Abstract. We study the growth of online peer-to-peer markets. Using data from TaskRabbit, an expanding marketplace for domestic tasks at the time of our data, we show that growth is highly heterogeneous across cities. To disentangle the potential drivers of growth, we separately look at demand and supply imbalances, network effects, and geographic heterogeneity. First, we find that supply is highly elastic: in periods when demand doubles, sellers work almost twice as hard, prices hardly increase and the probability of requested tasks being matched only slightly falls. The first result implies that in markets where supply can accommodate demand fluctuations, growth relies on attracting buyers at a faster rate than sellers. Second and perhaps most surprisingly, we find no evidence of network effects in matching: doubling the number of buyers and sellers only doubles the number of matches. Third, we show that cities where the market fundamentals promote efficient matching of buyers and sellers are also the cities that grow fast in the number of buyers. This heterogeneity in matching efficiency is related to two measures of market thickness: geographic density (buyers and sellers living close together), and level of task standardization (buyers requesting homogeneous tasks). The last two results imply that when network effects are limited by the local and time-sensitive nature of the services exchanged, growth of peer-to-peer markets largely depends on strategic geographic expansion, and competition can prevent a winner-take-all equilibrium in the long run.

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1 Introduction

The Internet has facilitated the diffusion of peer-to-peer markets for the exchange of underutilized goods and services. Users rent rooms on Airbnb, arrange rides on Uber, and find cleaning and moving help on TaskRabbit. These markets, which may compete with more traditional service providers, act as marketplaces for decentralized buyers and sellers to meet up and transact. Their growth has been highly heterogeneous. Uber, for example, is over ten times as big as Lyft, its closest competitor in the US. Even within a single marketplace, growth can vary by geography. For example, although Chicago and New York have similar numbers of hotel rooms, Airbnb is much bigger in New York than in Chicago. This paper studies the drivers of growth of peer-to-peer markets.

Since peer-to-peer markets help match many fragmented buyers and sellers, their growth depends on balancing demand and supply. It is not enough to attract buyers if sellers’ participation cannot accommodate their demand. At the same time, sellers will leave the marketplace if demand is too low. Peer-to-peer markets are also often thought to benefit from scale economies, or network effects: doubling both buyers and sellers can more than double the number of matches, and can speed up growth. Finally, since many peer-to-peer markets are designed for location-specific services such as rides or house-cleaning, growth can be faster in some cities than others.

We empirically explore two key strategic decisions affecting the growth of peer-to-peer markets. The first decision relates to the basic chicken-and-egg problem. In a two-sided market both buyers and sellers join only if the other side is already on board, so a peer-to-peer market must choose in what proportions to attract buyers and sellers. Too few sellers per buyer will drive buyers away, and analogously too few buyers per seller will drive sellers away. The second decision is about entry across different geographies. When a peer-to-peer market is designed to match buyers and sellers of local services, cities can vary in buyer and seller propensity to transact on the platform. In addition, if network effects exist so that doubling the number of buyers and sellers in one city more than doubles platform matches, small initial differences across cities can compound into much larger differences in long-run platform success.

We use data from TaskRabbit, an online marketplace where buyers (formerly known as posters) can hire sellers (rabbits) to perform a wide range of domestic tasks and errands. We work with internal data from the company that allows visibility into all posted tasks, offers, and transactions. The setting allows us to think about the efficiency and benefits of online marketplaces because successful matches must happen rapidly and locally. This feature, common across virtually all

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online peer-to-peer markets, lets us divide the activity on the marketplace into separate sub-markets by time and geography, and use the large and plausibly exogenous fluctuations in buyers and sellers to explore the matching of supply and demand.

The opportunity to observe multiple spot markets where variable numbers of buyers and sellers match while using the same marketplace technology is empirically relevant. In the past a common challenge that researchers have faced in studies of online platforms is that it can be difficult to define and compare separate markets. In studying eBay, for example, it is hard to divide buyers and sellers into geographically segregated markets given the prevalence of cross-state and cross-country transactions. There also can be a selection problem related to the fact that only platforms which have achieved a certain level of success are in use and can be studied. The fact that TaskRabbit operates essentially separate markets in different cities, and that we can observe these markets as they grow over time creates useful variation for understanding demand and supply decisions and how scale economics might or might not arise.

In principle, there are several ways in which the market might function given fluctuations in buyers and sellers. One possibility is that with fewer sellers, buyers may not be able to have tasks performed, either because of higher prices which deter them, or because a smaller fraction of posted tasks receive offers. Another possibility is that seller labor supply expands. We establish that in this context, seller effort, or labor supply, is the key equilibrating factor. When demand is high relative to the number of sellers, the latter sharply expand their effort with very little price adjustment and little reduction in the ability of buyers to consummate trades. The elastic labor supply is a major contributor to the growth of the marketplace because it increases the number of matches created relative to a setting in which seller effort is fixed, and because it increases buyer retention. Because sellers adjust effort in response to demand increases, the marketplace success depends on the level of task requests. This observation, combined with the finding that buyers’ posting rate of tasks is fairly constant, implies that management efforts should be focused on attracting buyers more than sellers.

Perhaps surprisingly we find that matching does not display economies of scale. Doubling the number of requests and offers for tasks proportionally increases the number of successful matches. We confirm that this result is consistent with one possible mechanism driving scale economies. As the marketplace grows within a city, we find that the distance between the location of buyers and sellers stays constant.

We find large differences across cities in the efficiency with which requests and offers for tasks are converted into productive matches. Cities where a higher share of requests and offers are turned into successful matches are also cities that attract and retain demand at higher rates. We relate
matching efficiency to two measures of market thickness. The first measure is geographic density: the closer buyers and sellers live to each other, the higher the match rate between tasks and offers. The second measure is the level of task standardization: match rate is higher when buyers request tasks in a few standardized categories, such as cleaning or delivery.

We start in Section 2 by presenting the relevant literature on multi-sided platforms, network effects, and platform growth. Section 3 describes TaskRabbit, in particular how buyers post tasks such as cleaning or grocery shopping, and how sellers submit offers to perform those tasks. We then introduce the key motivating fact for our paper: growth is highly heterogeneous across the cities where TaskRabbit operates. We intentionally separate the growth of a peer-to-peer market in intensive and extensive margins. The extensive margins include platform adoption by new users and attrition, while the intensive margins include the frequency of use by current users. We focus on the intensive margins in Section 4, while in Section 5 we study the extensive margins. We conclude our work by discussing some managerial implications of our findings for TaskRabbit and other peer-to-peer markets more generally in Section 6.

2 Literature Review

Our research contributes to a growing literature studying multi-sided platforms as a distinct business model (Evans (2003), Rysman (2009), Allon et al. (2012), Hagiu and Wright (2015)) that competes with more traditional service providers (Seamans and Zhu (2013), Zervas et al. (2016), and Farronato and Fradkin (2018)). Specifically, we touch on three distinct themes: platform market design, network effects, and platform adoption and growth.

From a market design perspective, theoretical work by Rochet and Tirole (2003), Parker and Van Alstyne (2005), Armstrong (2006), and later generalized by Weyl (2010)) has focused on how to set platform fees as a function of users’ participation decisions. Other non-price choices, such as information disclosure and search, have been explored by Boudreau and Hagiu (2009), Casadesus-Masanell and Halaburda (2014), and Economides and Katsamakas (2006) among others. Until recently, the empirical platform literature has focused on the interplay between the platform services and those of complementary service providers, or sellers in our setting (Jiang et al. (2011), Huang et al. (2013), and Rietveld et al. (2016)).

Lately, a subset of the empirical platform literature has specifically focused on online peer-to-peer markets such as eBay, Airbnb, and Upwork, that match buyers and sellers of goods and services. Recent work in this area has studied the micro-structure of specific marketplaces, estimating search inefficiencies (Fradkin (2014)), heterogeneity in the matching process and problems of
congestion (Horton (2016), Arnosti et al. (2016)), the differences between distinct types of pricing mechanisms (Einav et al. (2018)), and the consequences of search frictions and platform design for price competition (Dinerstein et al. (2014) and Li et al. (2016)). There is also a large literature on trust and reputation systems (Luca and Zervas (2016), and Hui et al. (2016)), which dates back to early work by Resnick and Zeckhauser (2002), Dellarocas (2003), and Dellarocas and Wood (2008).

Our work is complementary to this literature in that we empirically evaluate market equilibration in response to fluctuations in demand and supply, and we study the effects of platform design and how market efficiency depends on fundamentals at the city level. Our approach abstracts from many forms of individual heterogeneity and asymmetric information that are emphasized in other papers, and from issues of strategic pricing and reputation. Instead, we offer a framework that enables us to shed light on the growth of peer-to-peer markets, which are commonly characterized by highly variable demand and supply (Hall and Krueger (2015) and Cachon et al. (2017)). The estimation strategy we propose is in principle applicable to other peer-to-peer marketplaces that match buyers and sellers of local and time-sensitive services.

Our analysis of scale economies touches on the literature on platforms and network effects. We highlight the main results on entry and competition from this literature. When network effects are strong, multi-homing is costly, and users have homogeneous needs, users will end up using only a few platforms (Katz and Shapiro (1985), Zhu and Iansiti (2012), and Gawer and Cusumano (2014)). At the extreme, a single winner may take the entire market, and because network effects compound small initial differences a platform that by chance earns an early advantage in adoption may end up as the leader (Arthur (1989) and Ellison and Fudenberg (2003)). One way to obtain a small initial advantage is simply by moving first, as emphasized by Lieberman and Montgomery (1988). Empirical studies such as Bohlmann et al. (2002) and Cennamo and Santalo (2013) have analyzed the first-mover advantage and winner-take-all hypotheses in a multiplicity of industries, and Bresnahan and Greenstein (1999) have focused on the evolution of platform competition in the computer industry.

We find that in this specific context where network effects can only arise locally and in a time-sensitive manner scale economies per se are not a major determinant of market efficiency, for instance compared to basic fixed features such as the geography of a given city. The lack of scale economies is perhaps the most surprising result, and it challenges some of the theoretical predictions of the existing literature on first-mover advantage and the winner-take-all equilibrium. Our results lend support to alternative strategies for platform growth, such as platform envelopment (Eisenmann et al. (2006)) and product convergence(Greenstein and Khanna (1997)).

When we look at platform growth through adoption and attrition decisions, we also connect to a
large literature on product and innovation diffusion pioneered by Griliches (1957) and Bass (1969), and how the speed of growth of new technologies can depend on information flows, technology improvements, and network effects (for example, Tucker (2008) for an empirical analysis and Young (2009) for a theoretical contribution). Our specific empirical setting requires balanced adoption of both buyers and sellers, a topic that has been studied mostly theoretically until now (Caillaud and Jullien (2003), and Hagiu (2009)). In this study we empirically quantify demand and supply elasticities a way to identify platform’s relative efforts in attracting buyers and sellers.

3 Setting and Data

This section describes the TaskRabbit marketplace. We first describe how the marketplace operates, how tasks are posted, and how offers are made and accepted. We then show that matches are either made quickly and locally, or not at all. Finally, we provide a first look at differences in market growth across cities, the issue that motivates our paper, and some preliminary evidence on the drivers of growth.

3.1 The TaskRabbit Marketplace

TaskRabbit is an online peer-to-peer market that allows posters to outsource domestic tasks to rabbits. Between 2009 and mid-2014, it operated in 18 major cities in the United States, and London, UK. Posters post a description of the requested task in a flexible manner. Rabbits can search through posted tasks on city-specific lists and respond with offers (Fig. 1). We will refer to posters as buyers and rabbits as sellers of services.

Buyers on TaskRabbit can post virtually any sort of domestic tasks or errand (e.g. pet sitting for a goldfish), but the majority of tasks are relatively standard and generic. The five largest categories out of the 38 are delivery (20%), moving help (13%), cleaning (10%), minor home repairs (7%), and shopping (6%). These tasks typically do not require sellers with highly specialized skills.

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3 The active cities in the US are, in order of entry: Boston (2008), San Francisco (June 2010), Los Angeles (June 2011), New York (July 2011), Chicago (September 2011), Seattle (December 2011), Portland (January 2012), Austin (February 2012), San Antonio (August 2012), Philadelphia and Washington DC (July 2012), Atlanta, Dallas and Houston (August 2013), Miami and San Diego (October 2010) Phoenix and Denver (November 2011).
4 Leah Busque first formulated her idea for TaskRabbit when one evening she realized she had ran out of dog food. With her husband she started contemplating the idea of “a place online where we could say we needed dog food, name the price we’d be willing to pay, and see if there was someone in our neighborhood who would be willing to help us out” (http://www.fatbit.com/fab/young-self-made-millionaires-women-entrepreneurs-making-difference-us-economy-part-1/).
5 The 38 task categories include the following, from largest to smallest: Delivery, Moving Help, Cleaning, Minor Home Repairs, Shopping, Research, Furniture Assembly, Yard Work & Removal, Event Staffing, Usability Testing, Computer Help, Office Administration, Packing & Shipping, Marketing, Organization, Carpentry & Construction,
The nature of the tasks implies that services generally are provided locally and on relatively short notice. Almost all users (93.6% of them) participate in just one city. At the same time, of the 48.5% of tasks that are matched, 97% are filled within one or two days.\(^6\)

The matching process can work in two ways. A buyer can post a task-specific price and then accept the first offer, or ask for bids and review the prices offered by sellers. Fixed price tasks are slightly more standardized (65% of them are in the top 5 categories versus 48% of auctions), and prices are lower ($49 versus $63), but their share on the marketplace, at 41%, has not changed considerably over time or across cities. About 78% of tasks receive an offer, and of them 63% result in a match. Matches can fail because the buyer finds a better alternative and does not select any of the bids received, or because the buyer and seller cannot coordinate on specific task details.

Users on TaskRabbit tend to be either buyers or sellers, but not both. Indeed, 80.3% of users have only ever posted task requests, and 16.3% have only ever submitted offers. The buyers on the site are predominantly female (55% of buyers) and relatively affluent. Among those for which information is available, the modal buyer is a woman between the age of 35 and 44 with a household income between $150,000 and $175,000. The sellers are younger and not surprisingly have lower income. The modal seller is 25-34 years old and has a household income between $50,000 and $75,000.

Buyers go through a basic verification process that checks their identity on social networks and their payment method. There is a more rigorous screening process for sellers. Until the spring of 2013, applicants received a background check, a digitized survey of their motivations, skills, and availability, and were interviewed by TaskRabbit employees to determine their fit. Acceptance rates of sellers’ applications varied widely. They ranged between 7 and 49% in different months, and on average they were very low - only 13.6%. In the spring of 2013 TaskRabbit reduced the amount of screening in a successful attempt to add more sellers. As of May 2014, the end of our sample period, the process involved simpler background checks and social controls – Facebook or Linkedin verification – paired with a system of users’ reviews.

\(^6\)To add to the local and urgent nature of tasks, TaskRabbit’s ranking algorithm prioritizes newly posted tasks within each city. Indeed, to every seller searching through posted tasks, TaskRabbit shows a list of local tasks, ranked according to their posting time (most recent at the top).
### 3.2 Data

Our study uses internal data from TaskRabbit. We focus on the period from June 2010 to May 2014. During this period, TaskRabbit operated in 18 cities, although entry in these cities was staggered over time. Since we have no record of the actual entry date, we define the month of entry into a city as the first calendar month in which 20 or more local tasks were posted.\(^7\)

The data include all posted tasks, offers, and matches that occurred on TaskRabbit during the study period. We exclude virtual tasks\(^8\) (10.4%) and tasks posted in not yet active cities (0.23%). We also drop 10.3% of tasks that use other assignment mechanisms and keep only auction and posted price tasks. We merge the tasks with the corresponding offers, and we drop extreme price outliers (top and bottom 1% in bids or charged prices). To deal with the fact that posted price tasks occasionally receive multiple offers (6.04% of them did), we only keep the matched offer in case of success, or select one of the received offers at random. This simplification restricts posted price tasks to receive either one or no offers. Finally, for much of the paper we will aggregate activity at the city-month level, and drop city-months with less than 50 buyers posting tasks or less than 20 sellers making offers.

Table 1 shows summary statistics for the data. In the first panel, an observation is a posted task. Out of all posted tasks 78% receive offers, and those tasks receive 2.8 offers on average. Of the tasks receiving offers, 63% are successfully completed at an average price of $57. TaskRabbit charges a 20% commission fee on successful tasks.\(^9\)

In the second panel of Table 1, an observation is a city-month. We define a buyer to be active in a city-month if she posts at least one task in that city-month. Analogously, a seller is active if he submits an offer to a task posted within the city-month. On average, there are 708 active buyers and 255 sellers in a city-month, but there is large variation across cities and months. Each buyer posts 1.6 tasks, and each seller submits 6.4 offers. The task success rate is 46% and the average price paid is $56. Of these four variables (tasks per buyer, offers per seller, task match rate, and prices), the number of offers per sellers varies the most across city-month observations, with limited variation in tasks per buyer, matches, and prices.

A first key feature of the platform is that its success is highly heterogeneous across geographies. During the 4-year period we study, TaskRabbit was growing in all cities, but much more rapidly in some cities than others. Figure 2 plots the number of successful matches for the 10 oldest

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\(^7\)We verified the accuracy of our definition through media coverage of the marketplace and by talking with TaskRabbit employees.

\(^8\)A task is classified as virtual if the service does not require the seller to be at a specific location. Examples include writing and editing, or usability testing of mobile applications.

\(^9\)The commission fee can sometimes depart from 20%, for example in the case of coupons, referral bonuses, or other credits that reduce the price paid by buyers without affecting the price received by sellers.
Over the period considered, some cities grew from a few monthly matches to thousands of exchanges, like San Francisco and New York, while some others grew at a reduced pace, like Portland and Seattle. It is quite possible that the way in which the market equilibrates demand and supply is different across cities. It might also be the case that scale economies magnify small initial differences in city growth.

A second key feature is that here are large fluctuations in demand and supply. Since matches must be made quickly and locally, this raises the question of what happens when demand is especially high or low relative to the number of sellers. Figure 3 shows the variability of demand relative to supply in the 10 oldest cities at a monthly level. Specifically the figure plots the number of active buyers in the city-month divided by the number of active sellers. As before, activity is defined as posting at least one task (for buyers) or submitting at least one offer (for sellers). There are sizable fluctuations in the ratio of active buyers to active sellers, both within a city over time, and across cities within a month. In San Francisco, for example, certain months have two buyers per seller, while other months have six buyers. During the same calendar month, some cities may have only one buyer per seller, while other cities have five. The variability is not due to a single time trend. Month-to-month changes in the buyer to seller ratio are both positive and negative in no clear pattern. Finally, we emphasize some persistent heterogeneity across cities and across months. For instance, San Francisco has many more buyers per seller than Los Angeles.

In principle, there are several ways in which the market might function given this variability. One possibility is that with fewer sellers, buyers may not be able to have tasks performed, either because of higher prices which deter them, or because a smaller fraction of posted tasks receive offers. Another possibility is that seller labor supply expands. We show that the latter occurs, and that labor supply is sufficiently elastic that the level of price increase needed to generate a supply response is small.

Figure 4 first shows that the number of posts per buyer does not adjust when sellers are in short supply. Here, we divide the 336 city-months into four groups, corresponding to the four quartiles of the distribution of the buyer to seller ratio. For each group we compute the average number of tasks per buyer and offers per seller. The figure shows that regardless of the number of buyers per seller, buyers always post 1.6 tasks each on average.

Figure 4 also shows that unlike buyers, sellers submit many more offers when they are scarce relative to demand. For the city-months in the lowest quartile of the buyer to seller ratio (1.5 buyers per seller on average) sellers submit 4.4 offers on average. For the city-months at the other extreme (3.8 buyers per seller) sellers each submit twice as many offers, 9.1. Offers do not fully double as

\footnote{Similar patterns to those in Figure 2 are found in the 8 youngest cities.}
buyers double relative to sellers, so the match rate of tasks slightly declines (Figure 5). However, the sellers’ intensive margin response, together with buyers’ constant rate of task posting, translate into a large expansion in the number of trades as the number of buyers per seller increases.

Perhaps surprisingly, transacted prices move very little when sellers are scarce or abundant. Figure 5 shows the average price of completed tasks for the city-months sorted by the buyer to seller quartiles. Average transacted price is always between $52 and $59, even if the number of buyers per seller doubles and each seller chooses to work harder. Putting aside possible issues of task composition and seller heterogeneity, an apparent implication is that not much price increase is needed to generate a large intensive margin increase in labor supply.

In the next section we provide a parsimonious framework to think about market equilibration in the presence of fluctuations in demand and supply, and we attempt to establish causality of these preliminary findings.

4 Evidence on Short-Run Market Equilibration

In this section, we describe a simple static model of market equilibration, where buyers choose to post task requests, sellers choose to submit offers, and matches and prices are aggregate functions of total requests and offers. We also present how we apply the theoretical framework to the TaskRabbit data. We describe our estimation strategy, discuss our results, and robustness checks.

4.1 Model of a Market for Services

We now propose a parsimonious model of how the TaskRabbit marketplace matches tasks and offers, and how buyers and sellers make decisions about whether to post tasks and how much effort to put into making offers. Our modeling approach draws on the literature on frictional search and matching in labor markets (Pissarides (2000)). We assume for simplicity that buyers are all identical and in equilibrium choose the same number of tasks to post. Similarly, sellers are identical and choose the same intensity with which to search and submit offers. We also treat tasks as homogeneous. Obviously, this is a large simplification, but it does correspond to our earlier observations that most tasks on TaskRabbit are relatively standard and generic, and that they do not require specialized skills. More importantly, it allows us to focus on the problem of widely fluctuating supply and demand and increasing market size, without the complications of a heterogeneous matching framework. We take long-run participation decisions as given. Instead of focusing on users’ decision to join or leave the marketplace, we model the choice of how intensely to use it conditional on participation. Separately, Section 5 looks at adoption and attrition (extensive
margins) as additional drivers of growth.

We assume there is a measure $B$ of identical buyers and a measure $S$ of identical sellers. Each buyer will choose a number of tasks, $\beta$, to post. Each seller chooses a number of offers, $\sigma$, to make. The total number of services requested in a market is $b \equiv B\beta$, while the total number of offers submitted is $s \equiv S\sigma$. The number of trades between buyers and sellers is given by the matching function $m = M(s, b)$. $M(s, b)$ is continuous and differentiable, and increasing in both its arguments. Each request is matched with probability $q^b = \frac{m}{b}$ and each offer is successful with probability $q^s = \frac{m}{s}$. We assume that $M(s, b) \leq b$ and $M(s, b) \leq s$ to guarantee that matches are never larger than total requests or offers. The matching technology displays constant returns to scale if doubling the number of tasks $b$ and offers $s$ doubles the number of matches $m$, or $M(2s, 2b) = 2M(s, b)$. In each match, the buyer pays price $p = P(s, b)$, the seller receives $(1 - \tau)p$, and the marketplace keeps $\tau p$ as commission fee. In particular, price is determined as a function of services requested and offered, and is assumed to be a continuous and differentiable function, increasing in $b$ and decreasing in $s$.\(^{11}\) The price function is invariant to scale if doubling tasks and offers does not affect the price $p$, or $P(2s, 2b) = P(s, b)$.

 Buyers and sellers choose how many requests to post and how many offers to submit with full knowledge of the matching and price determination processes, but without the possibility to affect either of those with their individual choices because each participant is small relative to the market. Each buyer randomly receives a number of potential needs to outsource.\(^{12}\) Each need is worth $v - p$ to its buyer, where $v$ is the fixed value of having the task completed. There is a random cost of posting each task. The buyer’s problem is to choose whether to post each needed service. The decision is separable across service needs. If a buyer makes a request for a need, she pays the posting cost and expects payoff $q^b(v - p)$. So $\beta$, the expected number of requests posted by a representative buyer, will be increasing in $q^b$ and decreasing in $p$.

 Each seller chooses a level of effort $\sigma$ spent searching through buyers’ requests. An effort level $\sigma$ corresponds to a discovery process of profitable requests, to which the seller submits offers. Higher effort $\sigma$ makes it more likely to find a higher number of profitable submissions.\(^{13}\) Specifically, we assume that the number of suitable tasks identified and offers submitted is a random draw from a discrete distribution, with mean equal to the chosen effort level $\sigma$ and independent across sellers. Given this assumption, we will interchangeably refer to $\sigma$ as the level of search effort or the expected

\(^{11}\)In fact, several matching models of the labor market assume that the wage is either a parameter altogether or pinned down by other parameters. See, for example, Montgomery (1991) and Hall (2005).

\(^{12}\)For the conditions under which a continuum of independent and identically distributed random variables sum to a nonrandom quantity in large economies, see Judd (1985), and Duffie and Sun (2012).

\(^{13}\)Specifically, we assume that the distribution of application arrivals for a given $\sigma$ first order stochastically dominates the distribution for any $\sigma' \leq \sigma$. 
number of offers submitted by a representative seller. Search effort is costly, and its cost rises at an increasing rate.\textsuperscript{14} Conditional on matching a submitted offer, the seller’s profit is \((1 - \tau)p - c\), where \(c\) is the fixed cost of completing the task. So \(\sigma\), the expected number of offers submitted by a representative seller, will be increasing in \(q^s\) and \(p\).\textsuperscript{15}

Equilibrium in the market is defined as a state in which buyers and sellers maximize utility subject to the matching and pricing technologies, and to expectations of other agents’ behavior. The equilibrium requires consistency of individual optimal choices (\(\beta\) and \(\sigma\)) with expectations on average behavior in the market. In equilibrium, all buyers choose the same strategy in terms of the decision to post tasks, which in turn is consistent with the expected posting rate. The model explains differences in the actual number of requests across buyers as arising from a random arrival rate of needs and from different posting costs. Analogously, in equilibrium, all sellers choose the same level of search intensity, which in turn is consistent with the market average intensity. Differences in the rate of offer submission across sellers arise from the random process with which they discover profitable requests.

We now apply this framework to TaskRabbit. Our framework envisions a single static market, while trades occur continuously in the data. To create an empirical analogue, we define distinct markets in the data. Given that 94\% of users post or work in a single city, it is natural to treat cities as separate. The fact that 97\% of successful tasks are matched to offers within 48 hours of posting suggests segmenting the data in time as well. One option is to treat each city-month (e.g. San Francisco in October 2013) as a separate market. Within a city-month, we treat buyers and sellers, as well as their tasks and offers, as homogeneous, following the model, and discuss this further in Appendix A1. This definition allows us to consider each participant as small relative to the size of the market, which is our modeling assumption, and also lets us smooth shorter time variation due to potential task heterogeneity. Other market definitions do not change our qualitative results, as shown in Appendix A2.

\textsuperscript{14}We model sellers’ search costs as increasing in the intensity of search at an increasing rate. This assumption can be better understood in terms of time needed before finding a new task to which a seller chooses to make an offer. Conditional on a level of effort, it is likely that the first profitable task is easier to find than the second, the second is easier than the third, and so on. If a seller wanted to double the number of profitable tasks found, his level of effort would then be more than twice as costly. In addition, search costs are decreasing in the number of total tasks posted. In a market with many posted tasks, a seller is likely to spend less time finding the same number of profitable applications as in a smaller market. If a seller wanted to send the same expected number of offers in a large market his level of effort would then be less costly.

\textsuperscript{15}Buyers’ choice to post tasks and sellers’ choice of search effort are not symmetric. On the buy side, there is an exogenous arrival of tasks, and a decision to post each of them separately conditional on arrival. A buyer in need of moving help selects whether to post it or find an alternative solution - another service provider or informal help - as a function of the expected value from each option. On the sell side, the setup is truly a choice of marketplace usage intensity. A seller selects his optimal level of search effort, and if he finds profitable tasks he submits offers for sure. In this case, a seller chooses his time allocation between leisure and searching for services to sell as a function of the expected benefits from the two activities.
Our market definition is motivated by several additional considerations. First, we do not separate markets along the various task categories - cleaning, furniture assembly, and so on - because sellers do not specialize: of the sellers who submitted 10 offers or more 63.6% did so in more than 10 categories, and of the sellers who were successfully matched to more than 10 tasks, 43% did so for tasks in more than 10 categories. Second, we follow TaskRabbit business practice and do not separate markets into geographic partitions smaller than the metropolitan boundaries. Third, we choose the calendar month as the relevant time window as a way to balance the short time period over which tasks receive offers with the need to have enough offers and tasks in each market to estimate match probabilities, average prices, and search and posting intensities.

4.2 Tasks per Buyer and Offers per Seller

The theoretical framework above highlighted that buyer decisions to post tasks and seller decisions to submit offers are a function of match probabilities and prices. These outcomes are a function of market conditions such as market size and relative numbers of buyers and sellers. When sellers are scarce relative to buyers, their offers will be more likely to be accepted and pay higher prices. If in addition the overall number of participants makes the platform search and matching more efficient, sellers might find it easier to identify tasks to submit offers to, and their offers might be more likely to be accepted.

In order to quantify how buyers choose to post tasks and how sellers choose to submit offers as a function of market size and seller relative scarcity, we estimate OLS regressions of the following type:

\[
\log(y_{ct}) = \alpha_1 \log \left( \frac{B_{ct}}{S_{ct}} \right) + \alpha_2 \log \left( \sqrt{S_{ct}B_{ct}} \right) + \eta_c + \eta_t + \nu_{ct} ,
\]

where \( c, t \) denote city \( c \) and year-month \( t \), \( \frac{B_{ct}}{S_{ct}} \) is the buyer to seller ratio, \( \sqrt{S_{ct}B_{ct}} \) is the geometric average of buyers and sellers, or market size. The outcome is one of two relevant variables: tasks per buyer, and offers per seller. The vector \( \eta_c \) controls for city-specific propensities to use TaskRabbit which are time invariant. Similarly, \( \eta_t \) captures time-specific adjustments to usage intensities that are common across all active cities. Therefore \( \alpha_1 \) and \( \alpha_2 \) are identified from variation in the number of active buyers and sellers within cities over time and within months across cities. We cluster standard errors at the city level.

What \( \nu_{ct} \) represents is a shock to user propensity to post tasks and submit offers that we assume to be independent of prior decisions to join or stay on TaskRabbit. On the buyer side, it can be thought of as a city-month specific driver of demand for services among participating buyers. On

\[16\] We do not observe any sort of clear neighborhood partitioning in the data, although the setup on TaskRabbit does not preclude it.
the seller side it can be interpreted as a city-month increase in time availability among participating sellers.

A first issue threatening the assumption that the number of buyers and sellers is uncorrelated with \( \nu_{ct} \) is that existing buyers and sellers might anticipate the future value of exchanges on the marketplace and base their decision to stay or leave on these rational expectations. Two empirical features of TaskRabbit lead us to think that forward-looking behavior is not prevailing: the low level of retention and its response to future outcomes. Only a small share of buyers active in a given market (31% on average across markets) post again at least once in the subsequent three months. For sellers, this share is 66%. Moreover, in Section 5, we will consider the decision of current buyers and sellers to stay active on TaskRabbit and find that there is little empirical support for forward-looking anticipation of future outcomes,\(^{17}\) although there is evidence that both buyers and sellers respond to past outcomes.

A second issue is that participation decisions of new buyers and sellers might also depend on the future value of exchanges on the marketplace. On the buyer side, there is relatively little cost of joining TaskRabbit, and we believe that during our study period adoption may have been driven significantly by people simply becoming aware that the new online marketplace existed. Our indication is that buyer sign-ups tended to increase notably after media mention, which we do not believe were tied to specific market conditions. On the seller side, a significant source of month to month variation in new participation was driven by changes in the screening process. For a period, sellers were rigorously screened and interviewed by TaskRabbit employees. Acceptance rates of received applications depended on employees’ time to conduct interviews, were usually very low (13.6%) and varied greatly month to month. Further, these interviews introduced a certain delay between the sign-up decision and the actual participation on the marketplace. We have no evidence that they varied by city-months in response to expectations of higher demand or of lower time availability of each seller. In the spring of 2013 TaskRabbit decided to ease sellers’ screening, and started to require simpler background checks and social controls (automatic Linkedin and Facebook verification). This resulted in an acceleration of sellers’ acquisitions. Together, the varying screening policies and acceptance rates led to fluctuations in the relative number of buyers and sellers for reasons arguably unrelated to individuals’ activity within each city-month.

The results for the number of tasks requested per buyer are shown in Table 2, while the results for the number of offers submitted per seller are in Table 3.\(^{18}\) The first column shows the regression

\[\log(y_{ct}) = \hat{\alpha}_1 \log B_{ct} + \hat{\alpha}_2 \log S_{ct} + \eta_c + \eta_t + \nu_{ct}, \text{ where } \hat{\alpha}_1 = \alpha_1 + 0.5\alpha_2 \text{ and } \hat{\alpha}_2 = -\alpha_1 + 0.5\alpha_2. \]

\(^{17}\)The lack of correlation between attrition and future outcomes is not per se definitive evidence that users do not anticipate the future when choosing whether to stay or leave TaskRabbit. This can happen if there are events that are correlated with both the number of users and with future prices or transaction probabilities.

\(^{18}\)Given the log-specification, we can transform the right-hand side to be a function of the number of buyers and sellers: \(\log(y_{ct}) = \hat{\alpha}_1 \log B_{ct} + \hat{\alpha}_2 \log S_{ct} + \eta_c + \eta_t + \nu_{ct}, \) where \(\hat{\alpha}_1 = \alpha_1 + 0.5\alpha_2 \) and \(\hat{\alpha}_2 = -\alpha_1 + 0.5\alpha_2. \) The results in
results without fixed effects, while the second column shows results with fixed effects. Adding fixed effects does not change the response of buyers or sellers to fluctuations in the buyer to seller ratio, not in sign, size, or significance. This provides some confidence that TaskRabbit is used by buyers and sellers in a similar way both over time and across cities.

The results correspond to our earlier evidence. An increase in the number of buyers per seller has virtually no effect on how many tasks each buyer posts. On the other hand, doubling the number of buyers per seller of the median city-month, where the median is selected according to the distribution in the buyer to seller ratio and holding everything else constant, increases the number of offers submitted by each seller from 5.6 to 7.5.

We cannot fully rule out endogeneity of the number of buyers and sellers active on the platform. In particular, exogenous growth on one side of the market might be anticipated by the other side. For example, if the weather forecast anticipates heavy snow in Chicago in January, more buyers will join the platform to request snow plowing. Now, sellers will also know about the weather forecast, and in anticipation of higher demand they will join TaskRabbit in higher numbers. Platform policies can also facilitate seller response by advertising or loosening their screening process during these periods. This endogenous supply-side adjustment would reduce the variability in the buyer to seller ratio. At the extreme, if the number of sellers perfectly adjusted to an exogenous demand shock, we would not even be able to see the fluctuations in buyer to seller ratio shown in Figure 3. So in this sense our estimates of the effect of buyer to seller ratio on buyer and seller usage intensity are biased towards zero. The fact that we still find a positive effect of changes in buyer to seller ratio on the number of offers submitted suggests that sellers are truly responsive to demand and supply imbalances, and at least more responsive than buyers.

TaskRabbit advertising and marketing decisions might be another reason why the number of buyers and sellers could be correlated with shocks to request and offer intensity. However, we are not overly concerned with the possibility that marketing and advertising could affect both the number of buyers and sellers and their posting and search decisions for mature cities. This is because according to internal conversations, during the period of our study TaskRabbit did not spend heavily to attract buyers and sellers. Marketing targeted at the city level occurred only for a

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Tables 2 and 3 imply that buyers post the same number of tasks, regardless of how many users are active. Each seller submits more offers when there are more buyers, holding constant the number of sellers, but submits fewer offers when there are more sellers. We do still prefer the specification from equation 1 because of the particular nature of network externalities on TaskRabbit: users benefit from the marketplace insofar as it allows them to trade services, and users’ participation affects the terms of trade. A seller benefits from a market with relatively more buyers, where his services are highly demanded, but is hurt in a market with relatively more sellers, where his services face fierce competition. At the same time, holding the relative number of buyers and sellers constant, a seller can like a large market more or less than a small market. A preference for larger markets can arise because of scale economies, while one for smaller markets may be due to congestion.

19 We thank an anonymous referee for providing this useful example of possible sources of endogeneity.
few weeks around the time of entry into that city. TaskRabbit would start by acquiring some sellers before opening the marketplace to buyers, and would train them to perform services by assigning them to a small number of marketing tasks - e.g. flyer distribution. By only keeping markets with more than 50 active buyers and 20 active sellers, we are fairly confident that TaskRabbit’s marketing efforts are not the driving activity within a market.

To account for remaining sources of endogeneity, we can use instrumental variables. We need two instruments, one shifting overall participation, and another shifting participation of sellers more than participation of buyers. Unemployment rate is likely to disproportionately affect the number of sellers joining the platform. When more people are unemployed, more sellers sign up for TaskRabbit relative to buyers. Media coverage, on the other hand, is likely to shift overall participation on the platform. Indeed, after the initial marketing campaign at the time of entry, advertising relied on articles mentioning TaskRabbit in newspapers and blogs. 40% of these articles were not pitched by TaskRabbit directly, but rather made reference to TaskRabbit while discussing the sharing economy.20 In addition, about 65% of them were on national media, as opposed to local newspapers.21 This media coverage, or at least its 1-month lag, is unlikely to be specifically tied to market conditions affecting posting or search effort at a city-month level. So we use the 1-month lag of media articles mentioning TaskRabbit as a reasonable instrument that affects the task posting and offer submission propensity of current users only through its effect on the number of active buyers and sellers.

We can also use another set of instruments in the spirit of Bartik (1991). Specifically, we instrument the buyer to seller ratio in city-month \( c, t \) with the average ratio in month \( t \) in cities other than \( c \). We compute an analogous instrument for the number of participants. These averages produce measures of market conditions that are unrelated to city-month specific circumstances.

Instrumental variable estimates of equation 1 are reported in the last two columns of Tables 2 and 3. Column (3) uses Bartik instruments, while column (4) uses 1-month lags of media articles mentioning TaskRabbit from Factiva, and unemployment rates from the Bureau of Labor Statistics as instruments.22 Results are remarkably similar to the OLS results. In addition, we find a slightly larger response of sellers to an increase in the number of buyers per seller, in support of our earlier discussion that endogeneity is likely to bias our estimates towards zero. Buyers do not respond to fluctuations in the relative number of buyers and sellers, while sellers adjust their effort level

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20 The sharing economy (or collaborative consumption) is the term often used to refer to online peer-to-peer marketplaces like Airbnb, Uber, or TaskRabbit. In the sharing economy, owners rent or share something they are not using (e.g., a car, house) or provide a service themselves to a stranger using peer-to-peer markets.

21 The numbers rely on TaskRabbit’s tracking activity of its media presence in 2012, and on the media articles mentioning TaskRabbit retrieved from Factiva.

when they are scarce or abundant relative to demand. The Kleibergen-Paap rk Wald F statistic, which tests whether instruments are weak for both our endogenous variables while adjusting for clustered standard errors, allows us to reject the null hypothesis of weak instruments (Stock and Yogo (2005)). Also, we cannot reject the null that platform size and buyer to seller ratio are exogenous in the second stage regression for both the number of tasks per buyer and offers per seller.

There is one data issue that we have not yet discussed. Since we only observe task posting and offer submission, in the data we cannot distinguish between buyers and sellers who were considering posting tasks and submitting offers but did not because of unfavorable market conditions, and those who were completely disengaged from TaskRabbit. If there were no heterogeneity across buyers, then the number of buyers posting tasks would coincide with the number of buyers participating on the platform. In practice that is not true: the number of tasks requested varies across individual buyers. So it might be the case that a participating buyer would be more likely to post a request in a market where buyers are scarce relatively to sellers than in a market where buyers are abundant.

To account for the fact that some participating buyers might not post any task in a given month, we consider a buyer active since the first month they post a task, and for two months since their most recent action. If for example, a buyer posts tasks in January and May 2013, the buyer will be considered active January through March, and May through July. Analogously, we consider a seller active since the first month they submit an offer, and for two months since their most recent offer. We re-estimate equation 1, where the number of active buyers and sellers, as well as the average number of tasks per buyer and offers per seller are adjusted accordingly. The results are presented in Appendix table A1, and confirm that sellers are the side of the market that most responds to fluctuations in participating users. Appendix A2 also offers additional robustness checks that rely on changes in TaskRabbit’s screening policies for sellers, and on different market definitions.

4.3 Matches and Prices

We now want to evaluate the effect of buyer and seller behavior on equilibrium number of matches and prices. To do that, we estimate regressions of the following type:

$$\log(y_{ct}) = \beta_1 \log b_{ct} + \beta_2 \log s_{ct} + \eta_c + \eta_t + \nu_{ct}, \quad (2)$$

where $s_{ct}$ and $b_{ct}$ are the total number of offers submitted and tasks requested in a city-month, and $y_{ct}$ is either the number of transactions or the average transacted price. As we did in Section 4.2, we discuss OLS results, endogeneity issues, and IV estimates. We also use these results to discuss
scale economies in matching.

If we were to interpret the coefficients structurally, this specification would be analogous to assuming that the total number of matches and average prices in a market are Cobb-Douglas functions of the number of tasks posted and offers submitted. The sum $\eta_c + \eta_t + \nu_{ct}$ is a market level productivity shifter, where $\eta_t$ is a month effect common across cities, $\eta_c$ is a time-invariant city-specific parameter of match efficiency, and $\nu_{ct}$ is an idiosyncratic shock to matching, which is not anticipated by buyers or sellers.

In this specification, we expect that the number of matches will be increasing in both inputs, i.e. $\beta_1 \geq 0$ and $\beta_2 \geq 0$. The market exhibits increasing returns in matching if $\beta_1 + \beta_2 > 1$, and constant returns if $\beta_1 + \beta_2 = 1$. Under increasing returns, doubling the number of tasks and offers more than doubles the number of matches. For pricing, we expect more posted tasks will drive up prices, and more offers will reduce them, so that $\beta_2 \leq 0 \leq \beta_1$ when $y_{ct}$ is the average transacted price. If $\beta_1 + \beta_2 = 0$ price is not affected by scale: doubling both the number of offers and tasks has no price effect.

The assumption of exogeneity here means that buyers and sellers do not anticipate $\nu_{ct}$ when joining the platform nor when making their posting and offer submission decisions. These shocks can result from unexpected concentration of offers among a small number of tasks, for example due to variation in the time when users access the marketplace: if all sellers in a market find themselves looking for tasks at the same time within a month, offers will tend to be sent to the same tasks, more so than if sellers search for tasks at different times. This could decrease the rate at which offers and tasks are converted into matches and the price at which matches trade. Our assumption essentially requires that buyers and sellers cannot anticipate these coordination problems.

The first two columns of Table 4 present OLS estimates of the number of matches. We discuss the results from column (2), noticing once again that including city fixed effects and month fixed effects does not affect our estimates of how tasks and offers contribute to matching. The coefficients can be interpreted as elasticities, because of the log-log specification. The first column shows that doubling the number of tasks, holding constant the number of offers, increases the number of matches by 41%. Similarly, doubling the number of offers, holding fixed the number of tasks, increases the number of matches by 52%. The estimates suggest that scaling up either tasks or offers contributes about equally to the creation of successful matches.

The sum of the two elasticities provides an estimate of the returns to scale in the matching technology. Work on two-sided platforms has emphasized the importance of increasing returns to scale for market structure (Parker and Van Alstyne (2005)). The hypothesis is that active and

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23Petrongolo and Pissarides (2001) summarize the wide empirical support for a Cobb-Douglas matching function with constant returns to scale. For its micro-foundation, see Stevens (2007).
thick markets may lead to easier matching. Our estimates, however, show no evidence of increasing returns to scale. Returns are slightly (and significantly) less than constant when estimated by ordinary least squares.

The bias arising from endogeneity would likely work in favor of finding economies of scale. If for example TaskRabbit took advantage of the snow forecast to advertise to both buyers and sellers, the increase in number of participants to the platform would be positively correlated with an increase in the number of matches. This would bias our estimates towards estimating positive network effects, unless compositional changes would make both the marginal tasks and the marginal offers inferior. We cannot rule this possibility out completely, but we can check whether entrants are systematically different as a function of market size.

To check whether entrants are systematically different in markets with a higher number of participants, we run robustness regressions of the following type:

$$match_{rct} = \alpha_1 first_{rct} + \alpha_2 \log \left( \frac{B_{ct}}{S_{ct}} \right) + \alpha_3 \log \left( \sqrt{S_{ct}B_{ct}} \right) +$$

$$\alpha_4 first_{rct} \ast \log \left( \frac{B_{ct}}{S_{ct}} \right) + \alpha_5 first_{rct} \ast \log \left( \sqrt{S_{ct}B_{ct}} \right) + \beta X_{rct} + \epsilon_{rct}.$$ 

We run these regressions for requests and offers separately, and the outcome variable is equal to one if the request or offer is successful. So for requests, $r$ denotes a request posted in market $c,t$, and $first_{rct}$ is equal to 1 if it is a buyer’s first request ever posted. For offers, $r$ denotes the offer submitted, and $first_{rct}$ is equal to 1 if it is a seller’s first offer ever submitted. The coefficient of interest is $\alpha_5$. If $\alpha_5$ were negative it would imply negative selection of offers and requests when markets are larger. Results are presented in Table 6, and show that the coefficient is not statistically different from zero for offers (column 2), and positive but quantitatively very small for requests (column 1). This result supports the hypothesis that entrants in large markets are not systematically different from entrants in small markets.

The regression results allow us to emphasize an interesting source of heterogeneity. First requests do not seem to be overall less likely to match, while first offers are. The difference between buyers and sellers highlights the fact that it is more important to screen for service providers than for customers on this platform. Another result is that when sellers are scarce in a city-month, buyer requests are less likely to transact, but first requests are twice less likely to transact. On the supply side, when sellers are scarce their offers are more likely to be accepted, but first offers benefit less than offers from experienced sellers.

We confirm that our estimates of the matching parameters are robust to relaxing our identification assumption. We estimate equation 2 using three separate sets of instruments, all of which
are motivated in Section 4.2. By definition, \( s \equiv S \sigma \) and \( b \equiv B \beta \), so we can instrument for \( s \) and \( b \) directly with the number of active buyers \( B \) and sellers \( S \), or with the sets of instruments used above for the number of active buyers and sellers – Bartik-style instruments, and media coverage and unemployment rate. The results are shown in the three last columns of Table 4.\(^{24}\) The results broadly confirm the OLS estimates, and do not allow us to reject the null hypothesis that the number of tasks posted and offers submitted are exogenous. Table 4 does not report the city and time fixed effect estimates. We will return to these estimates in Section 5 where we discuss the differences in the marketplace success across cities.

Table 5 reports estimates of the market pricing function. Now including fixed effects changes both the magnitude and the significance of our price coefficients, suggesting that there is some degree of heterogeneity in the type of services provided across cities and months. We discuss this heterogeneity in Section 5. Instrumental variables do not affect the estimates. When fixed effects are included, prices move very little with the number of tasks and offers. Doubling the number of tasks, holding constant the number of offers, increases the average transacted price by 1.5%, while doubling offers decreases it by 1.3%. This is perhaps a little surprising from the standpoint of strategic pricing, especially for the auction tasks where buyers choose from competing offers, but it holds true even in a restricted sample of auctions. More details are in Appendix Table A3. The results further confirm that the average price is invariant to market scale: the sum of the price elasticity to tasks and to offers is virtually zero.

We conclude this section observing that our estimation of the matching function leaves very little unexplained. The R-squared of the regression (second column of Table 4) is 0.996. About 50% of the differences between actual and predicted matches across markets are fewer than 9 matches. The amount of residual variation in the pricing function is a little higher, given a R-squared of 0.727 (second column of Table 5). However it corresponds to a discrepancy of $3 or less in most markets.

### 4.4 Implications for Platform Growth

The two subsections above have presented the following key findings: a highly elastic labor supply, fixed prices, and constant returns to the matching technology. Here we discuss their implications.

The fact that prices do not depend on fluctuations in buyers and sellers on the platform is consistent with the competitive context in which TaskRabbit operates, and has also been found more recently for wages on Uber (Hall et al. (2017)). The platform is relatively small during the

\(^{24}\) As before, the Cragg-Donald Wald F statistic and the Kleibergen-Paap rk Wald F statistic allow us to reject the null hypothesis of weak instruments.
period of our study, and the tasks requested do not require high skills. Data from Crunchbase, the most comprehensive database of startups and larger companies, suggest that TaskRabbit faces many competitors. A search for “Home Services” companies based in the US and started before June 2014 returns over 137 results, ranging from similar online platforms such as Thumbtack to publicly listed companies such as HomeServe. In addition it seems reasonable to believe that similar services could be exchanged through informal connections and word of mouth.

However, the fact that prices are fixed still leaves a couple of ways in which the market could equilibrate in response to demand increases. One option is adjustments in seller effort, the other option is buyer rationing. If sellers did not expand effort, doubling the number of task requests would not double the number of matches unless the platform contemporaneously recruited new sellers. Our paper is the first to establish empirically the high supply elasticity in peer-to-peer platforms. Subsequent work has confirmed that it is a common feature across many other online peer-to-peer markets for local services, such as Uber (Chen et al. (2017)) and Airbnb (Farronato and Fradkin (2018)). In order to evaluate the benefits of this elastic labor supply for marketplace growth, we compare it to the alternative where supply is fixed.

We present a simple exercise to illustrate the intuition. Consider a market with 1,000 posted tasks, and suppose that the number of offers submitted is 1,400. Using our estimates for the matching function, 488 matches would be created out of these two aggregate inputs. Now assume that demand doubles to 2,000 posted tasks. A perfectly elastic supply would lead to a doubling of the number of offers, and would create 930 total matches. Analogously, if demand halved to 500 tasks and supply adjusted downward to 700 offers, the number of matches created would be 256. Regardless of the size of demand, tasks would always match at the same rate.

In the alternative scenario, supply is held fixed at 1,400 offers, and equilibration occurs through buyers’ rationing: when demand is low, it is easier for buyers to find a match, and when demand is high it becomes harder to trade. In the low-demand market (500 tasks), the number of matches created would be 367 and each task would match with a 73% probability. In the high-demand market (2,000 tasks), 649 tasks would be matched, implying a 32% match rate. Overall, if we compare the total number of matches between the two scenarios, the marketplace with an elastic labor supply is able to create 11% more matches. This is evidently optimal from the marketplace perspective: since its revenues are a 20% commission on actual matches and prices barely move, in this simple example having an elastic supply raises its short-term revenue by 11%. Since it also

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25 Data were accessed from https://www.crunchbase.com/search/organization.companies in December 2017.
26 Note that doubling the number of tasks and offers does not double the number of matches because of the slightly decreasing returns to scale estimated for the matching function (shown in Table 4).
27 The result comes from the fact that the matching function is concave in both inputs, so that $M(b', s') + M(b, s) > M(b', s) + M(b, s')$ where $b' > b$ and $s' > s$. 

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raises retention, which we show in Section 5, it benefits the marketplace by accelerating its growth.

The absence of increasing returns in the matching technology was perhaps unexpected given the specific nature of the market. In a platform like TaskRabbit where tasks typically require a buyer and a seller to meet, efficiency can come from matching buyers and sellers who live close to each other. But interestingly it does not seem to be the case that distances between matched buyers and sellers shrink as a market grows. Figure 6 plots the median distance within a city-month, where the distance is measured between the zip codes reported by buyers and sellers.\textsuperscript{28} The top line takes a seller who made an offer at a specific time, and pairs him to every buyer who posted tasks in the preceding 48 hours. The median distance is computed among all such pairs within a city-month. The middle line is just the pairing of tasks and their corresponding offers, and the distance is computed between the zip codes of buyers who posted those tasks and sellers who submitted those offers. The bottom line is the pairing of buyers and sellers from successful matches. The figure plots the median distance for the three largest cities over time, and the other cities display similar time trends. None of these measures of buyer-seller distance shrinks as a market scales up.

Because sellers flexibly expand effort in response to increases in demand, a direct implication is that peer-to-peer markets should focus on increasing demand rather than supply. In addition, the absence of economies of scale means that maintaining an efficient matching process is crucial for marketplace success. The next section explores demand growth across cities, and how it relates to market efficiency.

5 Growth and City Heterogeneity

The motivating feature of the data for our paper is that some cities exhibit striking growth in the number of matches, and others exhibit more moderate growth (Figure 2). The previous section has demonstrated how growth relies on attracting buyers, given that supply is highly elastic.

In principle, two types of theories can explain differences in how cities attract and retain a large number of buyers. The first type relies on scale economies and strategic complementarities between the adoption patterns of buyers and sellers. If market frictions were reduced by market scale, we would expect that cities which started off with a large user base grew much faster than cities of modest size, exactly because growth led to more growth. However in Section 4 we found no evidence supporting scale economies in matching. Therefore initial differences in adoption cannot explain increasing heterogeneity over time.

\textsuperscript{28}We compute the geodetic distance, i.e. the length of the shortest curve between the two zip codes, where the input coordinates are assumed to be based on the WGS 1984 datum. The distances are ellipsoidal distances computed using equations from Vincenty (1975).
A second set of hypotheses rely on city differences in facilitating interactions between buyers and sellers. To develop this idea, we show that user attrition is lower in more efficient markets and that markets vary greatly in their matching efficiency, summarized by the fixed effects of equation 2. Combining these results, we see a strong relationship between the rate at which tasks and offers are converted into successful matches and city growth rates. We conclude the section with evidence that relates match efficiency with measures of market thickness at the city level: geographic distance between buyers and sellers, and task specificity.

5.1 City Differences in Growth

Marketplace user growth is a combination of adoption and retention of existing users. Given the high elasticity of supply, growth depends on buyers’ participating decisions. Figure 8 plots buyer adoption and retention separately for the 10 largest cities. The left-hand side panel shows the number of new buyers, in log scale, over time. A buyer is defined as new in a city-month if she posts her first task in that city during that particular month. Buyers join the marketplace at a linear rate, different in all cities. At visual inspection, this rate seems to be correlated with the city-specific retention rate. For every city, the right-hand side of Figure 8 plots the share of active users in a month who posted again at least one task in the following three months. San Francisco is successful at both attracting new buyers and retaining current ones, while Philadelphia has both lower adoption and retention rates.

The literature on innovation diffusion (Young (2009)) has focused on three types of mechanisms leading users to adopt new technologies: network effects, technology improvements, and information diffusion. The first two assume that different users adopt at different points in time because of heterogeneous benefits: early adopters have a large intrinsic value from a new technology, while late adopters join because of scale economies or technical upgrades. We have argued that marketplace efficiency does not increase with market scale, and for the period under consideration TaskRabbit did not implement major changes of their marketplace. Word of mouth and information diffusion, then, seem to be the most plausible alternative in this context, and cities can differ both in the rate at which information spreads and the rate of take-up conditional on receiving that information. For example, in San Francisco adoption might be fast because people there are eager to experiment with new technologies and because current users spread the information at a faster rate, with the second factor possibly driven by a positive experience on TaskRabbit. We measure the aggregate
effect by estimating the city-specific buyer adoption equation:\textsuperscript{29}

\[ \text{new}_{ct} = \phi_c \text{age}_{ct} + \epsilon_{ct} , \]

where \text{new}_{ct} is the number of new buyers joining city \( c \) in calendar month \( t \), and \text{age}_{ct} is the age of the marketplace in city \( c \) at time \( t \). For example, \text{age}_{ct} = 1 \text{ if month } t \text{ is the first since TaskRabbit became active in city } c. \text{ In Appendix A3, Table A13 shows the results, and we verify that deviations from the linear adoption rate are not driven by contemporaneous market conditions, in support of our earlier identification assumptions.}\

We compare adoption rates with retention. Retention can be city-specific and, within each city, further depend on current outcomes, match rates and prices:

\[ \log \left( \frac{\text{stay}_{ct}}{1 - \text{stay}_{ct}} \right) = \theta_0 X_{ct} + \theta_t + \theta_c + \epsilon_{ct} . \]

The variable \text{stay}_{ct} is the share of users active in city-month \( c, t \) who were active again at least once in the following three months within the same city. \( X_{ct} \) is a two-element vector of relevant outcomes in city-month \( c, t \): realized buyer match rate and average transacted price. We expect that a high match rate would increase the odds that a buyer will be active again in the next three months, while a high price would drive away more buyers. As with equation 3, Table A15 in Appendix A4 shows the results, which confirm our hypothesis, and we verify that retention is not correlated with future outcomes, in partial support of our earlier identification assumption.

Figure 9 plots the estimates of \( \phi_c \) (city-specific adoption rate) and \( \theta_c \) (retention rate) from equations 3 and 4. A certain correlation exists between the rate at which a city is able to attract buyers and the rate at which it can retain them, although it is by no means perfect. San Francisco and New York are successful on both measures, while Houston, Atlanta and Phoenix lag behind on both. However, in San Diego buyers adopt at a fast rate but are also likely to leave the marketplace, while in Portland new buyers are just a few but they stay longer. Retention is arguably the decision that is mostly related to the experience on the marketplace, and indeed in the next section we show that it is associated with how efficiently the marketplace matches buyers and sellers in each city.

\textsuperscript{29}We assume a linear growth rate different across cities, given Figure 8. It can be rationalized within the Bass model of new product diffusion (Bass (1969)): \text{new}_{ct} = \phi_c + \text{new}_{c,t-1}, \text{ where } \text{new}_{c,t} \text{ is the number of new buyers joining city } c \text{ in calendar month } t. \text{ Two things differ from the standard specification. First, the total number of potential adopters is assumed to be large relative to the size of the marketplace, which is consistent with the population size of the metropolitan cities relative to the current users on TaskRabbit. Second, we assume that new adopters in the previous month are the only users spreading information, and not adopters of previous months. Each new adopter diffuses information so that exactly one extra adopter joins the marketplace in the following month.}
5.2 City Differences in Match Efficiency and Market Thickness

For tasks like cleaning and delivery, it is obvious to expect that buyers would care about how easy it is to find a seller willing to provide the service at the desired time and location, and the price to pay for the service. In this section we explore how differently cities perform in this respect. To do so, we take advantage of earlier estimates of the matching and pricing functions from Section 4.3.

Cities vary widely in the rate at which tasks and offers are converted into successful matches. Figure 7 plots estimates of $\eta_c$ from equation 2, ordering cities from the most efficient (San Francisco) to the least efficient (Miami). San Francisco is $2.37 \left( \frac{\eta_{SF}}{\eta_{Miami}} \right)$ times as effective as Miami in creating matches: out of the same number of tasks and offers, 100 matches are created in Miami while 237 matches are created in San Francisco. Other than San Francisco, among the cities with the highest match productivity are Boston, Portland, Austin, and New York City. The other extreme includes Miami, Denver, Phoenix, Philadelphia, and Atlanta.

There is limited heterogeneity in prices across cities, as Figure A3 shows. Here cities are ordered according to their ranking in the match efficiency parameter from Figure 7, and the plot displays estimates of $\eta_c$ from the pricing equation. Most prices range between $54 and $65, with Denver ($42) and Miami ($68) as outliers.

The most efficient cities are those able to retain the most buyers. In Figure 7 the size of the marker for the match efficiency parameter is proportional to the retention rate $\theta_c$ estimated from equation 4. The cities with high match productivity $\eta_c$ also have high retention rate $\theta_c$.

The next step is to try to understand what can explain efficiency differences across geography. To this purpose we look at two metrics related to market thickness. The first natural candidate is the proximity of buyers and sellers: cities that more easily match tasks and offers might be those where buyers and sellers live closer together and can more easily meet and exchange services. This hypothesis is strongly supported by the data, and in Appendix A6 we run task-level regressions to

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30 $\eta_{Oct2013}$ is normalized to 1.
31 The matching and pricing specifications from equation 2 also include time effects, which we briefly discuss here. Over time, there is a limited decline in match efficiency, but not sizable nor statistically significant. Figure A2 plots estimates of $\eta_c$ from the matching equation. The line is fairly flat between Spring 2011 and Summer 2013, with higher variability before and a small downward jump afterwards. This variation coincides with the staggered entry of TaskRabbit into the various cities. Indeed, prior to Spring 2011, only two cities were active, San Francisco and Boston. Around the Summer of 2013, TaskRabbit became active in the nine youngest cities, which are also those with lower match productivity estimates. Instead, there is a substantial increase in transacted prices over time. As Figure A4 shows, estimates of $\eta_t$ monotonically increase, from $30 in June 2010 to just above $60 in May 2014. The increase in price seems to closely track the task diversification on the marketplace towards more expensive tasks. Figure A5 presents the share of posted tasks in the 10 largest categories over time, combining all other categories in an eleventh group. It demonstrates how the period of fastest diversification, where the cumulative share of the top categories fell considerably, occurred in the Spring of 2011, exactly when the average price experienced the highest increase.
32 The most efficient cities also tend to correspond to those where TaskRabbit entered earlier on, and this still holds under different specifications of the matching function, as shown in the Appendix.
verify that buyer-seller distance matters for match success. Figure 10 plots the match efficiency parameter $\eta_c$ and the median geographic distance between buyers and sellers of paired tasks and offers. In cities like San Francisco, Boston, Portland, and New York, which convert tasks and offers into matches at the highest rate, the median distance between buyers and sellers of paired tasks and offers is around 7 miles. At the other extreme, the distance in Philadelphia and Miami is over 20 miles.

The second candidate measure of market thickness is related to task specificity. The idea is that an idiosyncratic task, which possibly requires specialized skills on the part of the seller, is harder to match than a standardized cleaning task, for which all that matters is location and time availability of one seller out of many good alternatives. To explore this idea, we look at the share of tasks posted in May 2014 within the top five categories, which include shopping, moving help, and cleaning. Figure 11 plots this share of more “standard” tasks against the match efficiency parameter $\eta_c$. In San Francisco, Boston, and New York over 60% of the tasks are posted within the top five categories, while Dallas, Miami, Atlanta, and Denver all have shares smaller than 50%.

As table 7 shows, all the correlations displayed in the plots are highly significant. We want to be careful in interpreting this correlations as causal given the small number of cities for which we have data. In addition, it is possible that more experienced buyers learn to post tasks better, i.e. in homogeneous categories, and that makes matching more efficient. It is also possible that experienced buyers and sellers learn to transact with users nearby, but that the distance between buyers and sellers on TaskRabbit is unrelated with the distance between buyers and sellers of similar services outside of the platform. It is important to highlight however, that at least the difference in geographic distance appears as soon as TaskRabbit becomes active in a city (Figure 6), reducing the likelihood of the learning hypothesis. It also seems that the growth of TaskRabbit in a city is correlated with the size of Craigslist, a competing platform (Figure 12). This correlation supports the possibility that the way buyers and sellers use TaskRabbit in one city is common across similar online platforms.

6 Managerial Implications and Conclusions

In this paper, we have studied how supply elasticity, economies of scale, and city-specific characteristics related to market thickness contribute to the growth of online peer-to-peer markets. This is an important question for the recently popular online peer-to-peer marketplaces for local and

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33 The correlation is maintained with the two other pairing definitions: median distance between buyers and sellers active around the same time window, and median distance between successfully matched buyers and sellers.

34 We thank Robert Seamans and Feng Zhu for sharing craigslist data from their research (Seamans and Zhu (2013)).
time-sensitive services, such as Uber, Airbnb, and TaskRabbit.

In order to study supply elasticity and scale economies, we have separated users’ decision of how intensely to use the marketplace in the short-run from the decision to join or leave the marketplace, both of which affect growth. We have studied short and long-run participation decisions on TaskRabbit, a growing peer-to-peer market for domestic tasks, using variation in market conditions across cities and over time.

Our analysis has unveiled three main findings. First, buyers post similar numbers of tasks regardless of their scarcity relative to sellers, while sellers expand their effort when they are scarce and contract it when they are abundant. This adjustment on the seller side has virtually no impact on average prices, suggesting a highly elastic labor supply. Second, the number of matches scales linearly with the number of market participants, suggesting that there are no network effects or match efficiency gains from increasing the number of participants. Third, geographical proximity of buyers and sellers, and task homogenization are positively associated with match efficiency, which helps explain differences in platform success across cities.

Our findings have four important implications for managing the growth of peer-to-peer marketplaces. First, the managerial challenge unique to two-sided platforms is striking a balance between demand and supply. This is the classical chicken-egg problem: limited demand discourages sellers from joining, and limited supply discourages buyers (Caillaud and Jullien (2003), and Hagiu (2007)). Our results suggest that managerial efforts should focus on attracting the most inelastic side of the market because the inelastic side constraints the volume of trades on the platform, and thus profits. On TaskRabbit, we found that demand is more inelastic, so the platform should spend resources attracting buyers at a faster rate than sellers because sellers flexibly adjust their effort in response to changes in relative demand, with almost no effects on prices or the probability that tasks are filled. It seems that TaskRabbit was initially devoting more resources to the recruiting and screening of sellers than to attracting buyers, as evidenced by their initially tight background checks. The fact that the platform changed their seller screening policies towards easier background checks in the middle of 2013 suggests a shift of focus away from sellers, in line with our findings. On other platforms however, the most inelastic side may be sellers rather than buyers, and our framework can be applied to other data to identify how responsive each side is to market conditions.

Second, the standard assumption is that two-sided platforms benefit from large network effects, so the challenge is to either achieve scale fast and deter competitive entry or drastically innovate. However, when it comes to peer-to-peer platforms for local and time-sensitive services, the nature of network effects can be limited to a specific geography and time interval, and our results suggest that other local characteristics are more important for growth than economies of scale. As a
consequence, managerial efforts should be targeted at strategically picking cities for geographic expansion, and the characteristics of those cities should promote market thickness. In the case of TaskRabbit, and more generally for marketplaces for personal services, a relevant characteristic is the distance between the locations of buyers and sellers.

Third, our results have implications for competition. Existing literature assumes that multiple platforms cannot coexist in equilibrium and that a single winner will dominate the market (Eisenmann et al. (2011)). In our setting where services are local, we find that the proximity of buyers and sellers is a main driver of efficiency. This implies that it is crucial to select which cities to operate in, but also that entry and competition are much more likely here than in other markets, such as those for remote work, where network effects are not local by nature. Indeed, a simple count of the number of active “Home Services” companies on Crunchbase returns 249 firms, against only 67 “Freelance” companies. Empirical studies of other factors contributing to the equilibrium level of competition in platform-based markets is a valuable avenue for future research.

Finally, the level of service standardization is a crucial strategic choice for platforms like TaskRabbit. We have found that standardization is positively associated with matching efficiency because it guarantees that fairly undifferentiated supply is available and task requests are more easily filled, which in turn increases user retention. This result suggests managerial efforts should focus on choosing a few standardized services to be exchanged on the marketplace, at least early on. Many other peer-to-peer markets have indeed started with narrow service offerings – e.g. rides on Uber, accommodation on Airbnb – and have later expanded – Uber to food delivery and Airbnb to local experiences to complementary service categories. When and how to diversify services exchanged on a platform is an important open question.

A slightly less direct implication of our findings is that when services are relatively undifferentiated (e.g. cleaning) and buyers’ tastes are not highly heterogeneous, peer-to-peer markets can design the search and matching mechanism to reduce search costs. Given the platform design where sellers need to submit offers to each individual task request, it seems costly for sellers to search through posted tasks, and with some probability profitable tasks are not found by any seller and are left unmatched, or are found by sellers who turned out to be unavailable to perform them. Indeed, 13% of the tasks that did not receive any offers were canceled because the buyer reported having the task done sooner, and 19% of the tasks that did receive offers were canceled because one of the parties reported inability to resolve scheduling conflicts. So, what would happen if instead of having sellers search for profitable submissions, the marketplace let sellers directly list their availability.

On Crunchbase platforms similar to TaskRabbit are classified as "Home Services", while platforms similar to Upwork are classified as "Freelance". The database was accessed in December 2017.

on a calendar and within a specific geographic area? This would eliminate search costs of supply, while benefiting buyers and the marketplace by raising task match rates.

The benefits of reducing sellers’ search costs and improving match efficiency provide a rationale for a re-design of the marketplace, which actually occurred in the Spring of 2014. Buyers can now select the category, location, and time for a given task request, and then either choose among the sellers available to perform that task type at the specified time and location, or have TaskRabbit automatically choose for them. The benefits of reducing search frictions and increasing match efficiency may however come at a cost. Specifically, listing time availability may decrease flexibility of seller schedules, which recent research shows to be valuable for service providers of peer-to-peer markets (Chen et al. (2017)). Automatic matching might also reduce seller opportunity to trade more specialized skills at a premium. These examples highlight the fact that the two sides of a peer-to-peer market have conflicting interests, and design choices benefiting one side might hurt the other.

Our paper has primarily focused on aggregate measures of scale economies, supply elasticity, and city differences as contributors to growth of peer-to-peer markets, leaving aside buyer and seller heterogeneity. A valuable avenue for future research would be to study dynamic participation decisions of buyers and sellers in more detail than done here. Better understanding the drivers of user adoption can help explain competition between peer-to-peer markets, both between multiple peer-to-peer marketplaces and between the online marketplace model and more traditional service providers.
References


Figure 1: The TaskRabbit Marketplace between January 2009 and May 2014.

(a) Example of a posted task.

(b) City list of posted tasks for sellers to search.

Screenshots from TaskRabbit, accessed on December 14, 2013. Buyers post task requests with details about the task requirements, the time and location (top panel). Sellers search through lists of posted tasks within their city (bottom panel) and submit offers.
Figure 2: Market Size.

The figure plots the number of successful matches in selected cities over time. The y-axis, in log scale, is normalized by the value in San Francisco in May 2014. The picture shows the large heterogeneity in the growth of TaskRabbit across cities.
Figure 3: Buyer to Seller Ratio.

The figure plots the active number of buyers relative to sellers in selected cities over time. A buyer is active in a city-month if she posts at least one task within the city-month. A seller is active if he submits an offer to one of the tasks posted within that city-month. The picture shows the large fluctuations in the number of buyers relative to sellers across cities and over time.
The figure plots city-month average number of tasks per buyer and offers per seller. We divide the 336 city-months into four groups, corresponding to the four quartiles of the distribution of the buyer to seller ratio. For each group we compute the average number of tasks per buyer (light color) and offers per seller (dark color). Confidence intervals are displayed in lighter colors. The picture shows that, regardless of how many buyers per seller are active in a city-month, buyers post on average 1.6 tasks each. On the other hand, when sellers are abundant relative to buyers, sellers submit less than 5 offers each, while when sellers are scarce they submit more than 9 offers each.
City-month average of task match rate and transacted price. We divide the 336 city-months into four groups, corresponding to the four quartiles of the distribution of the buyer to seller ratio. For each group we compute the average share of completed tasks (dark red, the y-axis is normalized by the largest match rate to protect company’s information) and price paid (light red). Confidence intervals are displayed in lighter colors. The picture shows that, regardless of how many buyers per sellers are active in a city-month, both prices and task match rates stay relatively constant.
The figure plots the median distance within a city-month between three different pairings of buyers and sellers, for the three largest cities over time, and confirms that even if the platform is growing in size in every city, the distance between buyers and sellers does not decrease. The distance is measured as the length of the shortest ellipsoidal curve between the buyer zip code and the seller zip code (Vincenty (1975)). In each plot, buyers and sellers are paired in three different ways. The first pairing (top line) takes a seller who made an offer at a specific time, and pairs him to every buyer who posted tasks in the preceding 48 hours. The median distance is computed among all such pairs within a city-month. In the second pairing (middle line) a buyer is paired with a seller if her task received an offer from that seller. Each pair is weighted by the number of their task-offer pairs within a city-month, and the median is computed among all such pairings. In the third pairing (bottom line) a buyer is paired with a seller if they actually exchanged services. As before, each buyer-seller pair is weighted by the number of their successful matches within a city-month.
The figure shows $\eta_c$ from the OLS regression of equation 2 where the outcome variable is the log number of matches in a city-month. The marker size is proportional to the retention rate parameter $\theta_c$ from the estimation of equation 4 (for Denver and Miami too few months of activity are recorded to estimate it). The picture shows the positive relationship between the retention rate (marker size) and matching efficiency (y-axis).
**Figure 8:** *Buyer Adoption and Retention Over Time.*

(a) Number of new buyers by city over time. A buyer is defined as new in a city-month if she has never posted tasks in that city prior to that month.

(b) Buyer retention by city over time. For every city-month, the figure plots the share of current buyers posting again in the same city in the following three months.

The figures plot adoption and retention patterns of buyers across cities over time, for selected cities.

**Figure 9:** *Buyer Adoption and Retention by City.*

The figure plots the estimates of $\phi_c$ (city-specific adoption rate) from equation 3, and $\theta_c$ (retention rate) from equation 4. For Denver and Miami too few months of activity are recorded to estimate $\theta_c$. The picture shows that it is not always the case that in cities where adoption is fast, retention is also large. Figures 10 and 11 relate retention to matching efficiency on the platform.
The figure plots the median distance between buyers and sellers in a city against the city estimate of the match productivity parameter $\eta_c$ from equation 2. The distance between buyers and sellers is computed according to the second definition from Figure 6: a buyer is paired with a seller if her task received an offer from that seller. Each pair is weighted by the number of their task-offer pairs within a city, and the median is computed among all such pairings at the city level. The size of each bubble is proportional to the retention rate parameter $\theta_c$ from the estimation of equation 4. The correlation with the overall marketplace growth by city is also positive. The full correlation matrix is displayed in Table 7.
The figure is identical to Figure 10 except that on the x-axis we plot the share of tasks posted in May 2014 within the top 5 task categories. Alternative measures of standardization (other time frames, top 3 categories) display similar patterns. The correlation with the overall marketplace growth by city is also positive. The full correlation matrix is displayed in Table 7.
Figure 12: TaskRabbit and Craigslist.

The figure plots the number of posts on Craigslist in 2007 and the linear growth rate on TaskRabbit, inclusive of adoption and retention. Data on the size of Craigslist were collected by Seamans and Zhu (2013).
### Table 1: Summary Statistics.

<table>
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<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>25th Percentile</th>
<th>Median</th>
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<td>1</td>
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<td>1</td>
<td>1</td>
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<tr>
<td>Nr. Offers Received (≥ 0)</td>
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<tr>
<td>Price of Successful Tasks ($)</td>
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<td>57</td>
<td>44.24</td>
<td>25</td>
<td>45</td>
<td>75</td>
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<tr>
<td>Commission Fee (%)</td>
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<td>0.04</td>
<td>0.18</td>
<td>0.2</td>
<td>0.2</td>
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#### (a) Task level summary statistics.

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<th>Mean</th>
<th>Standard Deviation</th>
<th>25th Percentile</th>
<th>Median</th>
<th>75th Percentile</th>
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</thead>
<tbody>
<tr>
<td>Number of Active Buyers</td>
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<td>132</td>
<td>272</td>
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<td>Number of Active Sellers</td>
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<td>326</td>
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<td>Number of Tasks per Buyer</td>
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<td>1.63</td>
<td>0.22</td>
<td>1.49</td>
<td>1.62</td>
<td>1.76</td>
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<td>Number of Offers per Seller</td>
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<td>6.45</td>
<td>3.04</td>
<td>4.22</td>
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<td>Task to Offer Ratio</td>
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<td>Average Price Charged($)</td>
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<td>56</td>
<td>8.69</td>
<td>52</td>
<td>57</td>
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</tbody>
</table>

#### (b) City-month level summary statistics.

Summary statistics. Data include posted price and auction tasks, offers submitted to those tasks, and matches created in the 18 US cities between June 2010 and May 2014. In the first panel, an observation is a posted task. In the bottom panel, an observation is a city-month. We define a buyer to be active in a city-month if she posts at least one task in that city-month. Analogously, a seller is active if he submits an offer to a task posted within the city-month.
<table>
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<td></td>
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<tr>
<td>Market Size</td>
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<tr>
<td></td>
<td>[0.009]**</td>
</tr>
<tr>
<td>Constant (SF Oct '13)</td>
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<tr>
<td></td>
<td>[0.041]**</td>
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<tr>
<td>City FE</td>
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<tr>
<td>Month FE</td>
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<tr>
<td>Instruments</td>
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<td>Observations</td>
<td>336</td>
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<tr>
<td>R-squared</td>
<td>0.222</td>
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The table shows results from OLS and IV regressions of Equation 1. The outcome variable is the number of requests per buyer. Column 1 shows estimates without city fixed effects or year-month fixed effects. Column 2 adds city fixed effects and year-month fixed effects. Column 3 uses Bartik instruments for the buyer to seller ratio and market size. Column 4 uses the 1-month lag of the number of national and local media articles mentioning TaskRabbit and the 1-month lag of the unemployment rate as instruments. In column 4, the instruments are interacted with city-specific fixed effects for cities active for more than 25 months. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robustness checks with alternative market definitions are shown in Appendix A2.
### Table 3: Offers per Seller.

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<td>Buyer to Seller Ratio</td>
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<td>0.474</td>
<td>0.534</td>
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<td></td>
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<tr>
<td>Observations</td>
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<td>R-squared</td>
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The table shows results from OLS and IV regressions of Equation 1. The outcome variable is the number of offers submitted per seller, and otherwise the table is identical to Table 2.
The table shows results from OLS and IV regressions of Equation 2. The outcome variable is the number of matches. Column 1 shows estimates without city fixed effects or year-month fixed effects. Column 2 adds city fixed effects and year-month fixed effects. Column 3 uses the number of active buyers and sellers to instrument for the number of tasks requested and offers submitted. Column 4 uses Bartik instruments for the number of active buyers and sellers. Column 5 uses the 1-month lag of the number of national and local media articles mentioning TaskRabbit and the 1-month lag of the unemployment rate as instruments. In column 5, the instruments are interacted with city-specific fixed effects for cities active for more than 25 months. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robustness checks with alternative market definitions are shown in Appendix A2.

<table>
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<td></td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Instruments</td>
<td>No</td>
<td>No</td>
<td>Nr. Buyers &amp; Sellers</td>
<td>Bartik</td>
<td>Media &amp; Unempl.</td>
</tr>
<tr>
<td>Observations</td>
<td>336</td>
<td>336</td>
<td>336</td>
<td>336</td>
<td>319</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.973</td>
<td>0.996</td>
<td>0.996</td>
<td>0.996</td>
<td>0.997</td>
</tr>
</tbody>
</table>
Table 5: Transacted Prices.

<table>
<thead>
<tr>
<th>Transacted Prices</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tasks</td>
<td>0.185</td>
<td>0.015</td>
<td>0.016</td>
<td>0.020</td>
<td>0.108</td>
</tr>
<tr>
<td></td>
<td>[0.057]***</td>
<td>[0.049]</td>
<td>[0.072]</td>
<td>[0.079]</td>
<td>[0.120]</td>
</tr>
<tr>
<td>Offers</td>
<td>-0.137</td>
<td>-0.013</td>
<td>-0.016</td>
<td>-0.032</td>
<td>-0.115</td>
</tr>
<tr>
<td></td>
<td>[0.044]***</td>
<td>[0.042]</td>
<td>[0.063]</td>
<td>[0.056]</td>
<td>[0.106]</td>
</tr>
<tr>
<td></td>
<td>[0.116]***</td>
<td>[0.152]***</td>
<td>[0.112]***</td>
<td>[0.274]***</td>
<td>[0.076]***</td>
</tr>
<tr>
<td>City FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Instruments</td>
<td>No</td>
<td>No</td>
<td>Nr. Buyers &amp; Sellers</td>
<td>Bartik</td>
<td>Media &amp; Unempl.</td>
</tr>
<tr>
<td>Observations</td>
<td>336</td>
<td>336</td>
<td>336</td>
<td>336</td>
<td>319</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.108</td>
<td>0.727</td>
<td>0.727</td>
<td>0.726</td>
<td>0.718</td>
</tr>
</tbody>
</table>

The tables show results from OLS and IV regressions of Equation 2. The outcome variable is the average transacted price, and otherwise the table is identical to Table 4.
Table 6: Task and Offer Success Rates.

<table>
<thead>
<tr>
<th></th>
<th>Task Match Rate</th>
<th>Offer Match Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>First</td>
<td>-0.008</td>
<td>-0.093</td>
</tr>
<tr>
<td></td>
<td>[0.011]</td>
<td>[0.016]***</td>
</tr>
<tr>
<td>Buyer to Seller Ratio</td>
<td>-0.048</td>
<td>0.052</td>
</tr>
<tr>
<td></td>
<td>[0.008]***</td>
<td>[0.005]***</td>
</tr>
<tr>
<td>Market Size</td>
<td>0.011</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>[0.006]*</td>
<td>[0.004]***</td>
</tr>
<tr>
<td>First*BK Buyer to Seller Ratio</td>
<td>-0.078</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td>[0.005]***</td>
<td>[0.007]**</td>
</tr>
<tr>
<td>First*Market Size</td>
<td>0.006</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>[0.002]***</td>
<td>[0.003]</td>
</tr>
<tr>
<td>Constant</td>
<td>0.801</td>
<td>0.463</td>
</tr>
<tr>
<td></td>
<td>[0.037]***</td>
<td>[0.023]***</td>
</tr>
<tr>
<td>Observations</td>
<td>415,027</td>
<td>804,826</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.047</td>
<td>0.060</td>
</tr>
</tbody>
</table>

Regression estimates of the following equation: \( \text{match}_{rct} = \alpha_1 \text{first}_{rct} + \alpha_2 \log \left( \frac{\text{R}_{ct}}{\text{N}_{ct}} \right) + \alpha_3 \log \left( \sqrt{\text{S}_{ct} \text{B}_{ct}} \right) + \alpha_4 \text{first}_{rct} \times \log \left( \frac{\text{R}_{ct}}{\text{N}_{ct}} \right) + \alpha_5 \text{first}_{rct} \times \log \left( \sqrt{\text{S}_{ct} \text{B}_{ct}} \right) + \beta \text{X}_{rct} + \epsilon_{rct}. \) We run these regressions for requests and offers separately, and the outcome variable is equal to one if the request or offer is successful. So for requests, \( r \) denotes a request posted in market \( c,t \), and \( \text{first}_{rct} \) is equal to 1 if it is a buyer’s first request ever posted. For offers, \( r \) denotes the offer submitted, and \( \text{first}_{rct} \) is equal to 1 if it is a seller’s first offer ever submitted. Standard errors are clustered at the city level.
Table 7: Correlation Matrix.

<table>
<thead>
<tr>
<th></th>
<th>Match Efficiency</th>
<th>Median Distance between Tasks and Offers</th>
<th>Share of Tasks in Top 5 Categories</th>
<th>Retention Rate</th>
<th>Growth Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Match Efficiency</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Distance</td>
<td>-0.7626*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>between Tasks &amp; Offers</td>
<td>[0.0004]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share of Tasks in Top 5 Categories</td>
<td>0.7208*</td>
<td>-0.5843</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.0011]</td>
<td>[0.0138]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retention Rate</td>
<td>0.8004*</td>
<td>-0.8326*</td>
<td>0.6941*</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.0003]</td>
<td>[0.0001]</td>
<td>[0.0041]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Growth Rate</td>
<td>0.4529</td>
<td>-0.3668</td>
<td>0.7350*</td>
<td>0.638</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>[0.0679]</td>
<td>[0.1476]</td>
<td>[0.0008]</td>
<td>[0.0105]</td>
<td></td>
</tr>
</tbody>
</table>

Correlation matrix between task standardization, buyer-seller distance, matching efficiency, retention, and growth. An observation is one city where TaskRabbit is active. Task standardization is measured as in Figure 11, buyer-seller distance is measured as in Figure 10, matching efficiency is measured by the estimated parameter $\eta_c$ from Equation 2, retention is measured by the parameter $\theta_c$ from Equation 4, and the growth rate is the linear growth rate, net of adoption and retention. Significance levels are in parenthesis. The star denotes significance at 1% level.