for additional outcomes calculated at the market level. Otherwise, the figure is identical to Figure 8a.*

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



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

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

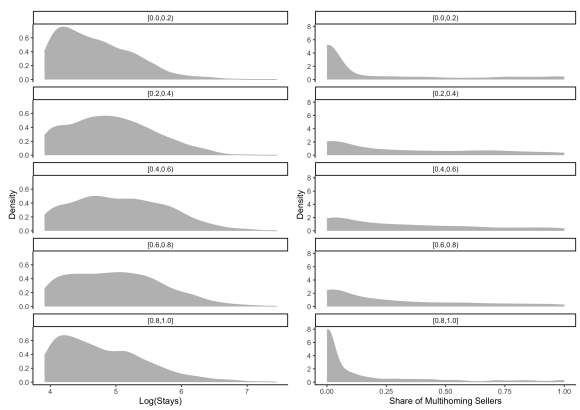


This figure displays results for multi-homing users. Multi-homing users are defined as those who engaged in booking inquiries on both Rover and DogVacay in the previous year. Otherwise, the figure is identical to Figure 6.

A.1 Heterogeneous Effects Across Markets and Users

Our results suggest that the two scenarios of a single combined platform or separate platforms are, at least in the short-run, similar for buyers' value. This is true on average, but network effects may dominate over platform differentiation in certain markets and not in others. We explore two dimensions of heterogeneity across markets: market size, and propensity to multi-home. The distribution of these characteristics across zip codes is plotted in Appendix Figure A.7.

Figure A.7: Heterogeneity Across Market Share Groups



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

Markets differ in their total number of transactions. Among zip codes with at least 50 transactions in 2016, the average zip code had 171 stays in the same year, but with a standard deviation of 146, demonstrating that there is substantial heterogeneity across zip codes. It is possible that the benefits of network effects change with the size of the platform. For example, there may be some amount of sellers that sufficiently cover the characteristic space. If a platform reaches this scale, then additional users may not improve average utility. If this were the case, we would expect platform-level network effects to be larger after the merger in smaller markets. It would also be more likely that network effects are large enough to justify a single platform in smaller markets compared to larger markets.

To test these hypotheses, we split zip codes into those with more or fewer than 250 transactions in 2016. A large share, 81%, of our zip codes are considered small markets. Figure A.8a plots the estimates testing Hypothesis 1 on the top row and Hypothesis 3 on the bottom row.[34] 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. For both small and large markets, the transactions by existing Rover users go up monotonically in the influx of new users from the acquired platform (top row), while the market-level transactions do not increase relative to the control group (bottom row).

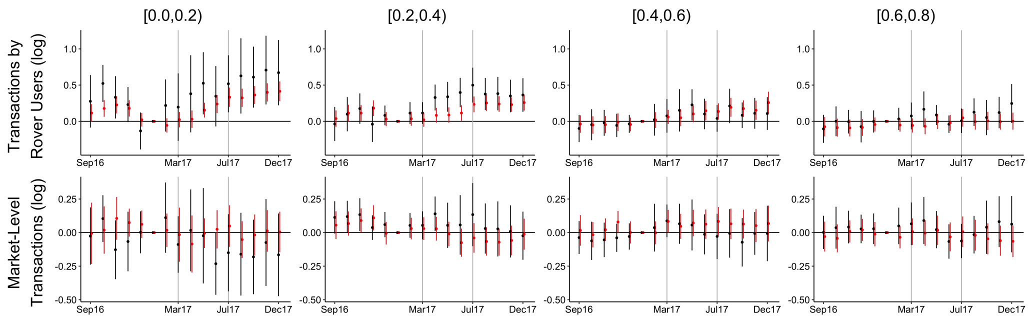
We should note that there is likely to be selection into the markets that experienced a small versus large number of transactions in 2016, so we have only suggestive evidence that our results are independent of market size. In other words, it may very well be that markets that were large in 2016 would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

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

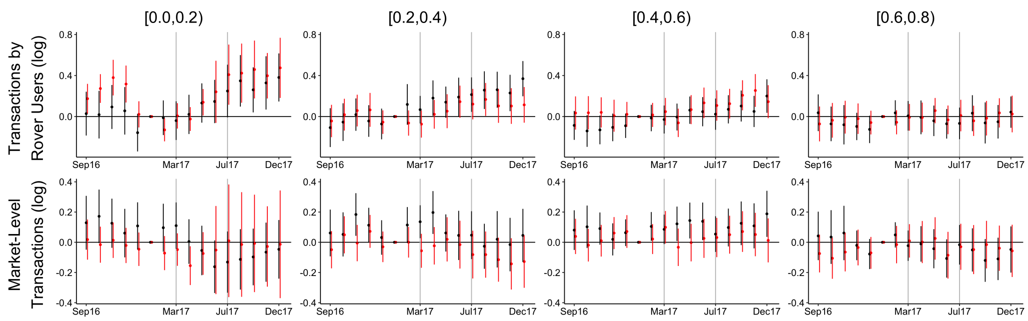
Figure A.8b displays the results of matched sample regressions for markets with low propensity (red) and high propensity to multi-home (black). Similarly to what we found for market size, transactions by Rover users increase monotonically in the market share of the acquired platform, while market-level transactions are similar between treatment and control groups, regardless of sellers' propensity to multi-home. There are no obvious differences in the magnitudes of merger effects between the two groups. This may be

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

Figure A.8: Estimates of Merger Effects – Heterogeneity by Market Type



(a) *Small* versus *Large* Markets



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

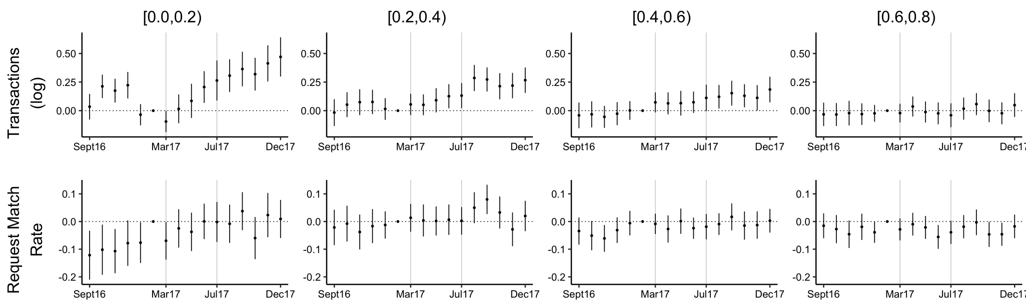
Estimates of Equation (5) *for different markets. In Panel (a) the zip codes are divided into two groups: markets with 50-250 transactions in 2016 (in red), and markets with more than 250 transactions (in black). In Panel (b), the zip codes are divided into two groups: markets whose share of 2016 transactions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

explained by the fact that even in the high multi-homing markets, multi-homing sellers typically comprised a minority of all sellers.

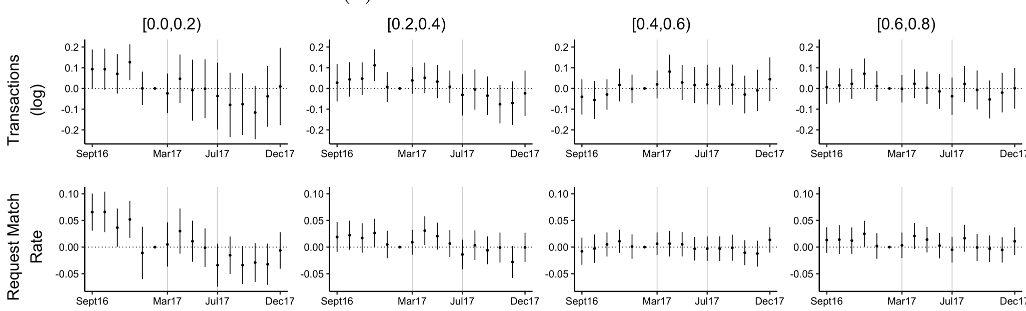
A.2 Robustness to Alternative Estimators

Our results are robust to alternative matching and estimating procedures. First, Figure A.9 matches zip codes not just on the number of sellers, but also on the number of buyers and number of animal caretakers per 1,000 jobs.

Figure A.9: Estimates of Merger Effects – Matched on number of buyers, sellers, and outside option



(a) Outcomes for Rover Users



(b) Market Outcomes

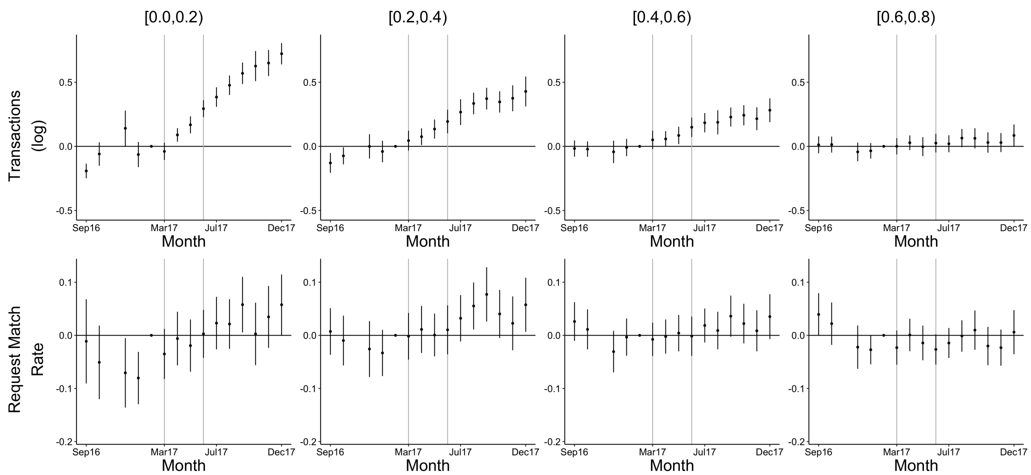
Regression estimates of Equation (5)*. Markets are matched on the number of buyers, sellers, and the outside option, which is proxied using the number of animal caretakers per 1,000 jobs. Otherwise, Panel a is identical to Figure 6a and Panel b is identical to Figure 8a.*

Second, we estimate our main specifications with a difference-in-differences estimator without matching zip codes. This non-matched estimation is expected to have a worse pre-period match in trends between treatment and control groups. We replace Equation (5) with the following, non-matched, equation:

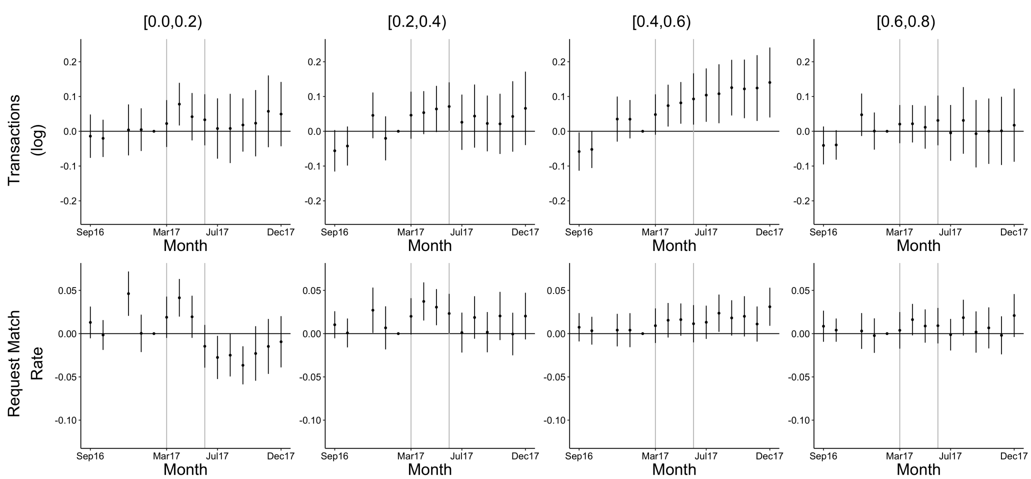
$$y_{zt} = \beta_{s(z)t} + \gamma_{s(z)}t + \delta_{s(z)}\mathbb{1}\{t \geq Dec2016\} + \mu_t + \mu_z + \epsilon_{zt}. \tag{8}$$

By adding $\gamma_{s(z)}t + \delta_{s(z)}\mathbb{1}\{t \geq Dec2016\}$, we allow for the observations in the treatment and control groups to have a different linear pre-trend. Results are presented in Figure A.10.

Figure A.10: Estimates of Merger Effects – Unmatched



(a) Outcomes for Rover Users



(b) Market Outcomes

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

Finally, in recent years there have been concerns that the specific implementation of a difference-in-differences strategy may affect the outcome. For example, Orchinik and Remer (2020) show that synthetic controls, two-way fixed effects, and matching sometimes give differing results for the effects of airline mergers. To address this concern, we confirm that our results are robust to the synthetic difference-in-differences (SDID) estimator (Arkhangelsky et al. (2021)), which combines several desirable features of synthetic control estimators and difference-in-differences estimators. Like the synthetic control method, it creates a comparison group that matches pre-treatment trends between treatment and control groups. Like difference-in-differences, it allows for unit-level shifts (i.e., differences in levels between treatment and control groups) and inference with many treated units. Lastly, the method flexibly estimates weights placed on pre-treatment time-periods, reducing concerns regarding researcher flexibility in the choice of pre-treatment period length.

In particular, SDID estimates two types of weights not present in a standard difference-in-differences analysis. The first of these is a weight for each unit, drawn from the set of control markets (those with 80% to 100% Rover market share). The second is a weight for each pre-treatment time period (September 2016 to February 2017). The unit weight is present in the standard synthetic control estimator but the time weight is not.

We use the package 'synthdid' in R to estimate the SDID results for the main outcomes in our paper and present these in Figure A.11. The figures display the treatment group in blue and the synthetic control group in red. They also display the counterfactual trends in the dashed line and the average treatment effect on the treated (across the post-treatment period) with an arrow. The 95% confidence interval is displayed in text for each outcome and group. The results are largely consistent with our main findings. Outcomes substantially improve for Rover users but not as much at the market level. At the market level, we find a small increase in transactions for the 40% to 60% group but find no improvements in the match rate.

Figure A.11: Estimates of Merger Effects – Synthetic Difference-in-Differences

(a) Outcomes for Rover Users

(b) Market Outcomes

Estimates derived using synthetic difference-in-differences (R package 'synthdid') rather than a regression with matching. The red line is the control group and the blue line is the treatment group. Otherwise, Panel a is identical to Figure 6a and Panel b is identical to Figure 8a.

A.3 Robustness to Alternative Market Definitions

We have previously defined markets at the zip code level. A potential problem with this definition is that outcomes across zip codes may not be 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) and Li et al. (2021)).

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,[35] 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,[36] 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

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

[36] We 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.[37] 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.[38] 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 $2 \underset{d_{0,ij}<\infty}{max} d_{0,ij}$. 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

[37] We have search results data from 2017 for Rover.

[38] For 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 $\mathcal{P}_n^\alpha$ where each of the n zip codes is a separate cluster. At each following step k, for each cluster $\mathcal{C}_k^\alpha$ we compute the mixed pseudo inertia as

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

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

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

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

1. We divide zip codes into Core-Based Statistical Areas (CBSAs). We perform steps 2-4 separately for each CBSA, which means that we choose α, k separately for each CBSA.[39]

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

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.[40]

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

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

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

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

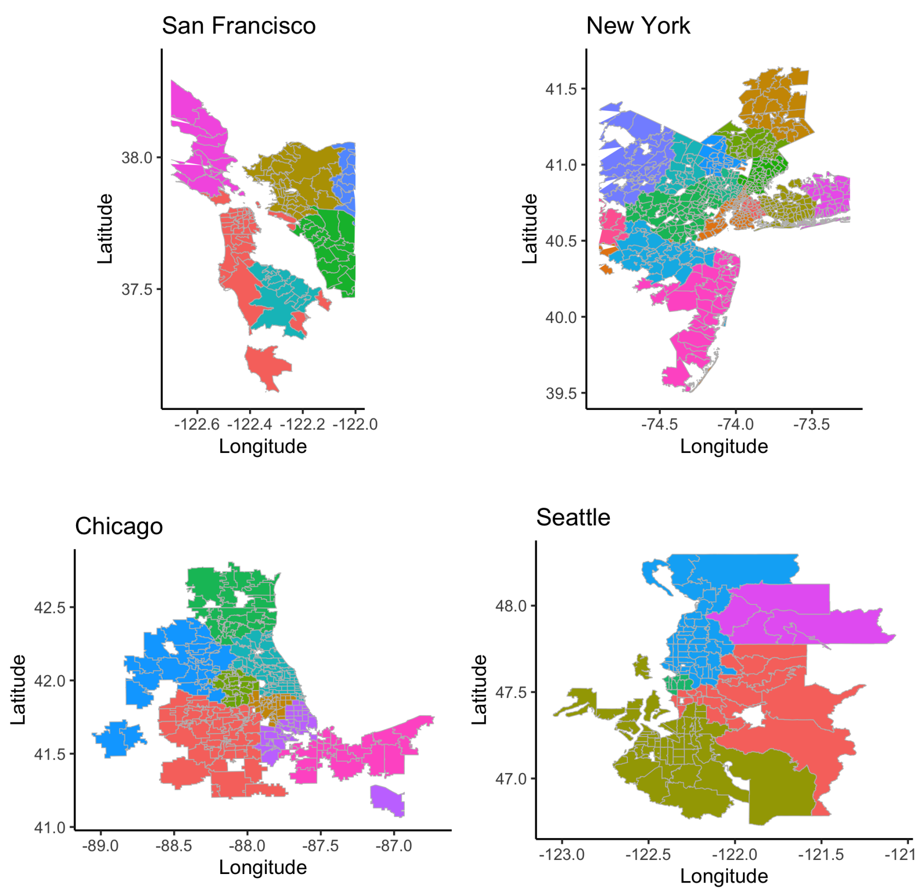
Intuitively we find the partition with the most distinct clusters subject to a minimum quality threshold that controls the potential interdependencies across clusters. Setting the threshold at 65% means that on average 65% of requests have booking inquiries only within the cluster. Note that this threshold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

Figure A.12 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 (5) with cluster-month as unit of observation. Results are presented in Figure A.13.

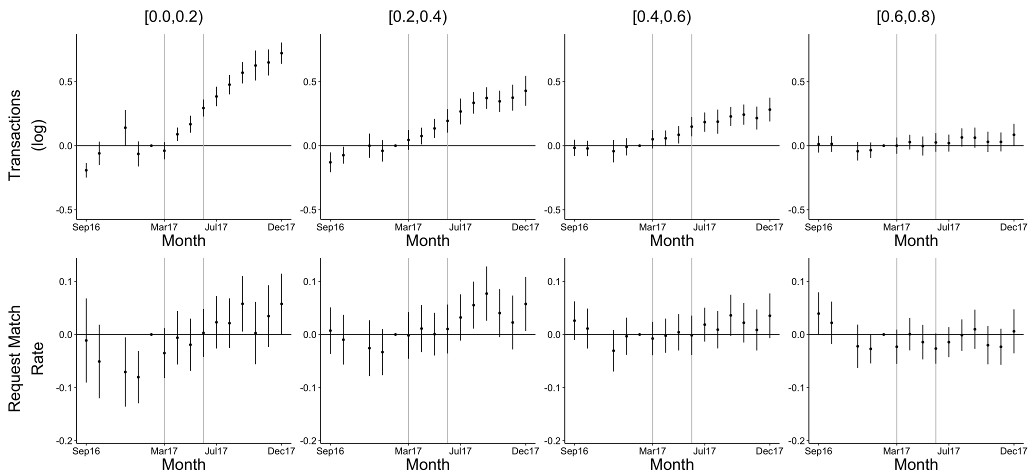
[40] For CBSAs with more than 200 zip codes the 25 limit can be binding in practice, so we use k between 1 and $min(50, n)$, where n is the number of zip codes in the CBSA.

Figure A.12: Cluster Maps - CBSAs

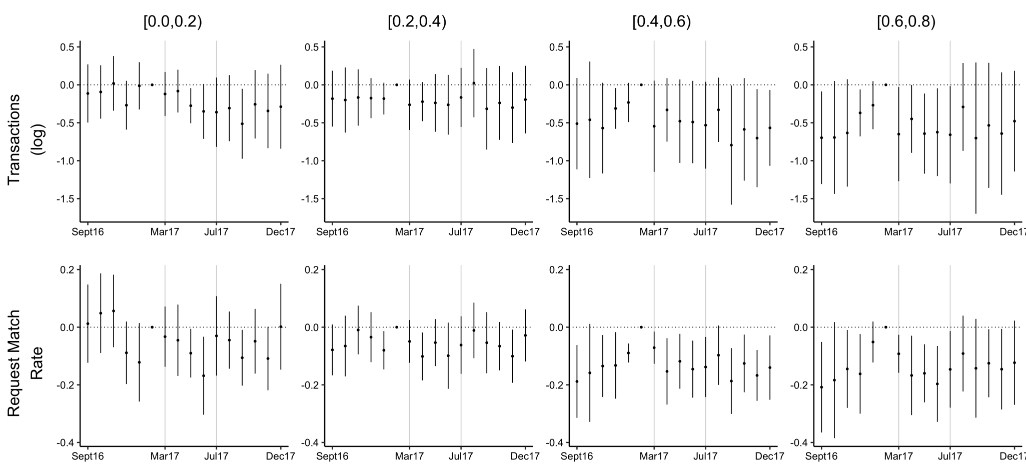


The figures plot the clusters for four Core-Based Statistical Areas (CBSAs) formed by aggregating zip codes using hierarchical clustering with geographic constraints.

Figure A.13: Estimates of Merger Effects – Geographic Clusters



(a) Outcomes for Rover Users



(b) Market Outcomes

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

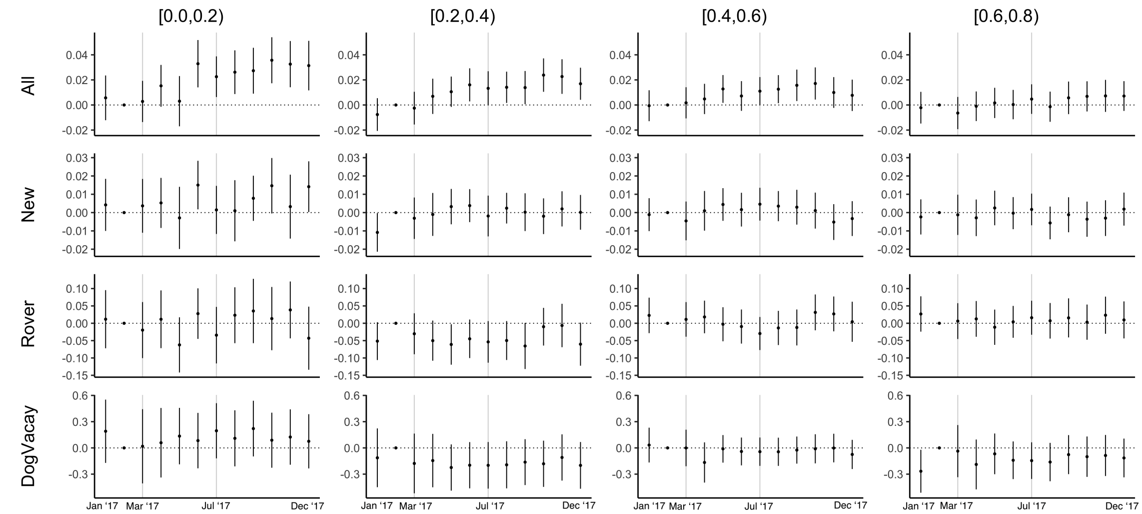
B Additional Results Based on Search Data

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 B.1) from search to booking inquiry. The first row shows that conversion rates increase by up to 3 percentage points in markets with the lowest Rover market share pre-acquisition (first plot on the first row), but we do not see significant differences post-acquisition in conversion rates for existing or new users (last three rows of Figure B.1).

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



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

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

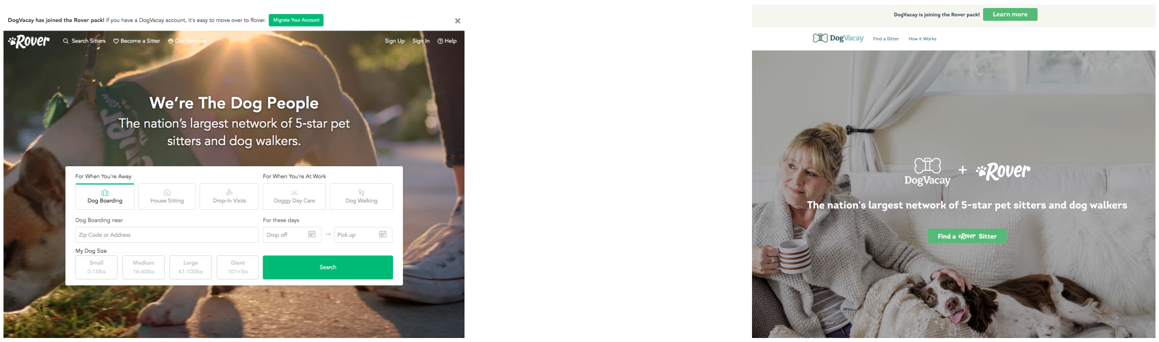
Period	Rover Share	All	New	Rover	DogVacay
Transition	[0.0,0.2)	0.011*	0.003	-0.017	0.015
	[0.2,0.4)	0.012**	0.006	-0.02	-0.137
	[0.4,0.6)	0.007*	0.001	-0.007	-0.054
	[0.6,0.8)	0	0.001	-0.011	0.024
Post-Merger	[0.0,0.2)	0.026***	0.005	0	0.049
	[0.2,0.4)	0.021***	0.006	-0.015	-0.109
	[0.4,0.6)	0.013***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

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

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

C Additional Figures and Tables

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



(a) Rover.com, July 2017.

(b) Dogvacay.com, July 2017.

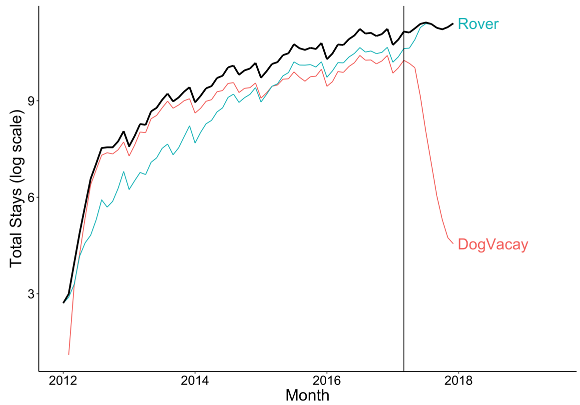
The figures show the landing page of Rover and DogVacay after the merger of the two platforms was completed. The screenshots are accessible on Wayback Machine (`https://web.archive.org/web/20170714115852/https://www.rover.com/` *and* `https://web.archive.org/web/20170704144306/https://dogvacay.com/`*).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

Table C.1: Prices on Rover and DogVacay

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

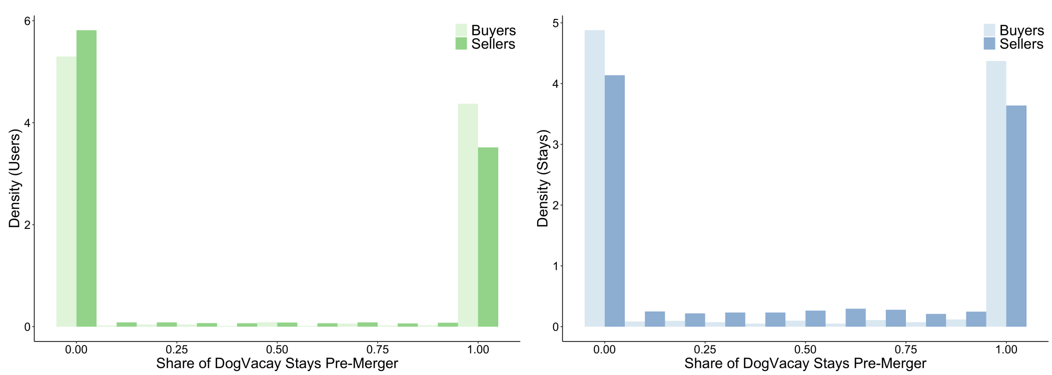
Estimates from OLS regressions of seller prices on a dummy for whether the transaction occurred on DogVacay. The data include all successful transactions between 2012 and March 2017, when the acquisition was announced. Controls include fixed effects for the duration of the stay (columns 1-3), zip code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

Figure C.2: Growth of Rover and DogVacay



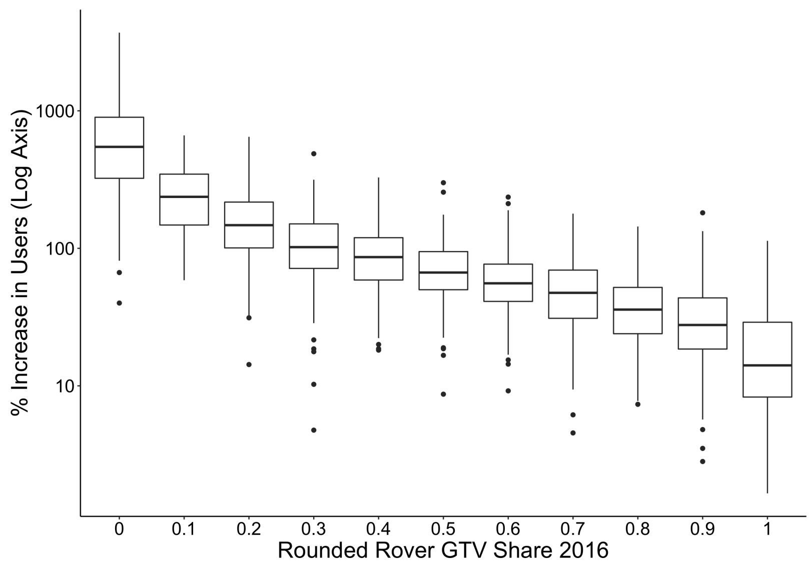
The figure plots the number of monthly overnight boarding stays on DogVacay and Rover in log scale. The black line is the sum of matches on both platforms. The vertical line corresponds to March 2017, when the acquisition between the two platforms was announced. The number of transactions does not completely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

Figure C.3: Multi-Homing



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

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



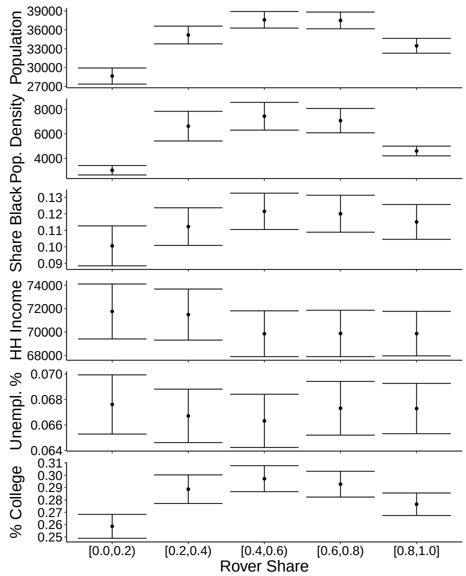
Box plot of the percentage change in the number of transacting users post-acquisition due to DogVacay users switching to Rover as a function of Rover market shares in 2016. Specifically, the percentage change in users is the number of DogVacay users who migrated their profiles to Rover and transacted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

Table C.2: First Movers and Rover Market Share

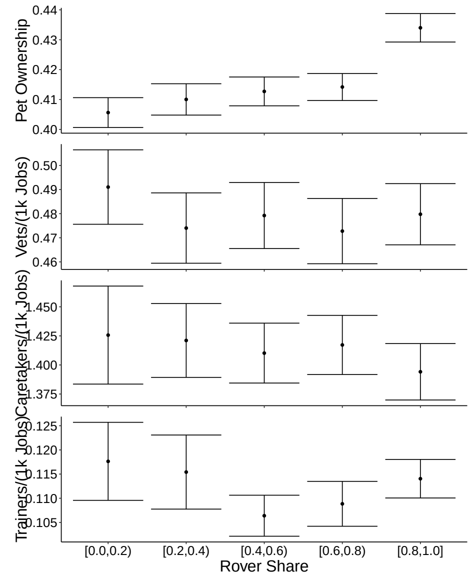
	Dependent variable:			
	2016 Rover Market Share			
	(1)	(2)	(3)	(4)
1{First Mover = Rover}	0.081***	0.078***	0.069***	0.071***
	(0.007)	(0.007)	(0.007)	(0.007)
State FE	N	Y	N	N
CBSA FE	N	N	Y	Y
Year Month FE	N	N	N	Y
Observations	8,200	8,200	8,200	8,200
R^2	0.017	0.055	0.155	0.162
Adjusted R^2	0.017	0.049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

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

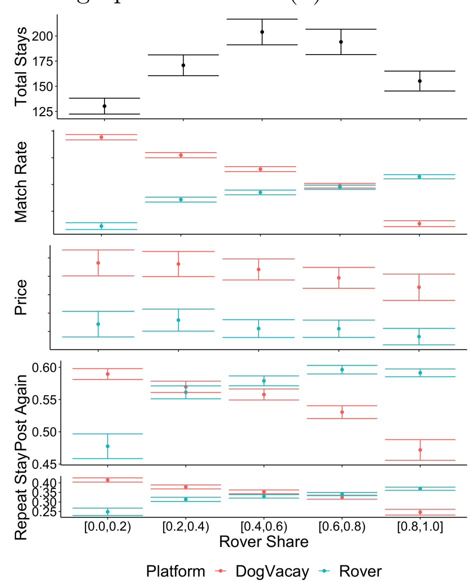
Figure C.5: Differences Across Zip Codes



(a) Population Demographics.



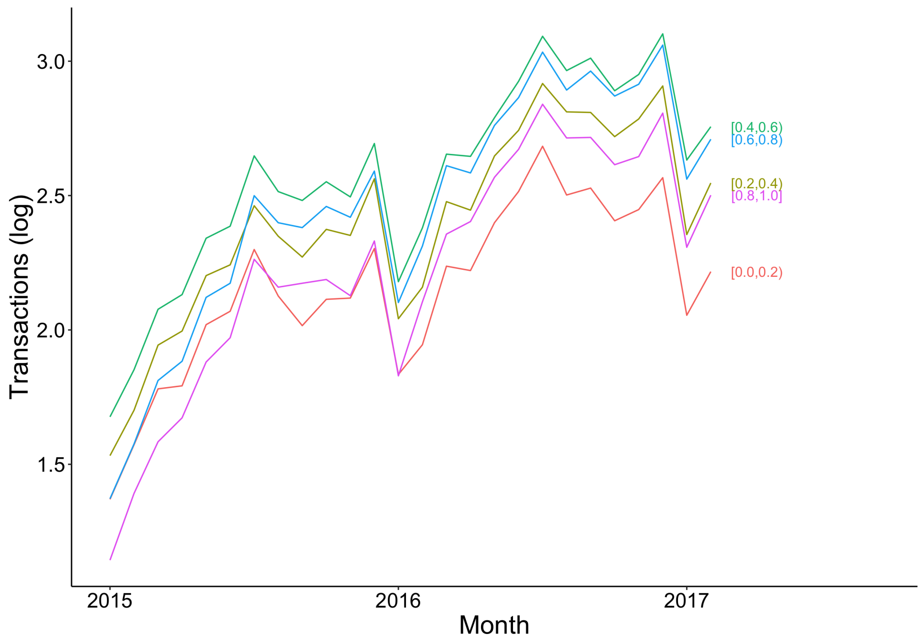
(b) Pet Ownership and Services.



(c) Platforms' Performance.

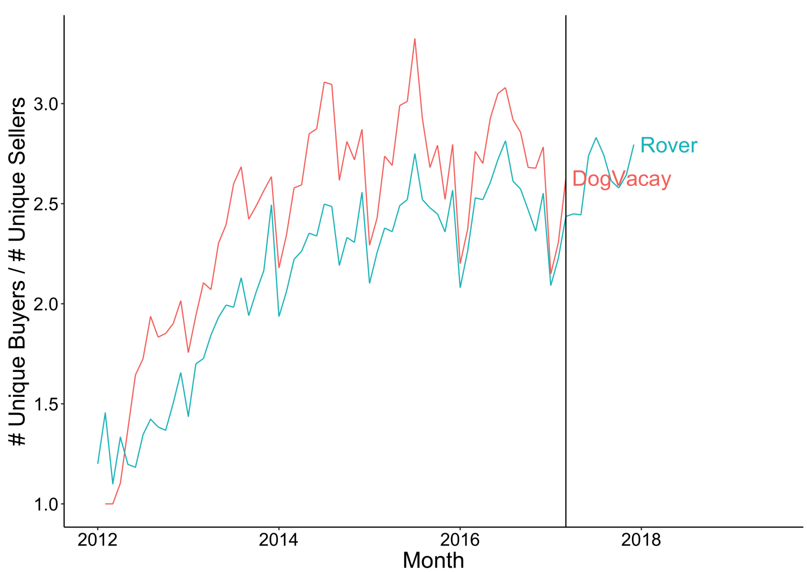
Differences across zip codes in population demographics (left), pet ownership and services (right), and Rover and DogVacay's performance (bottom). Each zip code is grouped by market share – the groupings are defined in Figure 5. The plot on the left shows average population demographics within each market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

Figure C.6: Transactions over Time



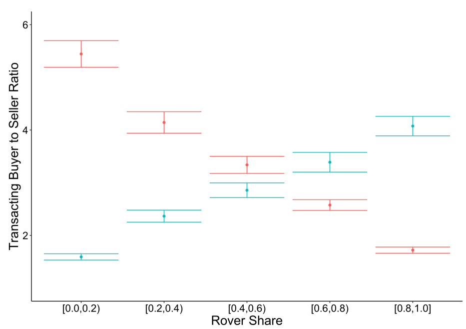
The figure plots the average number of monthly transactions across market share groups.

Figure C.7: Buyers Relative to Sellers

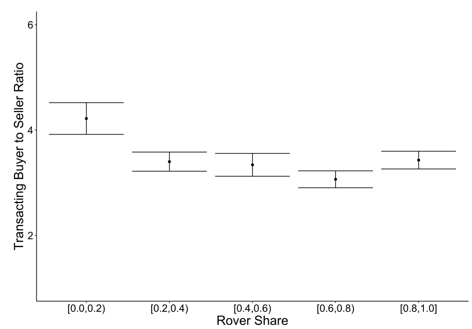


The figure plots the number of buyers over the number of sellers who exchanged at least one service in a given month, separately for Rover and DogVacay. The vertical line identifies March 2017, when the merger was publicly announced.

Figure C.8: Buyers Relative to Sellers



(a) Second half of 2016.



(b) Second half of 2017.

The figures show the number of buyers divided by the number of sellers who exchanged at least one service in a given month. The left panel focuses on the second half of 2016, before the merger, and separates Rover (in blue) from DogVacay (in red). The right panel focuses on the second half of 2017, after the merger, where all activity was concentrated on Rover. The figures plot the average number of buyers relative to sellers and the corresponding 95% confidence intervals.

Table C.3: Comparison Across Market Share Groups

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

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

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

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

Table C.4: Comparison Across Matched Market Share Groups

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

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

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

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

Table C.5: Transactions of Sellers After DogVacay is Shut Down

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

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