There have always been unused assets and people who are not working. Without transaction costs, many of these assets and people could be employed in productive ways, if only for a short time. These transactions could generate value by expanding market capacity, offering new products, and providing sources of income for sellers. However, until recently, the costs of transactions between unacquainted individuals in developed economies have been so large that people preferred to transact exclusively with traditional firms.

Over the past 20 years, peer-to-peer digital marketplaces have narrowed the transaction cost gap between peer and firm transactions. In turn, they have greatly expanded transactions in markets such as short-term apartment rentals (Airbnb), used goods (Ebay), labor services (Upwork and Taskrabbit), and rides (Uber and Lyft). In this paper I use the setting of Airbnb to study the ways in which these marketplaces reduce transaction costs.

Airbnb, like other digital platforms, provides many services—including search, payments, reputation, communication, and customer service. I focus specifically on the role of the search engine, which is particularly important in this setting because search can often be a frustrating experience for potential guests.

Specifically, the short-term rental market is characterized by many options, heterogeneity in preferences, and by uncertain availability of listings. As a result, searchers on Airbnb see only a small share of options in the market, take more time to search than on hotel booking sites, and frequently get rejected by hosts. These rejections are viewed as a particularly large transaction cost and often cause guests to leave the platform altogether. I show that guests who are initially rejected are 51% less likely to book a specific trip on the platform than those who are accepted.

The platform can alleviate these search frictions by carefully selecting which options to show to the searchers and by giving searchers tools—such as map and price filters—to ensure a good match. However, there are countless ways of arranging the search engine, making it difficult to choose among alternative designs. For example, Craigslist, which has a vacation rentals section, has historically not tracked the availability of listings or whether these listing were already booked. Furthermore, Craigslist’s search ranking was in reverse chronological order and the filters were often inaccurate. In contrast, Airbnb has an explicit calendar feature that automatically hides listings from search when they’ve already been booked for a set of dates, or when the host has marked a date as unavailable.
The second part of my paper develops a framework for studying the effects of these search engine designs on market outcomes. These models are useful for understanding how the market works and for understanding the potential effects of changes to the marketplace.

My framework consists of three separate components. The first component determines which options searchers see; the consideration set. For example, I just conducted a search for a place to stay in Boston in early August. There are 300+ listings shown as available, which Airbnb states comprise just 28% of the total listings. Furthermore, the search engine displays just 18 listings per page. These listings are determined by a ranking algorithm designed to show the most relevant listings for each search. A searcher will browse through these results by filtering for location, price, and room type. I use proprietary data from Airbnb to model this process.

The second component of my framework determines how searchers choose which options to try to book. I model this decision as follows: For each searcher, I see which options they saw while searching, and which option, if any, they attempted to book. I then predict the chosen option as a function of all of the observed characteristics (e.g. location, size, price, and reviews) as well as what options the searcher filtered for. In this way, a searcher who filters for a particular neighborhood is more likely to choose an option from the neighborhood.

The last component of my framework determines whether hosts accept or reject a particular attempt to book. I model this decision in the following way: If a host eventually updates their calendar to be unavailable, then I call that rejection a “stale vacancy.” This occurs if hosts don’t exert effort to update their calendar or are uncertain about their availability. I find that stale vacancy rejections occurred over 10% of the time in my sample.1

The second rejection reason is congestion, which occurs when multiple searchers try to book the same place at once. I find that congestion rejections are relatively rare. The last rejection reason occurs due to screening, where hosts prefer certain types of trips and guests to others. I estimate a model of screening rejection as a function of trip characteristics (e.g. nights, number of guests) and guest characteristics (e.g. reviews, demographics).

With all three components in place, I can then ask the following question: What if Airbnb’s search engine were designed in a different manner? I first consider what would happen if Airbnb were more like Craigslist. This involves three changes to the way searchers form a consideration set: First, I assume that listings are not removed from search once they are booked. This mirrors Craigslist, which does not know when transactions occur.

Next, I assume that the ranking algorithm is random and that searchers cannot filter. The effects of these changes can be analyzed in two steps: Attempt to book and acceptance. In the first case, the share of searchers who try to book at least one listing decreases by a small amount. This metric does not change much because many of the listings that were booked by previous searchers are high quality, even if they are unavailable. In the second case, the share of rejected inquiries among those who attempt to book increases from 32% to 78%. This occurs because searchers can’t tell whether a given listing has already been booked by a prior searcher. I then study what happens once already booked listings

---

1 My sample represents searchers in a large U.S. city between August 2013 and July 2014.
are removed from the results but there is still no filtering or ranking. In that case, the share of searchers that try to book falls by 13%.

Finally, I consider potential improvements to market efficiency relative to the state of the search engine as of 2014. This is useful as a way to test the potential of new algorithms and features without investing engineering effort into implementing them on the platform. I propose several new ranking algorithms and show that better algorithms can improve outcomes by a meaningful amount. For example, a ranking algorithm which personalizes search results with regard to both expected utility for the searcher and the probability of screening rejections by hosts would increase the share of searchers who attempted to book and were accepted to 34% from 24%.

The important idea behind this algorithm is that searchers do not know which listings are available, but the platform can use historical data to predict the availability of particular listings. Therefore, it can use ranking to guide searchers to listings that are less likely to reject them.

What are the lessons from this exercise? The design of a marketplace is a key determinant of its success. Even seemingly minor features like an availability tracker can make a substantial difference in transactions. My study focused on just the search engine, but successful marketplaces also require reputation systems, payments platforms, customer service operations, and other features. Each of these features can determine a marketplace’s success.

The full working paper can be found here.

Andrey Fradkin is a postdoctoral fellow at the Initiative on the Digital Economy at MIT Sloan. His research interests include the design of online platforms, the economic effects of digitization, and the economics of search markets. He’s provided expert input about the digital economy at the President’s Council on Science and Technology and the Federal Trade Commission. He previously worked as a data scientist at Airbnb while receiving a doctorate in economics from Stanford University in 2014.