Wages rates, types of work, and reputation on online platforms

by

Justin Tzeng

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Professor Marti G. Subrahmanyam

Faculty Adviser

Professor Arun Sundararajan

Thesis Adviser

Abstract

Advances in Internet and mobile technology have made finding employment easier for freelancers, enabling the rise of a growing labor market based online. In this paper, I discuss the efficiencies and frictions that online labor platforms present to both sides of the work relationship. Next, I explain how successful platforms maximize online efficiencies and minimize frictions by promoting trust, transparency, and socialization using a combination of design aspects. I then conduct regression analysis of data from profiles on TaskRabbit, a diversified online labor platform, to evaluate the benefits that online platforms provide to individuals over traditional labor markets. I identify desirable traits that workers believe justify higher wages, and task characteristics that help providers earn more than their traditional counterparts. Finally, I explain the consequences of my findings and extend them to broader economic implications for online labor platforms, ending by indicating areas for further research.

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1 Introduction

Over the last decade, advances in the Internet and mobile technology have contributed to significant changes in the way individuals and businesses alike view work. In particular, innovation in the digital space has enabled remarkable growth in the freelancer economy, helping individuals find contingent work increasingly common and uncostly to obtain. This trend is demonstrated by an increase in the number of U.S. individuals who engaged in freelance work from 42 million in 2004 to 53 million in 2014 – a 25 percent increase.[1] Factors that individuals cited to explain their shift to contingent work included an uncertain post-recession job market, desire for work schedule flexibility, the prospect of additional income, and increased access to tasks online.

The size of the freelancer economy has grown with a corresponding increase in demand for contingent work, with attitudes toward hiring on-demand shifting as a result of technological change. Online labor platforms, a more recent trend of websites and mobile applications which connect labor supply and demand, have contributed to both the ease and trust with which individuals seek workers online. By aggregating task providers in one space and providing standardized profiles and common metrics for all of them, online labor platforms enhance trust, transparency, and competition.

In this paper, I examine online labor platforms to analyze the benefits they provide to individuals over traditional labor markets. I aim to identify desirable characteristics that task providers

[1] See "Freelancing in America: a national survey of the new workforce."

believe can justify higher wage rates, and seek to reconcile them with the role of technology in promoting trust, transparency, and socialization between both sides of the work relationship.

I do so primarily by analyzing individual task provider asking prices for a variety of task categories on TaskRabbit, a diversified online labor platform operating primarily in U.S. urban areas. Using TaskRabbit as a frame of reference, I evaluate some online platform efficiencies others have identified in prior research, such as increased job availability for providers and lower search costs for task seekers (Agrawal, Horton, Lacetera and Lyons 2013). I also suggest some online-specific frictions, such as a relative lack of employer leverage. I then study the impact of individual profile features, such as rating and experience, on task provider asking prices using a fixed effects regression by city. Finally, I analyze characteristics of individual task categories, such as a physical colocation requirement, to examine how they affect task provider asking price behavior. Based on my findings, I indicate some implications for both sides of the freelance work relationship, and suggest some further research.

This paper builds upon an extensive body of research on how reputation affects outcomes for individuals online. One group of studies addresses customer reviews on online product markets such as eBay, focusing in particular on their impact on pricing power. In one of the earlier studies on this topic, Dellarocas (2003) identified some challenges presented by online reputation mechanisms, including the limited nature of information provided by a series of one-time transactions. Ghose, Ipeirotis, and Sundararajan (2007) suggested that information in customer reviews extend beyond just scalar values, demonstrating the economic value of opinions and their strength. Nosko and Tadelis (2015) provided evidence that sellers can benefit or suffer from platform-wide reputational externalities on eBay, indicating that a platform's overall reputation is also important to an individual's earning power.

Other studies address how reputation affects worker employment outcomes on labor platforms. Many studies have extensively studied Elance oDesk (now Upwork) and Amazon Mechanical Turk, two labor platforms primarily used for remote low-skill work such as data entry, due to their suitability for manipulation in researcher field experiments that provide granular data for low costs (Horton and Tambe 2015). Notably, Pallais (2014) found that simply providing employment to inexperienced low-wage workers on oDesk drastically increased their subsequent employment opportunities regardless of their performance reviews, suggesting that information on worker ability alone makes workers more valuable to employers. Kokkodis (2014) found that such information is not limited to specific work categories, and are transferable, to an extent, into categories for which a freelancer has relatively little experience.

I attempt to distinguish my research by focusing on the impact of individual profile features on asking prices, an approach not as extensively used for labor platforms as it has been for online markets. I also extend others' findings on low-wage remote work to diversified labor. Finally, I examine the impact of individual task characteristics on asking prices to provide more detail on the interaction between labor and the new environment presented by online platforms.

2 Labor market differences

Online labor platforms are markedly different from traditional labor markets in aspects including the nature of the work relationship, and characteristics of employer and employees alike. Some of these dissimilarities are driven by the nature of freelancing, whereas others are primarily influenced by platform-specific characteristics.

Contingent employment

Instead of providing traditional full-time jobs or even part-time jobs based on a certain term, online labor platforms connect employers and employees on a task-by-task basis. Each new job constitutes a new contractual relationship, which is terminated upon completion of each individual project. This distinguishes them from talent platforms such as LinkedIn or Monster, which generally help employers and employees form traditional longer-term work relationships, and categorizes them as technological enablers of freelance work.

Freelancing employees

Contingent work provides flexibility that allows freelancers to mix and match economic activity to suit their needs for work time and income. A 2014 study by the Freelancers Union categorized freelancers into five main categories:

1. Independent contractors: Individuals who don’t have an employer and whose sole source of income is project-based work.
2. Moonlighters: Individuals with a primary traditional job who also do freelance work either as a hobby or to supplement income
3. Diversified workers: Individuals whose income is derived from a mix of traditional employment and contingent work.
4. Temporary workers: Individuals with a single, temporary source of income.
5. Freelance business owners: Business owners with between one and five employees

whose work is primarily project-based.[2]

As a result, freelancer needs tend to vary more widely than for traditional workers, leading to a more diverse mix of motivations.

Transient employers

On the other side of the labor market, employers also use online labor platforms to a different spectrum of needs. Many task seekers on online labor platforms tend to be individuals rather than businesses, and their needs are often predicated on convenience or comfort rather than profit maximization considerations. Furthermore, unlike businesses who engage in routine economic activity, individuals often seek help for infrequent needs such as moving or plumbing, and don't always seek to establish lasting business relationships. Consequently, employers on online labor platforms can be less knowledgeable about the services they seek, and may use different criteria than traditional employers when selecting a provider.

Platform-native markets

Finally, online labor is heavily dependent upon the design and intentions of the platform providers themselves. By choosing the content and methods of communication between labor supply and demand on their platforms, providers shape outcomes for employers and employees alike. In many cases, providers standardize provider profiles and provide common metrics that generate trust and transparency. However, when provider interests are misaligned with those of users, platform providers can also distort information flow. In a drastic case such as Uber's, the

[2] See "Freelancing in America: a national survey of the new workforce."

threat of driver termination for poor ratings resulted in irregular behavior such as drivers refusing to pick up riders unless they promised to leave five-star reviews.[3]

3 Efficiencies and frictions

The differences mentioned above, whether caused by the nature of freelance employment or digital features, present certain efficiencies and frictions for online labor platforms over traditional labor markets. These characteristics span both sides of the work relationship.

Labor supply efficiencies

First, by aggregating an entire area's demand on a single platform, online labor platforms significantly increase the pool of available jobs for freelancers. Jobs previously only available through word of mouth or full-time employment with a firm, such as helping move a sofa or making small arts and crafts, are now clearly displayed online to anybody offering that service on the platform, regardless of their employment status or personal connections.

Furthermore, individuals exercise more individual agency in choosing tasks that suit their skills and preferences. Instead of being assigned projects by full-time employers, individuals can choose tasks that they believe will be the most productive use of their time, improving overall labor efficiency for tasks performed through the platform.

Finally, the flexibility accompanying contingent work can raise productivity and income for individuals who were previously restricted by the rigidity of consistent work schedules. Some

[3] See "Uber's ratings terrorize drivers and trick riders. Why not fix them?"

studies suggest that the reduced time commitment can induce women previously out of the labor market to consider working (Agrawal, Horton, Lacetera and Lyons 2013). Meanwhile, others may find that a combination of a full-time job and supplemental contingent work maximizes their income, and retirees may consider occasionally taking on a task.

Labor demand efficiencies

On the other side, prospective employers benefit tremendously from reduced search costs. Individuals seeking help can instantly find task providers in their vicinity and access basic information about their work history, experience, and even personality in a matter of minutes.

Standardized task provider profiles and performance metrics increase transparency for employers, which can significantly benefit employers who need help with an uncommon task they are unfamiliar with. Such transparency provides much-needed information and options for individuals to make employment decisions. Sundararajan (2016) suggests that this transparency can prompt individuals to actually seek services when they need them, since they are no longer bound to undesirable local supply. Accompanying this transparency is the possibility of more competitive wage rates and services, since employers have easy access to a wide variety of providers who can all complete the same task.

Labor supply frictions

The most significant inefficiency presented by online labor platforms is the cost of uncertainty, much of which stems from the contingent nature of employment. Individuals who could receive more tasks and income from just freelancing may still elect to keep their full-time job if they question the long-term viability of a freelancing career and are unwilling to tie their fate to an online platform. Similarly, freelancers on online platforms often charge higher rates than their full-time counterparts, since income is not guaranteed and can experience unexpected volatility.

Uncertainty extends to work relationships, which often last for only one task. For each new project, a worker faces uncertainty over the work environment and relationships with the employer, inhibiting the development of stable conditions and relationships that can improve labor productivity in a traditional workplace.

Labor demand frictions

The ephemeral nature of task-based work also reduces the amount of leverage an employer possesses in each work relationship. Employers cannot threaten to fire a worker for a poorly done task, nor do they fully enjoy the benefits of offering incentives such as bonuses. While employers do wield a powerful tool in the form of a user review, the direct impact a review has is not as significant as an action such as firing.

Individual task seekers also face hidden quality problems arising from a lack of prior interaction (Agrawal, Horton, Lacetera and Lyons, 2013). While ratings do provide some information on provider performance, they are hardly perfect, especially when the ratings are categorized by a binary positive-negative system. This problem is further compounded for remote work categories, where employers cannot easily gauge employee effort and performance without spending additional time evaluating their work – an example would be the usage of gold standard data on Amazon Mechanical Turk to assess worker accuracy.[4]

4 The role of online labor platforms

Online labor platforms integrate productivity considerations into their design to maximize platform efficiencies and minimize the impact of frictions. Broadly speaking, many of these design aspects promote one or more of three qualities: trust, standardization, and socialization. In this section, I examine some of these platform features using TaskRabbit as an example.

TaskRabbit task process

TaskRabbit is an online diversified labor platform that helps consumers find help with tasks such as handyman work by connecting them with freelance "Taskers" in their area. After consumers enter the type of help they need and indicate when they would like the task performed, TaskRabbit provides a list of Taskers who are available at that timeslot. Consumers can browse through each Tasker's profile to see reviews, hourly rates, and even hobbies for each individual Tasker. Consumers then choose a Tasker who completes the task. After the task is complete, all payments are processed online and the consumer can choose to leave a review.

Trust

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[4] See "Amazon Mechanical Turk Requester Best Practices Guide" at http://web.engr.oregonstate.edu/~burnett/CS589empirical/CS589-statisticalStudies/mechTurk_BestPractices-Amazon.pdf.

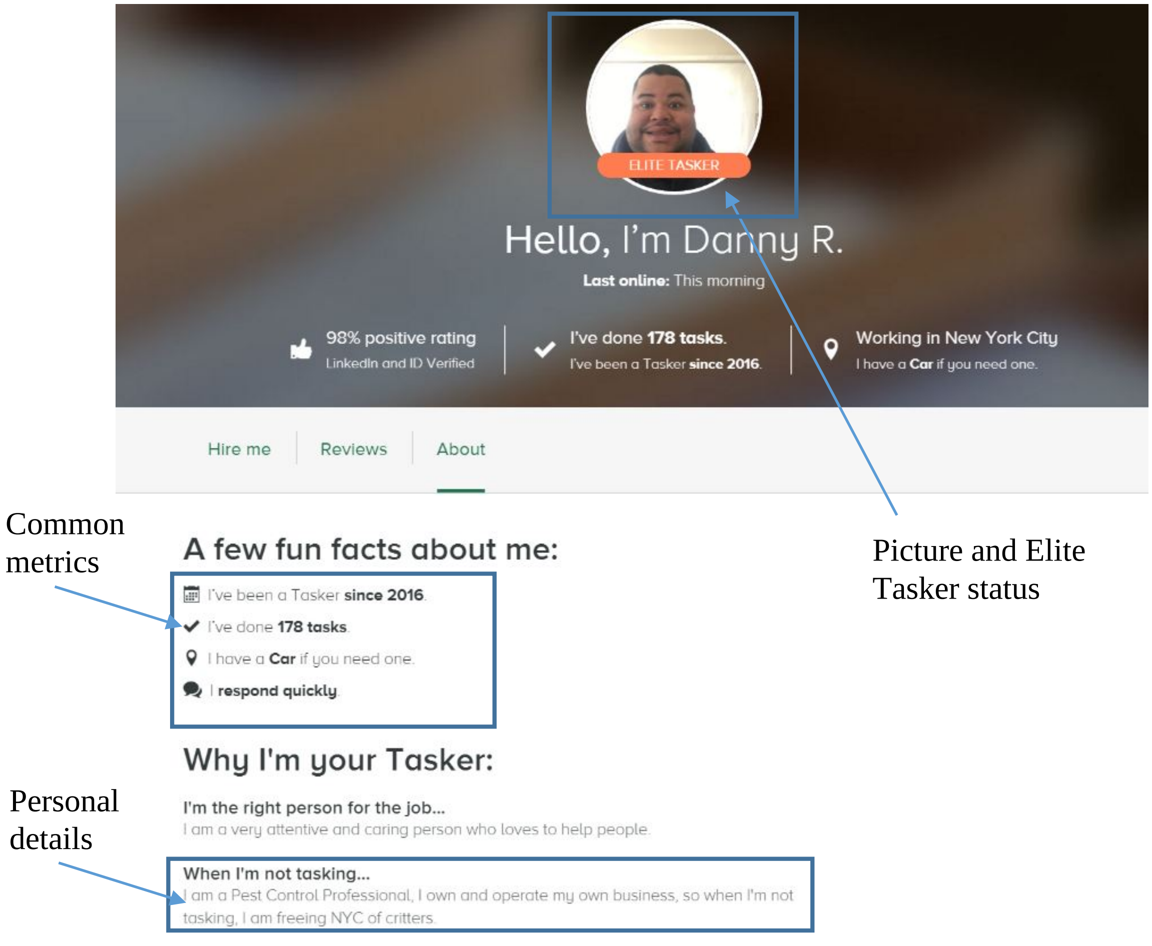
Extensive research on e-commerce purchase behavior in the past decade strongly indicates that online trust is a significant driver of transaction intent (Wang and Emurian 2005; Chen and Barnes 2007). Online labor platforms employ a number of methods to promote trust, many of which involve security and quality guarantees.

To ensure user safety, TaskRabbit conducts identity and criminal record checks on every Tasker, insures every task up to $1 million, and clears payment to Taskers only upon completion of a project. Furthermore, TaskRabbit offers “Elite” certification to Taskers who fulfill certain volume and quality-based requirements to indicate a level of quality that consumers can expect from them.

Standardization

To reduce search costs and promote transparency for prospective employers, online labor platforms attempt to ensure that a certain level of information is presented on each worker’s profile. These efforts usually involve a certain degree of standardization, as platforms provide common metrics on every task provider to help employers obtain a better grasp of work quality, in turn increasing demand and benefiting freelancers.

Figure 1: Tasker profile



TaskRabbit displays common metrics such as rating, tasks done, years of experience, vehicle ownership, and quick response time on every Tasker profile. The platform also provides a standard profile template for Taskers to upload their pictures and write a description about themselves. These features allow consumers to quickly get a general sense of each worker's experience and approximate quality.

Socialization

In addition to providing practical information about each worker, some online platforms also incorporate personal details into worker profiles. This social aspect can be interpreted as a way of personalizing the work relationship and creating further trust, assuaging reservations individuals may feel about receiving services from individuals that would otherwise be completely anonymous until they arrived at the doorstep. To an extent, these personal details function as the "personal interests" section of a resume or the behavioral portion of an interview.

On TaskRabbit, Tasker personal details are displayed on each individual profile, including a "When I'm not tasking" section explaining what they do outside of TaskRabbit. Taskers also submit a picture of themselves, and are offered the option to verify their ID using LinkedIn and Facebook in addition to government-issued ID.

5 Research objective and methodology

In this section, I aim to reconcile existing research on efficiencies and effects of reputation on online labor platforms with platform design. To do so, I examine the relationship between TaskRabbit design features and beneficial outcomes for Taskers in an effort to identify desirable traits on the site.

Data

To examine the impact of task and provider characteristics on asking prices, I analyzed over 8,000 individual Tasker profiles gathered in the fall of 2015 through an extensive crawl of the TaskRabbit site. The crawler code was written by two PhD students specializing in data science for my thesis advisor, Arun Sundararajan. The profiles covered six U.S. cities: Boston, Chicago, Los Angeles, New York City, San Francisco, and Seattle. Each profile contained site-wide common metrics and the Tasker's asking prices for each task category offered.

Study 1

In my first study I focus on the relationship between individual profile features and asking prices for each work category to evaluate the desirability of specific Tasker characteristics. To do so, I specify a set of predictive variables on which I will regress asking prices for each task category:

Table 1: Predictive variables for Study 1

Continuous Predictors	Categorical Predictors
1. Rating	1. "Elite" status
2. Years of Tasker experience	2. Social media verification
3. Number of tasks done	3. Vehicle ownership
4. Number of reviews	4. Lengthy profile description
5. Proportion of reviews to tasks	5. Response time

My model assumes that Taskers are aware of their profile characteristics, both in a vacuum and relative to those of their competitors, and price their services in a manner they believe will help them receive tasks and income. In addition to raw number of reviews, I set the proportion of reviews to tasks as a variable to explore whether providers with exceptional service who are more likely to elicit positive reviews per task reflect this in their pricing. For "lengthy profile description," I code all profiles with longer-than-average descriptions as 1, and all profiles with average or below-average length descriptions as 0. For the remaining categorical predictors, I set [Yes = 1] and [No = 0].

To account for wage rate and living standards disparities across U.S. cities, I conduct a fixed effects regression by city to mitigate the impact of Tasker origin. Instead of regressing raw asking prices, I calculate the city average for each task category and regress each Tasker's price premium or discount for that particular category.

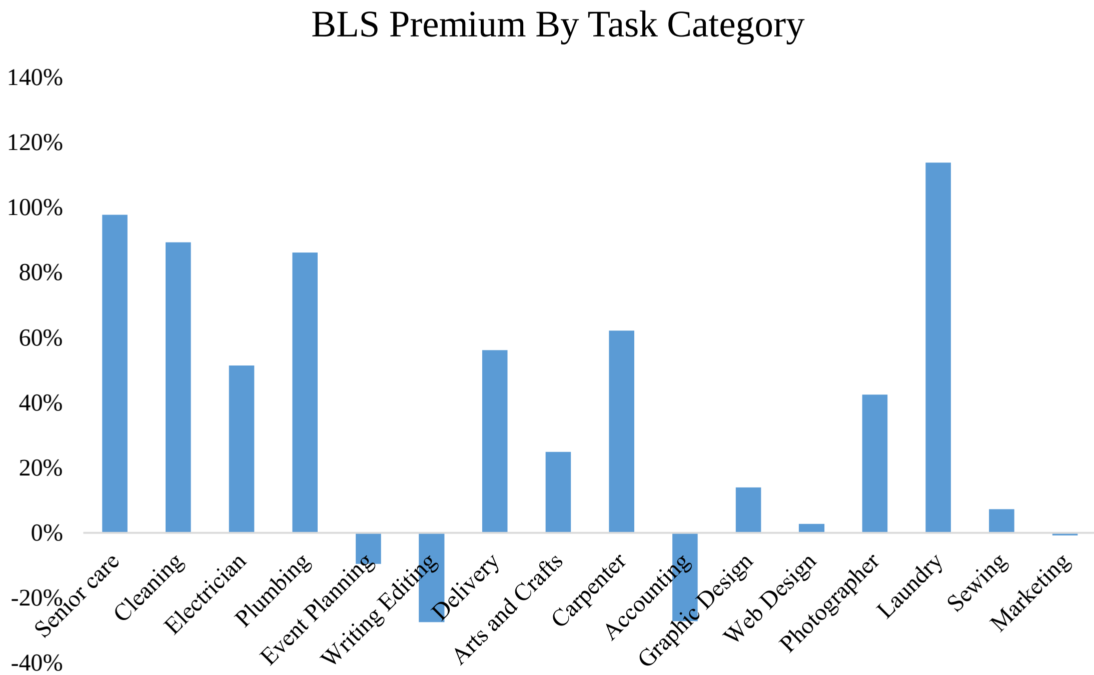
To reduce noise from outliers, I remove any asking prices that are more than three standard deviations away from their respective task category mean, as well as any Tasker profiles for which no tasks were done since the profile's creation.

Study 2

In my second study, I examine how certain characteristics of individual work categories affect Tasker income. In particular, I focus on the percentage premiums that Taskers receive over their traditional counterparts who do not receive work from TaskRabbit. I analyze the subset of Taskers located in New York City and compare their hourly income to Bureau of Labor Statistics (BLS) data on median hourly wages for workers in corresponding categories.[5] These premiums vary widely by task category.

Figure 2: Premium over BLS median wage by task category

[5] BLS median wage data for New York City can be found at http://www.bls.gov/oes/current/oes_ny.htm.



The three characteristics I included were whether a job requires Tasker physical colocation, whether a job's full-time equivalent typically requires certification, and whether a job is generally associated with higher levels of education or technological capabilities. I find sixteen TaskRabbit categories with a corresponding BLS occupation, and code their characteristics using a binary system, which can be found in table A1 in the appendix.

For most tasks completed, TaskRabbit charges a thirty percent commission, but takes reduced commissions as low as fifteen percent for certain Elite taskers. On average, a Tasker receives about seventy-five percent of his asking price as income. For the task categories indicated above, I regress the premiums (and discounts) that Taskers receive over the respective BLS counterpart median wage on each category's characteristics, setting [Yes = 1] and [No = 0].

6 Results

Study 1

My results show some profile traits that are significantly correlated with higher asking prices across categories, as well as some traits which are significantly correlated with asking prices for tasks with certain characteristics. These results suggest that certain profile traits are more desirable and impactful than others, although the magnitude of their impact can vary across task categories. The results of the multiple regression analysis are presented in tables A-2, A-3, and A-4 in the appendix.

Across most task categories, the number of reviews a Tasker has received is significantly correlated with higher asking price premiums ($p < 0.05$), while little evidence suggests a similar impact for the numbers of tasks done. This suggests that Taskers believe consumers do not care as much about sheer amount of Tasker experience as they do about the information that reviews can provide about Tasker quality.[6] Tasker ratings and proportion of reviews to task are not significantly correlated with asking premiums.

For some task categories such as cleaning, delivery, and electrician work, quick response times are significantly correlated with higher asking prices ($p < 0.05$). Others, such as accounting and graphic designs, do not exhibit these traits, indicating the possibility that Taskers account for the time-sensitivity of different tasks and incorporate these considerations into pricing.

TaskRabbit's "Elite" status is also positively related to higher asking prices for tasks including sewing, delivery, and marketing ($p < 0.05$). This suggests that TaskRabbit's certification does

[6] Since an overwhelming majority of reviews on TaskRabbit are positive, increased consumer willingness to pay could be influenced by an increase in the amount of positive quality indicators.

foster a degree of trust in each Elite Tasker's quality, which is then reflected in their asking prices. However, this benefit is not reflected across all task categories.

Finally, individual profile characteristics have different explanatory power across task categories. My model for moving price premiums, for example, has an R-squared of 0.861, while my model for photography price premiums has an R-squared of 0.106. This wide range implies that Taskers believe TaskRabbit's set of common metrics offers different degrees of useful information for each type of task, and price their services accordingly.

Study 2

My results show that physical colocation, certification, and reputation association are all significantly correlated with Tasker income premiums over their traditional counterparts.

Table 2: Regression results for premiums over BLS median wage

Constant	0.43
	(0.03)
Colocation	0.36***
	(0.03)
Certification	-0.12**
	(0.05)
High Tech/Education Reputation	-0.67***
	(0.03)
R-squared	0.151
No. observations	7133

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

Colocation is positively related with Tasker premiums ($p < 0.01$), suggesting that jobs which require physical worker presence receive greater benefits than jobs which can be performed remotely. This indicates the possibility that collocated jobs enjoy more online labor platform efficiencies because many remote work relationships are already based online.

Meanwhile, jobs requiring certification and jobs with a high education or technological skill reputation are negatively related with Tasker premiums ($p < 0.01$), suggesting that Taskers performing more "skilled" work do not receive premiums as high as their "unskilled" Tasker counterparts too. It is important to note that while a negative relationship indicates that Taskers receive lower premiums for certain task categories, many of them are still compensated at a higher hourly rate than their BLS counterparts.

7 Implications

My results yield some insight into Tasker behavior which, when extended to a broader economic context, offer some implications for online labor platform efficiencies over online labor platforms in general.

Additional information on quality benefits workers

The positive relationship between Tasker asking prices and both number of reviews and "Elite" status indicate that the additional information on quality provides a tangible benefit for Taskers. These features likely promote trust and transparency in the hiring process, lowering costs of search and uncertainty for consumers. Consequently, Taskers seem to believe that, when consumers are reassured of work quality either through peer experiences or platform guarantees, they are generally more willing to pay. To increase the positive effect of information flow, TaskRabbit could consider more strongly encouraging consumers to leave reviews. This is something another platform, Yelp, already does by designating “Elite” commenters on the app.

This also provides a plausible explanation for why Tasker ratings, which rarely fall below ninety percent and thus do not provide much distinguishing information on quality among Taskers, are not significantly correlated with price premiums. However, TaskRabbit may still be motivated to remain on a binary rating system which, despite its relative uselessness, can give the impression that all Taskers perform their tasks well.

Workers incorporate consumer needs into asking rates

A significant, positive correlation between higher asking prices and responding quickly to time-sensitive tasks such as delivery or owning a vehicle for tasks such as event planning suggests that Taskers who are prepared to fulfill certain task-specific needs will charge more. For example, while quick response times have a positive relationship with prices in tasks such as electrician work, delivery, and laundry, they do not seem to share this relationship with tasks such as graphic design or moving, which are often either planned beforehand or performed over longer time frames. This indicates that, similar to workers in a traditional labor market, workers on online labor platforms assess the needs of their employers and position themselves accordingly.

Platform design aspects vary in usefulness by task category

The widely varying predictive power of TaskRabbit profile features and different significant relationships across categories seem to imply that the standard set of platform features does not provide the same set of benefits to workers in different fields. Somebody offering graphic design services is unlikely to charge more if he owns a car, but consumers will still see which prospective graphic designer own vehicles and which don't. In the previous subsection I noted that Taskers incorporate consumer needs into asking rates – it appears that Taskers actively determine which profile characteristics are relevant or desirable for each task category, something which TaskRabbit itself does not highlight. However, it is possible that platforms believe the benefit of using a standard set of metrics across all tasks outweighs the benefit of customizing relevant metrics for individual tasks, which could confuse consumers and reduce the overall cohesiveness of the platform.

Online labor platform efficiencies differ in magnitude by task characteristics

The relationships between task requirements and Tasker income premiums over their BLS counterparts imply that some types of tasks may inherently benefit more from online labor platforms than others. My findings on colocation characteristics corroborate those of Sundararajan (2016), who explains that, for providers of collocated tasks such as plumbing, an online platform can increase the pool of available jobs and help providers find work without increasingly the area's labor supply. In contrast, for remote tasks such as graphic design, online platforms help graphic designers from all over the country find tasks in a local area, increasing competition for each task.

Meanwhile, lower income premiums for tasks requiring certification and more reputable tasks indicate that Taskers believe consumers do not highly trust worker quality on online labor platforms. Assuming Taskers adjust asking prices to meet what they perceive to be consumer demand, it appears consumers are more willing to pay, on a relative basis, for low-skill, convenience-based work than they are for higher-skill work. One possible explanation is a reluctance to give higher-stakes tasks such as accounting or web design to strangers on the Internet, and a degree of trust in a traditional business or certificate that online labor platforms do not considerably strengthen.

8 Conclusion

Online labor platforms present a set of efficiencies and frictions over traditional labor markets that are conveyed, to varying degrees, through contingent worker asking prices on TaskRabbit. In this paper, I demonstrated that different platform features can impact pricing on different task categories, and that different tasks with specific characteristics may benefit more from online platform efficiencies than others. As online labor platforms continue to mature and technology continues to reduce search costs and improve information transfer, we may find online platforms more attractive than ever, even for tasks that we currently do not trust them for. This will only be possible if platform providers continue to build upon their understanding of online interactions and optimize platform design elements to suit them.

To do so, I suggest further analysis of profile characteristics such as picture quality, gender, and perceived age, to uncover more insights on the online labor market relationship. I also suggest a more detailed examination of individual design aspects such as a platform's "Elite" designation to evaluate their effectiveness vis a vis the profile's other aspects and the platform's overall reputation. Incorporating the interaction between supply and demand in the form of pricing and tasks received, such as the work done by Pallais (2014), into profile analysis could also yield valuable information.

My research faces certain challenges, the most significant of which is endogenous relationship. Take the significant negative correlation between years of Tasker experience and asking prices for example. It does not seem intuitive that increased platform experience leads Taskers to lower their price – a plausible alternative explanation would be that Taskers who continually receive tasks and thus tend to stay on the platform are those who charge the lowest rates. I also use Tasker asking prices as a proxy for consumer willingness to pay, which may not always be true considering the diverse set of motivations for contingent workers. Future research can mitigate these limitations by incorporating supply and demand interactions between asking prices and tasks received for individual categories. Notwithstanding these limitations, I hope this paper provides some useful insight into design aspects, task pricing, and economic efficiencies on online labor platforms.

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Appendix

Table A-1: Task requirements coding

Task	Colocation	Certification	Tech/Education
Senior Care	Yes	No	No
Cleaning	Yes	No	No
Electrician	Yes	Yes	No
Plumbing	Yes	Yes	No
Event Planning	Yes	No	Yes
Writing Editing	No	No	Yes
Delivery	Yes	No	No
Arts and Crafts	No	No	No
Carpenter	Yes	Yes	No
Accounting	No	Yes	Yes
Graphic Design	No	No	Yes
Web Design	No	No	Yes
Photographer	No	No	Yes
Laundry	Yes	No	No
Sewing	Yes	No	No
Marketing	No	No	Yes

Table A-2: Regression results for premium over city average, set 1

	Plumbing / Moving	Event Planning / Senior care	Writing Editing / Cleaning	Electrician / Delivery
Constant	-36.26**	11.68	11.81**	10.90
	(2.32)	(8.88)	(4.72)	(50.80)
Rating	-0.40	6.85	3.20	-5.70
	(2.16)	(7.60)	(4.09)	(49.70)
Tasks Done	3.77***	-0.00	0.00	0.03
	(0.05)	(0.01)	(0.00)	(0.03)
Years	-0.617***	-5.85***	-5.27***	-4.29
	(0.19)	(0.92)	(0.52)	(2.71)
Reviews	-0.04***	0.09***	0.15***	0.06*
	(0.01)	(0.02)	(0.01)	(0.04)
Reviews/tasks	0.35***	0.11*	0.04	0.12
	(0.06)	(0.06)	(0.03)	(0.14)
Quick response time	-0.14	3.64**	3.55***	9.67**
	(0.67)	(1.54)	(0.82)	(4.51)
Lengthy profile description	0.49	0.02	0.60	-2.83
	(0.32)	(1.41)	(0.79)	(3.88)
Social media verified	-1.56	-6.62*	-5.05***	1.26
	(0.43)	(3.95)	(1.93)	(8.85)
Owns a vehicle	0.08	1.01	3.22***	2.33
	(0.35)	(1.48)	(0.81)	(5.35)
Elite tasker	-1.40	3.21	4.04*	6.89
	(0.15)	(5.95)	(2.08)	(7.90)
R-squared	0.863	0.183	0.251	0.135
No. observations	1,227	334	1048	166

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

Table A-3: Regression results for premium over city average, set 2

Constant	51.3	-1.86	10.02**	6.24
	(54.8)	(4.35)	(4.70)	(3.82)
Rating	-23.8	5.07	0.46	2.30
	(51.8)	(3.77)	(3.99)	(3.57)
Tasks Done	0.05	0.01*	0.00	0.00
	(0.04)	(0.01)	(0.01)	(0.00)
Years	-2.58	-2.78***	-3.54***	-4.99***
	(0.43)	(0.46)	(0.54)	(0.31)
Reviews	0.07	0.06***	0.07***	0.10***
	(0.04)	(0.01)	(0.01)	(0.01)
Reviews/tasks	-0.03	0.09***	0.07*	0.08***
	(0.19)	(0.03)	(0.04)	(0.02)
Quick response time	4.70	3.17***	2.37***	3.50***
	(5.67)	(0.79)	(0.88)	(0.54)
Lengthy profile description	-8.81*	0.85	-0.91	0.13
	(4.96)	(0.73)	(0.82)	(0.51)
Social media verified	-3.10	-0.49	-4.97**	-2.40**
	(11.60)	(1.67)	(1.97)	(1.19)
Owns a vehicle	-13.60	3.48***	2.72***	5.40***
	(8.40)	(0.76)	(0.87)	(0.56)
Elite tasker	10.00	5.54**	6.65**	4.82***
	(10.80)	(2.76)	(2.95)	(1.52)
R-squared	0.153	0.145	0.137	0.284
No. observations	106	990	842	2,021

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

Table A-4: Regression results for premium over city average, set 3

	Arts and crafts	Carpenter	Accounting	Graphic Design
Constant	-3.88	-5.4	7.10	-15.00
	(3.84)	(24.6)	(10.90)	(16.50)
Rating	5.88*	5.60	3.26	21.00
	(3.31)	(23.30)	(9.12)	(15.10)
Tasks Done	0.02***	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Years	-1.77***	-3.88**	-3.93***	-4.86***
	(0.43)	(1.75)	(1.27)	(1.44)
Reviews	0.08***	0.10***	0.11***	0.16***
	(0.01)	(0.03)	(0.03)	(0.05)
Reviews/tasks	0.00	0.03	0.03	0.10
	(0.03)	(0.07)	(0.07)	(0.13)
Quick response time	3.30***	7.25**	-2.64	2.06
	(0.74)	(3.13)	(2.12)	(2.32)
Lengthy profile description	-0.31	-5.37*	-1.71	0.12
	(0.68)	(2.77)	(1.93)	(2.24)
Social media verified	0.29	4.04	-0.10	2.67
	(1.58)	(6.85)	(4.42)	(4.88)
Owns a vehicle	0.83	8.56**	1.75	3.11
	(0.71)	(3.56)	(0.41)	(2.26)
Elite tasker	5.52**	4.50	15.07**	-0.22
	(2.44)	(0.49)	(6.01)	(0.97)
R-squared	0.136	0.227	0.203	0.142
No. observations	792	240	188	266

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.

Table A-5: Regression results for premium over city average, set 4

	Web design	Photography	Laundry	Sewing	Marketing
Constant	2.70	62.90***	4.15	-26.00	6.09
	(14.90)	(21.10)	(4.12)	(17.80)	(7.94)
Rating	12.40	-47.80**	-1.50	29.7*	1.70
	(12.90)	(20.4)	(3.39)	(17.1)	(6.78)
Tasks Done	0.01	-0.03	0.00	0.02	0.01
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
Years	-4.57***	-6.40***	-2.80***	2.67***	-3.70***
	(1.56)	(1.64)	(0.45)	(0.03)	(0.79)
Reviews	0.13**	0.15***	0.07***	0.13***	0.06***
	(0.06)	(0.04)	(0.01)	(0.03)	(0.02)
Reviews/tasks	-0.01	-0.15	0.07**	-0.33**	0.18***
	(0.26)	(0.12)	(0.03)	(0.14)	(0.05)
Quick response time	2.58	2.86	9.73***	6.12***	1.69
	(2.87)	(2.85)	(2.32)	(1.92)	(1.33)
Lengthy profile description	3.26	0.44	-0.39	0.47	1.74
	(2.71)	(2.75)	(0.70)	(1.85)	(1.24)
Social media verified	-6.03	-1.69	1.65	-2.10	-3.16
	(5.38)	(5.79)	(1.95)	(4.26)	(3.01)
Owns a vehicle	-0.17	2.36	3.32***	2.40	2.71**
	(2.95)	(2.90)	(0.74)	(1.84)	(1.28)
Elite tasker	15.40	4.10	9.73***	14.36**	8.64**
	(9.57)	(8.31)	(2.32)	(6.76)	(3.45)
R-squared	0.120	0.106	0.221	0.304	0.205
No. observations	196	342	560	123	478

Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.