More Than Money: Correlation among Worker Demographics, Motivations, and Participation in Online Labor Market

Wei-Chu Chen,[1] Siddharth Suri,[2] Mary L. Gray[2]
[1]Indiana University Bloomington, [2]Microsoft Research
chen273@iu.edu, suri@microsoft.com, mlg@microsoft.com

Abstract

Most prior research about online labor markets examines the dynamics of a single work platform and either worker demographics or motivations associated with that site. How demographics and motives correlate with each other, and with engagement across multiple platforms, remains understudied. To bridge this gap, we analyze survey responses from 1700 people working across four different online labor platforms to understand: What motivates people to participate in online labor markets and how do individual motives correspond to larger demographic patterns and structural dynamics that more broadly shape traditional employment opportunities? Our results show that age, gender, education, and number of income sources help explain who does on-demand work, when they do it, and why. Even more striking, these broader social dimensions of work correlate with when and why individuals work across multiple on-demand platform companies. Together, these factors structure on-demand labor markets more than individual choice or the presumed "flexibility" of on-demand work alone.

Introduction

To understand the diverse make up of online labor markets this paper systematically looks at how workers' demographics correlate with who does on-demand work and what motivates them to participate. More specifically, we examine how gender, education, scheduling constraints, and location shape and correlate with workers' expressed motivations, beyond getting paid, for participating in online labor platforms. Understanding these correlations is important because motivation may influence the types of on-demand work people do and how they pick up tasks.

According to a recent Pew report (Smith 2016), among people who do paid on-demand work, 56% reported that the money from doing such jobs is "essential or important", while others said the money is something "nice to have." Consequently, it is reasonable to suppose that the worker population of any single platform consists of a wide range of people with various backgrounds and personal needs. More broadly, such "personal needs" are always reflections of structural constraints and cultural forces, from gender norms to legacies of racism and geopolitical histories, that, at least in part, determine individual experience. While analyzing how demographic factors intersect to explain why people do on-demand work is beyond the scope of this paper, we can offer a starting point for substantiating links and key correlations between core social demographics and a mix of motivations animating this labor market. Designing, building, and sustaining diverse and inclusive platforms will require an understanding of the social dynamics and diversity of motivations drawing workers to these platforms in the first place.

We study four different online labor platforms with 1,700 surveys collected across the platforms to get a sense of how demographic differences may shape people's participation in online labor markets more broadly, beyond the specifics of any one platform. Our results show that, like peers in traditional workplaces, many on-demand workers identify earning money as the primary reason that they work. In fact, many of us might say that we keep our day job, whether we like it or not, because we must earn money to pay the bills. Less expected, workers who have other options to earn, whether that comes from their younger age, higher education, or other income sources, are more likely to have something besides earning money as their top reason for doing on-demand work. Bringing together these results shows that each platform may be featured differently, attracting distinct worker population for gaining specific benefits.

We also found that workers' gender correlate with how they schedule their work. Men are more likely to work during the nights and weekends and women are more likely to work during the day and less on the weekends. A possible explanation is that women are more likely to do on-demand work when their at-home work responsibilities permit whereas men are more likely to do on-demand work in the evenings and weekends, perhaps after fulfilling their responsibilities for jobs outside the home. In addition, we found that Indian workers are more likely to work during their nighttime presumably to get tasks launched by Western companies during their daytime. More highly educated workers are more likely to work during the day and during the week and less during the customary leisure times of the night and weekend. It is plausible that worker demographics such as age, gender, education and other individual characteristics may either afford or limit the opportunities of participating in online labor market. Therefore, demographic factors indeed represent social dimensions which leading to specific chances or limitations of doing on-demand work, such as who does on-demand work and why they do it.

Related Work

Most previous studies of online labor platforms provide worker demographics (who these workers are) and a number of prior papers specifically examine worker motivations (why they do on-demand work). We review each of these two literatures in turn. Since most online labor platforms do not disclose the composition of their digital labor force, surveys are a standard tool for studying worker demographics. Previous studies described features of a single on-demand worker population (Martin et al. 2016; Ross et al. 2010). The majority of these studies focus on Amazon Mechanical Turk (MTurk) workers. Overall, workers on MTurk mainly come from the U.S. and India, likely drawn by MTurk's ability to pay workers in these countries in monetary currency rather than gift cards (Difallah et al. 2018; Ipeirotis 2010; Martin et al. 2016; Ross et al. 2010). Workers' geolocation has been found to be correlated with other characteristics, such as gender, age, and income (Ipeirotis 2010; Martin et al. 2016). Shortly after it launched, there was a higher proportion of female workers in the U.S. and a higher proportion of male workers in India (Ipeirotis 2010; Ross et al. 2010); however, studies conducted after 2016 found that workers' gender distribution has reversed in both countries (Difallah et al. 2018; Martin et al. 2016). In terms of on-demand workers' age distribution, there is wide variation, though it tends to skew younger than the population as a whole, while Indian workers skew younger still (Gupta et al. 2014; Martin et al. 2016). In addition, a higher proportion of U.S. workers have relatively low income compared to the national average (Difallah et al. 2018; Gupta et al. 2014; Ipeirotis 2010; Ross et al. 2010). Workers in India were found to have higher education levels on average as com-pared to their U.S. counterparts or peers in India (Ipeirotis 2010; Ross et al. 2010). These findings suggest that there is substantial diversity among the on-demand worker population.

According to current theories the factors that motivate workers to do on-demand work can be divided into two categories: extrinsic and intrinsic motivations (Hossain, 2012; Kaufmann et al. 2011; Naderi et al. 2014; Posch et al. 2017). The extrinsic motivational factors include financial incentives and social incentives (e.g., networking, social interaction or be-longingness); the intrinsic motivational factors may refer to a worker's desire for autonomy and developing their skills for doing different tasks (e.g., computer skills). Indeed, previous work argues that extrinsic and intrinsic motivational factors influence on-demand workers differently (Brewer et al. 2016; Gupta et al. 2014; Martin et al. 2014). Among motivational factors, the extrinsic motivation of financial incentive has been proposed to be the leading factor motivating people to pursue on-demand work, even though the monetary reward is relatively low and the task-based work on many online labor platforms is unpredictable (Antin and Shaw 2012; Berg 2015; Ipeirotis 2010; Martin et al. 2014; Ross et al. 2010; Teodoro et al. 2014).

Compared to the significant influence of financial incentives, other incentives may motivate a relatively small fraction of people to perform on-demand work. For ex-ample, the intrinsic incentive of enjoyment-based motivation prompts some people to participate in on-demand work to accomplish something interesting or challenging (Brewer et al. 2016; Hossain 2012; Ipeirotis 2010); the intrinsic incentive to increase one's sense of autonomy induces some people to perform on-demand work to gain some "flexibility" or personal control over setting their own schedule or choosing certain tasks to do over others (Teodoro et al. 2014). These factors show varying degrees of influence on motivation in different studies.

This extant literature helps us illustrate that workers do have diverse incentives to pursue specific economic activities, beyond earning money. The above studies took a variety of research approaches, from interviewing and surveying workers to analyzing the content of worker discussion boards. Yet all of them found similar factors motivating on-demand workers, namely financial need, an interest in learning something new, and workers doing something with their spare time. We build on prior work by using these factors, across the intrinsic vs. extrinsic spectrum, to in-form our survey design so that we can understand the range of worker motivations.

Moreover, though various research approaches had been applied in previous studies, they were limited in different aspects, such as surveying workers of single plat-form, collecting content from discussion boards used mainly by workers from the same platform, or interviewing a handful of workers from a worker population which is large and diverse. While the range of research methods in these prior works suggests we know the general categories of motivations in online labor markets—why people do this work—we don't know much about how motivations might be shaped by worker demographics—who does this work. Indeed, the research subjects studied in the key studies of online labor markets reviewed here varied widely in their characteristics. Some studies only involve participants from either the U.S. or India (Brewer et al. 2016; Gupta et al. 2014); others include participants from multiple regions (Antin and Shaw 2012; Kaufmann et al. 2011). Most studies recruited participants or collected qualitative data exclusively from MTurk workers (Antin and Shaw 2012; Posch et al. 2017); some included participants from other on-demand platforms (Teodoro et al. 2014).

Studies of on-demand workers' show workers are diverse in their characteristics and motivations; however, how workers' characteristics are associated with their motivation has not been well evaluated. To better understand this emerging digital labor market, this study bridges the gap between our knowledge of the attributes common among on-demand workforces and what motivates workers to participate in these markets.

Data Collection

We collected survey data from four distinct online labor platforms. These four platforms were chosen purposefully to explore the wide range of platforms and types of work to improve the generalizability of our results regarding online labor markets as a form of employment. First, Amazon Mechanical Turk (MTurk) is widely-used as a microtasking platform and familiar to many researchers. Second, UHRS also primarily focuses on microtasks, such as search query relevance, image-tagging, and other classification tasks. We intentionally included UHRS as a representative example of the internal crowdsourcing platforms used by most, if not all, large Internet companies. Third, LeadGenius is a social entrepreneurial, commercial start-up that focuses on business to business (B2B) tasks like sales lead generation. Because of the limits of automatically determining the best information for a sales call, LeadGenius hires people to look at web searches linked to businesses to offer more fine-grained analyses, like specifics about how long a business has been open, whether they have other store locations, or if a business owner is in the middle of a lawsuit. Finally, Amara.org is a non-profit site dedicated to translating and subtitling content for transnational audiences and hard-of-hearing communities. Amara also provides paid work opportunities on its platform through clients paying for expedited translation and captioning services. We chose to study LeadGenius and Amara.org because tasks on these sites run the gamut of size and task type, from dealing with projects that require no more than 5 minutes and the skillset used to classify a search query, to larger, more complicated tasks than typically seen on MTurk or UHRS. These four platforms represent a range of traditional, office-related work rapidly shifting to online labor platforms.

Table 1: Time periods for data collecting on each platform

Platform	First submission	Last submission
Amazon MTurk	12/16/2013	02/02/2014
UHRS	09/19/2014	07/24/2015
LeadGenius	09/26/2014	02/12/2015
Amara	10/02/2014	12/24/2014

Table 1 shows the time range the survey was on each platform. Ideally, all surveys would have been administered at the same time for the same time horizon across all four platforms. Unfortunately, it took time to get permission from the platform operators to run a survey and set up mechanisms that would allow for confidential survey participation on UHRS, LeadGenius, and Amara (e.g., giving respondents a way to find our survey on-platform without making the data available to the platform opera-tors) as well as mechanisms to pay respondents and limit workers to one survey response from any given platform. Once those mechanisms were in place, we also made mi-nor revisions to the questionnaire itself based on respondent feedback from the MTurk survey responses and field-work-based interviews with research participants. We emphasize that all questions and their options were the same across the two survey iterations used for this paper's analysis.

The study's approach to surveying is comparable to how we might assess the characteristics of work settings where the population of individual respondents changes but the worksite remains constant. While the churn found in on-demand labor markets means that individual participation on these platforms is in constant flux, with few exceptions (Ipeirotis 2010), there have been no attempts to systematically track how the gender, geo-location, hours, age, and educational levels of crowdworkers maps onto the churn of individual participation on any given plat-form. In other words, even if individuals leave this line of work, there are no studies to help us understand who follows in their footsteps, whether they look like who dropped away in the churn, or if new workers come from the same or comparable socio-economic, ethnic, age, and educational backgrounds.

Previous studies suggest that some workers specialize in survey tasks (Chandler et al. 2014; Paolacci and Chandler 2014). So, to avoid oversampling survey specialists in addition to distributing the questionnaire as a paid survey task, we also recruited MTurk respondents by embedding the questionnaire in an email classification task. After completing several email classification tasks, workers received a pop-up message asking if they would like to do our survey for an additional bonus payment. This technique increased our odds of reaching a more diverse group of workers who choose a wider variety of tasks or, typically, avoid surveys. Due to the limitations of distributing tasks on the other online labor platforms we were only able to apply this method on MTurk. Third-party vendor relationships, rather than an open market place, manage worker access to the UHRS platform. This made it impossible to either embed the survey in a different task or offer workers an additional bonus payment as part of a separate task. LeadGenius and Amara centrally organize and distribute work on their respective platforms. Therefore, we got platform owners to circulate information and links to our survey task, hosted on SurveyGizmo, a commercial survey site, to *all* workers on the two platforms. Workers on these platforms received email blasts, newsletters, and message board posts, informing them that they would be paid for their participation and that their involvement and responses would not be shared with plat-form managers.

We chose to run a longitudinal survey that sampled a set of on-demand work platforms over time rather than targeting a single platform for a few weeks in hopes of gauging the larger population dynamics of on-demand labor markets and address our interest in the characteristics of those drawn to this growing sector of service work. Therefore, we believe that the survey approach we took to gauge the associations between workers' demographics and motivations addressed in this paper are valid and the results across platforms and survey instruments are comparable in spite of the fact that data were not collected in one survey run.

By the end of our collection period 2,762 workers came to some version of our survey from a recognized URL and consented to answering it. We paid workers for their time reviewing the questionnaire, whether they answered questions or not, so that they would feel free to skip questions, as desired. We applied attention check questions in our questionnaire to identify participants who didn't read the questions. Participants who didn't pass the attention check question were coded as disqualified and were removed from analyses. We amassed a total of 1,729 completed and valid respondents yielding a completion rate of about 63%. Among all valid respondents there are 451 MTurk users, 1144 UHRS users, 174 LeadGenius users, and 167 Amara users. After excluding disqualified participants, 47% participants used more than one online labor platform. In this paper, we focus only on analyzing questions regarding: 1) workers' demographics; 2) workers' motivations; 3) workers' choices of platforms and 4) workers' time and schedule for doing on-demand work. We give the specific text for each question, the possible responses, and describe how we analyzed them in the next section.

Result

Motivation for Doing On-Demand Work

In the past decade, many new online labor platforms have emerged with each creating different, but potentially overlapping, worker populations. This raises the question: do people participate in online labor platforms for different reasons? To address this question, we asked on-demand workers, *"What is the primary reason you do crowdsourcing?"* with pre-provided options:

1) To earn money
2) To do something with my spare time
3) To be my own boss
4) To gain experience that could lead to future job opportunity
5) To learn new skills

As mentioned in the Related Work section these pre-provided options were designed to cover a variety of major motivations found in previous studies (Ipeirotis 2010; Martin et al. 2014; Ross et al. 2010; Teodoro et al. 2014) and our own in-person interviews of on-demand workers. The first option reflects workers who do on-demand work mainly for monetary reward. The second and third options both suggest that workers do on-demand work for reasons of self-determination, by that we mean workers want to be free to choose when and what they work on. The fourth and fifth options reflect workers' desire to use on-demand work for self-improvement: to gain experience or learn new skills from the process of doing micro-tasks[1]. Accordingly, these pre-provided options were categorized into three major motivations driving people to do on-demand work: (1) monetary reward; (2) self-determination; and (3) self-improvement.

Workers' Different Needs for Monetary Reward

Based on the literature, we expect that monetary reward will be the dominant motivation held by most workers. However, we argue that even though most on-demand workers report that they are motivated by monetary reward, they turn out to have different levels of interest in doing so depending on their economic standing. To distinguish workers with different levels of need for monetary reward, as well as understand the characteristics associated with those who value other, non-monetary rewards, we further asked respondents *"What is the secondary reason you do crowdsourcing?"* This approach has two main advantages. First, for workers who consider monetary reward along with some other benefit from doing on-demand work as both of their main motivations, the secondary reason provides an opportunity for them to rank and report the

[1] We included a sixth option of "to have a sense of purpose" but we excluded it from our analysis because very few workers chose this option, and thus we have low confidence that we can interpret the results. Including this question does not change our conclusions.

different motivations without omitting one. Second, the secondary reason can help us distinguish workers who do not consider earning money to be of either primary or secondary importance. This approach allows workers to acknowledge the obvious—they are there to earn money—while also bringing into focus what other motivations might be at play.

For the purposes of understanding how demographics correlated with workers' desire to earn money, we categorize worker motivations based on whether they reported earning money as either their primary or secondary reasons for doing on-demand work. If they did not report earning money as either a primary or secondary reason, we categorize them as having earning money as a tertiary priority. Next, we use a multi-nominal logistic regression model to examine how workers' characteristics are associated with different motivations. More specifically, we model on-demand workers' motivations as a function of their age, gender[2], education level, geo-location, number of household income sources, and employment status and control for the platforms they work on. In Figure 1 each icon represents an outcome of a dependent variable. The three shapes correspond to the three categorical outcomes of the dependent variable: ranking earning money as either the top, secondary, or tertiary priority. The x-axis shows the odds ratio of that ranking relative to "Money is top priority" (i.e. the circle icon) which is normalized to one as the baseline. The icons represent specific values from the x-axis (i.e. odds ratio) which are denoted alongside the icons. Two icons joined with a line indicate the two odds ratios are *not* significantly different. The y-axis denotes different demographic factors which are significantly correlated with the dependent variable[3]. This plot enables us to examine all comparisons, not just the minimal set (Long & Freese 2014). For example, in Figure 1, when a worker's age increases a standard deviation, the odds of doing on-demand work for "Money (secondary)" (i.e. the triangle icon) decreases to 0.869, compared to the baseline "Money (Top priority)."

In brief, workers who are younger have significantly lower probability of doing on-demand work primarily for earning money, compared to workers for whom money is of secondary or tertiary importance. Workers who are more highly educated are less likely to do on-demand work mainly for earning money. Similarly, if workers have more income sources, they have higher probabilities of having earning money as secondary instead of primary importance. Taken as a whole, these results suggest that workers who have other options to earn, whether that

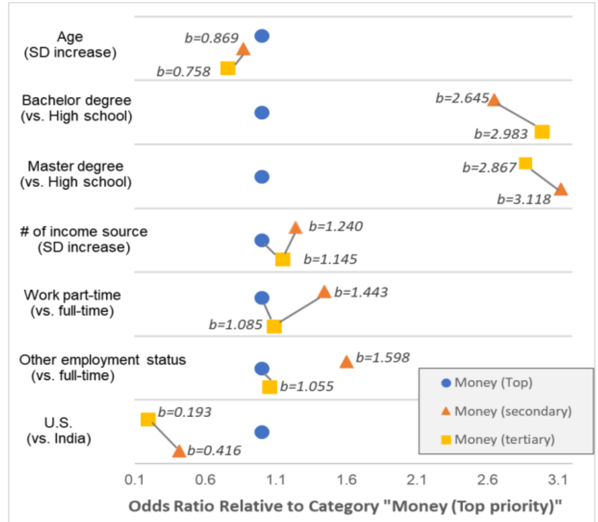

Figure 1: Odds ratio plot for workers' monetary motivation (baseline: "Money is top priority)

comes from their younger age, higher education, or other income sources, are more likely to have something besides earning money as their top reason for doing on-demand work. In the next section we will shed more light on what these workers prioritize besides money.

Finally, workers living outside the U.S. have a lower probability of doing on-demand work primarily for the money, compared to workers in the U.S. It is possible that this reflects a previously-documented cultural discomfort among India-based workers with listing money as more important than other motivations (Gupta et al. 2014). However, another plausible reason for this finding is that doing on-demand work requires the upfront costs of a computer and an internet connection. Statistically speaking, if a person in India can access the necessary tools of on-demand work and has the requisite language and computer literacy to participate in this online labor market, they already have some monetary resources and financial security before entering this workforce. Though workers in the U.S. may have less costly or easier access to computers and an internet connection, that does not mean they have the financial resources to make earning money a lower priority. Curiously, one demographic that does not seem to correlate with variation in need of earning is gender. This suggests that women and men share similar needs and motivations when it comes to earning money from their participation in on-demand markets.

Working for Non-Monetary Reward

We further analyze workers who do on-demand work primarily for non-monetary reasons by analyzing how their demographics correlate with the benefits they expect to get from doing on-demand work. To do so, our first step is to re-categorize workers. A worker's motivation is catego-

[2] Our questionnaire included "Male," "Female," and "Transgender" gender options; our analysis excludes Transgender respondents because very few workers chose this option leaving us unable to interpret the results

[3] Demographic factors not significantly correlated to the dependent variable were not presented in the plots.

rized as "Self-Determination" if he or she reported "To do some-thing with my spare time" or "To be my own boss" as the primary reason to do on-demand work. A worker's motivation is categorized as "Self-Improvement" if he or she reported "To gain experience that could lead to future job opportunity" or "To learn a new skill" as the primary reason.

We analyze how workers' characteristics correlate with these two different motivations with a multi-nominal logistic regression model. Figure 2 shows the odds ratio of demographic factors correlated with the different types of motivations which are marked as three different shapes. Again, if two icons are tied together with a line then their odds ratios are *not* significantly different. In the figure, the odds ratio of "Money (Top priority)" has been normalized to one as the baseline. Previously we saw that workers who are younger are less likely to place primary importance on earning money. Here we see workers who are younger have significantly higher probability of reporting their primary reason is "Self-Improvement". Previously we saw that more highly educated workers are less likely to have earning money as their primary reason for doing on-demand work. Here we see that higher educated workers have a higher probability of doing on-demand work both for Self-Determination and Self-Improvement. Among all demographic characteristics, being more highly educated increases the odds ratio of motivations other than earning money the most. So, workers' education is an important factor which significantly influences whether workers do on-demand work for money or not. Finally, we saw that workers living outside of the U.S. have lower probability of reporting that the monetary reward is their top reason to do on-demand work. Here we see these workers primarily do on-demand work for both Self-Improvement and Self-Determination.

Motivations and the Choices of Platforms

Since our data spans four platforms we next analyze how worker's motivation are correlated with their choice of platform. First, we analyze the correlation between platform choice and worker's desire for monetary reward and then discuss the correlation with non-monetary reward.

The results of the logistic regression model in Table 2 show that workers are less likely to work on Amazon MTurk if they consider monetary reward as secondary (*odds ratio=.563, p<.001*) or tertiary (*odds ratio=.631, p<.05*) than if they consider it to be their primary motivation. On the other hand, workers are more likely to work on UHRS when they consider monetary reward as secondary (*odds ratio=1.596, p<.01*) or tertiary (*odds ratio=1.854, p<.01*). Similarly, workers have higher chance to work on Amara when they think monetary reward as secondary (*odds ratio=1.949, p<.01*) or tertiary (*odds ratio=2.375, p<.01*). These results suggest that MTurk work-

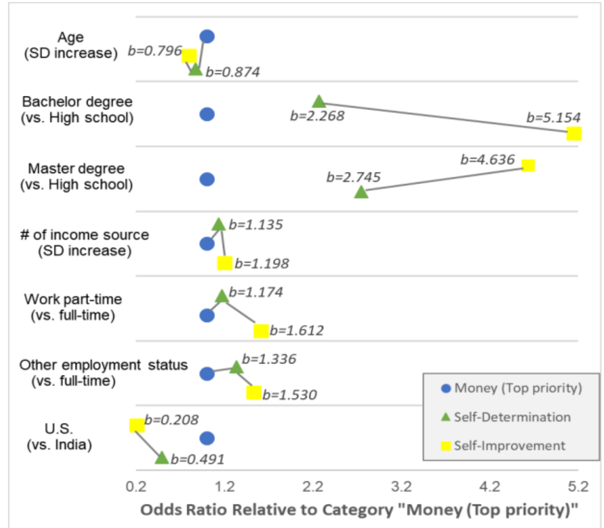

Figure 2: Odds ratio plot for worker's non-monetary motivation (baseline: "Money is top priority")

ers are primarily motivated by money whereas UHRS and Amara workers are not primarily motivated by money. Finally, choosing to work on LeadGenius is not significantly associated with workers' different needs of monetary reward (Table 2).

Next, we examine the association between workers' motivation for non-monetary reward and their choice of platforms. We'll see that the results, shown in Table 3, support those of the monetary rewards. Workers who consider self-determination as their primary reason are less likely to work on Amazon MTurk (*odds ratio=.450, p<.001*); in contrast, they have higher probability of working on UHRS (*odds ratio=2.553, p<.001*). Workers who note self-improvement as their primary reason to do on-demand work have higher probability of working on Amara (*odds ratio=3.926, p<.001*), compared to those for earning money. Finally, choosing to work on LeadGenius is not significantly correlated with working for either monetary reward, self-determination, or self-improvement (Table 3).

Overall, workers who do on-demand work on Amazon MTurk are more likely to note that earning money is the top reason to join this online labor market and show less concern about self-determination. Workers doing on-demand work on UHRS are less likely to regard getting monetary reward as the first priority and consider self-determination a significant reason. Workers doing on-demand work on Amara are also less likely to list monetary reward as their top reason, and moreover, considering self-improvement as the major non-monetary incentive.

Although most on-demand work platform operators do not disclose information about their own workers, our data show that workers may differ from platform to platform according to their demographic characteristics and moti-

Table 2: Logistic regression analysis of working on specific on-demand work platform by monetary reward

	b	*s.e.*	*odds ratio*
Amazon MTurk			
Monetary Reward			
Money (secondary)	-.574***	.144	.563
Money (tertiary)	-.460*	.186	.631
X^2=19.85, df=2			
UHRS			
Monetary Reward			
Money (secondary)	.468**	.135	1.596
Money (tertiary)	.617**	.185	1.854
X^2=20.08, df=2			
LeadGenius			
Monetary Reward			
Money (secondary)	-.218	.208	.804
Money (tertiary)	-.149	.269	.862
X^2=1.24, df=2			
Amara			
Monetary Reward			
Money (secondary)	.667**	.209	1.949
Money (tertiary)	.865**	.250	2.375
X^2=16.32, df=2			

*Note: *p<.05, **p<.01, ***p<.001*

Table 3: Logistic regression analysis of working on specific on-demand work platform by non-monetary reward

	b	*s.e.*	*odds ratio*
Amazon MTurk			
Non-Monetary Reward			
Self-Determination	-.798***	.151	.450
Self-Improvement	-.091	.174	.913
X^2=30.96, df=2			
UHRS			
Monetary Reward			
Self-Determination	.937***	.150	2.553
Self-Improvement	-.154	.165	.857
X^2=49.30, df=2			
LeadGenius			
Monetary Reward			
Self-Determination	-.290	.212	.748
Self-Improvement	-.020	.259	.980
X^2=1.99, df=2			
Amara			
Monetary Reward			
Self-Determination	.273	.231	1.314
Self-Improvement	1.368***	.225	3.926
X^2=33.54, df=2			

*Note: *p<.05, **p<.01, ***p<.001*

vations. Taken together, these results suggest that workers choose specific platforms to do on-demand work based on reasons more complicated than financial gains. It is important to note that differences across the four platforms—both the kind of work that they generate and the design of the platforms themselves—are part of why we might see workers selecting platforms that match their motivations. For example, each of the four platforms is available to anyone so they all share the quality of being worksites where anyone can show up and sign up for work. But they differ significantly in what happens after a person signs up for a work account. While we do not have causal data to qualify how workers' motivations might be differentially impacted by a platform's specific design, it seems reasonable to assume that the technological affordances of the platforms might confound workers' motivations to stick with or leave any given platform.

On-Demand Workers' Scheduling Patterns

To understand how workers' characteristics, such gender, location, age, and educational levels, and motivations may intersect to shape workers' behaviors, we further analyze how demographics and motivations correlate with workers' scheduling practices. We analyze how workers schedule their time because it is a behavior that workers must structure themselves. Absent of the motivation of a set schedule, we reason that workers' scheduling practices are a strong signal of the intermingling of what motivates a worker to look for on-demand work and how their own social identities and the structural constraints or freedom they afford may factor into their motivations. To understand workers' scheduling, respondents were asked a series of questions about their patterns of work with the following questions:

- On which day(s) in a week you usually do crowdsourcing?
- How many hours you usually spend on the day you do crowdsourcing?
- Which periods of time in a day you usually do crowdsourcing?

Next, we briefly describe how we analyzed the data gathered from these questions and then go on to describe the results and conclusions from doing so. We applied a Zero-Truncated Poisson regression model for count outcomes to analyze if workers' social characteristics, their motivations for doing on-demand work, and the platforms they participated in correlate with the number of days they do on-demand work (Table 4). Since workers participating in our survey have done on-demand tasks at least one day in a week, the Zero-Truncated Poisson regression model is more appropriate than the general Poisson regression model. In addition, we recoded the data into two new variables: *doing on-demand work during the week*, and *doing on-demand work during the weekend*, and both variables are recoded into *0 (No)* and *1 (Yes)* categories. Since the outcome variable is binary, we applied a logistic regression model to analyze what factors correlate with workers doing on-demand work during the week and during the week-end (Table 5). We also applied an OLS regression model to analyze potential factors associated with the number of hours per week workers spend on on-demand work, as a continuous variable (Table 6). Similarly, we applied an OLS regression model to study the number of hours workers spent working during the week and during the weekend (Table 7). Going a step further, we regrouped the periods of time into *daytime* (9am to 6pm) and *nighttime* (6pm to 9am). These two categories corresponded to when people are, typically, going to work/school (day time) and when they are usually off work/school (night time) in modern society. We then applied a logistic regression model to this recoded, binary data to examine if on-demand workers' characteristics and the platforms they participated in were associated with when they do on-demand work (Table 8). Since all the dependent variables in this section describe how workers spend their time, we will describe how each attribute affects worker scheduling (as opposed to walking the reader through each different regression).

Demographics and Scheduling

Gender Next, we analyze the relationship between gender and how on-demand workers schedule their time. The result (Table 5) indicates that gender significantly correlates with whether a worker will do on-demand work on a weekday or on the weekend. First, compared to male on-demand workers, female workers have higher odds of doing on-demand work on a weekday (*odds ratio*=2.40, *p*<.01). On the other hand, being a female on-demand worker shows lower odds of doing on-demand work on the weekend (*odds ratio*=.68, *p*<.05), compared to males. This implies that gender significantly influences which day workers do on-demand work: women tend to do on-demand work on weekdays, but they are significantly less likely to do on-demand work on weekends.

Given that on-demand workers of different genders behave differently in doing on-demand work on the weekday or weekend, we were curious if they differed in the hours they spend during the weekday and weekend. The result (Table 7) shows that, compared to male workers, females spend more hours on weekdays (*b*=1.62, *p*<.05); however, female workers spend significantly fewer hours on doing on-demand work on the weekend (*b*=-.74, *p*<.05). Moreover, being a female increases the odds of doing on-demand work during the day time (*odds ratio*=1.53, *p*<.001), holding other variables constant. On the other hand, being a female worker decreases the probability of doing on-demand work at night (*odds ratio*=0.52, *p*<.001) (Table 6).

Taken together, these results suggest that though female and male on-demand workers are not distinct in the numbers of days and total hours they spend doing on-demand work per week, they are very different from each other in how they schedule their time. These results suggest that men are more likely to work during the nights and weekends and women are more likely to work during the day and less on the weekends. More broadly, if we assume that males are more likely to work outside the home during the day and during the week, and females are more likely to work inside the home during the day and during the week, a pattern begins to emerge. As feminist researchers have noted, women working for wages must often juggle opportunities to earn with additional, unpaid household responsibilities (Hochschild and Machung 2012). As such, women are more likely to do on-demand work when at-home work responsibilities permit. Men, on the other hand, are more likely to do on-demand work in the evenings and weekends, perhaps after they have fulfilled their responsibility for their other jobs which are, most likely, outside of the home.

Table 4: Zero-Truncated Poisson regression analysis of the number of days doing on-demand work

	b	*s.e.*	*β*
Age	.002	.001	1.00
Female	-.006	.024	0.99
Education			
College/vocational	.074	.050	1.08
Bachelor	.147**	.043	1.16
Master	.116*	.047	1.13
Geo-location			
U.S.	.023	.042	1.02
Other areas	-.013	.050	0.99
Employment status			
Part-time	-.011	.029	0.99
Other	-.017	.025	0.98
Motivation			
Money (less important)	.013	.026	1.01
Self-determination	.017	.038	1.02
Self-improvement	-.050	.046	0.95
MTurk worker	.127***	.029	1.14
UHRS worker	.010	.034	1.01
LeadGenius worker	.064	.038	1.01
Amara worker	-.121*	.052	0.88
X^2=78.84, df=16			

*Note: (1) The β of age is presented in the units of a standard deviation; (2) *p<.05, **p<.01, ***p<.001*

Education Level Workers with different education levels schedule their work differently. Workers spend significantly more days doing on-demand work when they have a bachelor's degree (*b*=.147, *p*<.01) or master's degree (*b*=.116, *p*<.05), compared to workers with a high school degree (Table 4). Furthermore, the probability of doing on-demand work on a weekday increases if the workers have a bachelor's degree (*odds ratio*=2.92, *p*<.01), compared to workers with a high school degree (Table 5). Although education level is not associated with how many hours workers spend, it is indeed correlated with which periods of time they do on-demand work. Table 8 shows that workers who are higher educated are more likely to do on-demand work during the daytime, having a bachelor's degree (*odds ratio*=1.84, *p*<.01) or a master degree (*odds ratio*=1.84, p<.01) increase the probability respectively. In addition, having a bachelor's degree decreases the like-

Table 5: Logistic regression analysis of doing on-demand work during the week and during the weekend

	During the weekday			On the weekend		
	b	*s.e.*	*odds ratio*	*b*	*s.e.*	*odds ratio*
Age	-.012	.013	.989	.024*	.010	1.245
Female	.876**	.293	2.402	-.379*	.163	.684
Education						
College/vocational	.319	.455	1.376	-.138	.335	.871
Bachelor	1.070**	.350	2.915	-.233	.281	.792
Master	.520	.393	1.682	-.174	.311	.840
Geo-location						
U.S.	.473	.774	1.604	-.584	.313	.558
Other areas	-.886	.562	.412	-.117	.341	.890
Employment status						
Part-time	.285	.349	1.330	-.565**	.197	.569
Other	.032	.262	1.033	-.161	.182	.852
Motivation						
Money (less important)	.477	.292	1.611	-.056	.177	.945
Self-determination	.096	.367	1.101	-.108	.250	.897
Self-improvement	.129	.480	1.138	-.083	.301	.920
MTurk worker	2.564***	.671	12.994	.526*	.226	1.693
UHRS worker	.578	.508	1.783	-.171	.254	.843
LeadGenius worker	2.315**	.809	10.123	-.128	.271	.880
Amara worker	1.035	.679	2.815	-.421	.322	.657
	X^2=77.48, df=16			X^2=41.15, df=16		

*Note: (1) The odds ratio of age is presented in the units of a standard deviation. (2) *p<.05, **p<.01, ***p<.001*

lihood of doing on-demand work during the night (*odds ratio*=.60, *p*<.05).

In sum, workers with higher education levels tend to do on-demand work during the daytime on weekdays; that is to say, higher educated workers are less likely to do on-demand work during the customary leisure time. Combining this finding with the finding that workers with higher education levels are more likely to do on-demanding work for self-determination or self-improvement, our research suggests that these higher educated workers do not have to work for earning extra money outside the conventional working hours.

Geo-location: U.S. compared to India Studies of on-demand workers in India suggest that some India workers need to work at night to pick up work. This phenomenon, called "time-shifting", reflects a typical trend in global business activity, as most on-demand work posted by requesters in the U.S. requires foreign nationals to work during U.S. business hours (Gupta et al. 2014). Therefore, we want to know how the periods of time that on-demand workers do work vary based on their geo-location. Workers' geo-location is correlated with working during the day but is not significantly correlated with working during the night. More specifically, compared to workers in India, on-demand workers who live in the U.S. have higher probability of doing on-demand work during the daytime (*odds ratio*=3.19, *p*<.001); similarly, workers living in other areas also have higher chance to do on-demand work during the daytime (*odds ratio*=2.60, *p*<.01) (Table 8). Interestingly, the workers in the U.S. and India, two major sources of online labor market, demonstrate distinct patterns of "shift work." One possible interpretation of this difference is that most task requesters are from the U.S. and they tend to post tasks during U.S. business hours. Hence workers in the U.S. can work during typical "9-5" hours, and workers outside the U.S. have to adjust their scheduling to access more tasks.

Table 6: Regression analysis of hours per week spent on on-demand work

	b	*s.e.*	*β*
Age	.012	.044	.11
Female	.879	.875	.41
Education			
College/vocational	3.418	1.718	1.17
Bachelor	1.782	1.442	.89
Master	1.174	1.593	.52
Geo-location			
U.S.	2.789	1.518	1.02
Other areas	4.068*	1.781	1.38
Employment status			
Part-time	.389	1.042	.16
Other	1.113	.916	.55
Motivation			
Money (less important)	-1.434	.946	-.61
Self-determination	-.507	1.385	-.15
Self-improvement	-2.853	1.646	-.69
MTurk worker	6.933***	1.069	3.18
UHRS worker	-.759	1.219	-.36
LeadGenius worker	9.403***	1.398	2.98
Amara worker	-9.737***	1.824	-2.80
F(16,1433)=16.69, p<.001, *Adj.* R^2=0.15			

*Note: (1) The β of age is presented in the unites of a standard deviation; (2) *p<.05, **p<.01, ***p<.001*

Table 7: Regression analysis of hours spent on on-demand work during the week and weekend

	Hours spent during the weekday			Hours spent on the weekend		
	b	*s.e.*	*β*	*b*	*s.e.*	*β*
Age	.003	.035	.025	.009	.015	.085
Female	1.618*	.691	.756	-.739*	.302	-.345
Education						
College/vocational	3.024	1.357	1.034	.394	.593	.135
Bachelor	1.801	1.139	.901	-.018	.498	-.009
Master	1.355	1.258	.603	-.181	.550	-.080
Geo-location						
U.S.	3.372**	1.199	1.234	-.583	.524	-.213
Other areas	2.962*	1.407	1.002	1.105	.614	.374
Employment status						
Part-time	1.380	.823	.575	-.991**	.360	-.413
Other	1.620*	.724	.797	-.507	.316	-.249
Motivation						
Money (less important)	-1.144	.747	-.484	-.290	.326	-.123
Self-determination	-.237	1.094	-.068	-.270	.478	-.078
Self-improvement	-2.565	1.300	-.616	-.288	.568	-.069
MTurk worker	5.464***	.845	2.508	1.469***	.369	.674
UHRS worker	-1.143	.963	-.541	.385	.421	.182
LeadGenius worker	8.699***	1.104	2.756	.704	.482	.223
Amara worker	-7.457***	1.440	-2.146	-2.280***	.629	-.656
	$F(16,1433)=20.83$, $p<.001$, *Adj.* $R^2=0.18$			$F(16,1433)=4.94$, $p<.001$, *Adj.* $R^2=0.04$		

*Note: (1) The β of age is presented in the units of a standard deviation. (2) *p<.05, **p<.01, ***p<.001*

Employment Status Workers' employment status is correlated with when workers do on-demand work. First, compared to workers who have full-time jobs, doing part-time jobs (excluding on-demand work) decreases the probability of doing on-demand work on the weekend (*odds ratio*=.57, *p*<.01) (Table 5). Consequently, they also spend fewer hours doing on-demand work on the weekend (*b*=-.991, *p*<.01). In addition, workers with other employment statuses (e.g., unemployed or retired) spend more hours doing on-demand work during the week (*b*=1.62, *p*<.05) (Table 7). In terms of during which periods of time workers do on-demand work, doing part-time jobs significantly increases the chance of doing on-demand work during the daytime (*odds ratio*=2.06, *p*<.001), and decreases the odds of working in the night (*odds ratio*=.54, *p*<.001). Likewise, having other employment statuses significantly increase the chance of working during the day-time (*odds ratio*=2.47, *p*<.001) and decreases the likelihood of working in the night (*odds ratio*=.50, *p*<.001) (Table 8). These findings indicate that workers' employment status influences when workers do on-demand work. This could be a sign that workers are scheduling their on-demand work around their other work obligations, again showing how workers are fitting this type of work into their lives.

Platform and Scheduling

In addition to demographic characteristics, working on specific platforms also correlates with workers' scheduling. Compared to non-MTurk counterparts, MTurk workers spend significantly more days (*b*=.127, *p*<.001), and more hours per week (*b*=6.993, *p*<.001) doing on-demand work. MTurk workers also are more likely to work during the weekday (*odds ratio*=2.564, *p*<.001) as well as the weekend (*odds ratio*=.526, *p*<.05). Moreover, MTurk workers spend more hours during both the weekday (*b*=5.464, *p*<.001) and the weekend (*b*=1.469, *p*<.001). Taken together, MTurk workers have an intensive work schedule compared to workers on the other platforms that we studied. This result corresponds to our finding that MTurk workers are more likely to work for monetary incentives while other study indicates that the majority of MTurk workers are lower paid (Hara et al. 2018).

LeadGenius workers show a similar pattern. Compared to non-LeadGenius workers, they are more likely to work during the weekday (*odds ratio*=2.315, *p*<.01). LeadGenius workers also spend more hours per week on on-demand work (*b*=9.403, *p*<.001), and they have a higher chance of spending more time during the weekday working (*b*=8.699, *p*<.001). However, LeadGenius workers are not significantly different from non-LeadGenius workers in terms of working on the weekend and the number of hours spent on the weekend.

Amara workers shows a distinct work schedule. Compared to non-Amara workers, Amara workers significantly spend fewer days (*b*=-.121, *p*<.05) and fewer hours per week (*b*=-9.737, *p*<.001) on doing on-demand work. Accordingly, Amara workers spend significantly fewer hours during the weekday (*b*=-7.457, *p*<.001) as well as on the weekend (*b*=-2.280, *p*<.001) than non-Amara workers. Although platforms are correlated to different types of

Table 8: Regression analysis of hours spent on on-demand work during the week and weekend

	During the daytime			During the nighttime		
	b	*s.e.*	*odds ratio*	*b*	*s.e.*	*odds ratio*
Age	.006	.006	1.052	-.007	.006	.938
Female	.427***	.119	1.533	-.646***	.123	.524
Education						
College/vocational	.400	.236	1.492	-.216	.266	.806
Bachelor	.607**	.196	1.835	-.512*	.222	.599
Master	.610**	.217	1.840	-.356	.244	.700
Geo-location						
U.S.	1.159***	.221	3.188	-.305	.237	.737
Other areas	.956**	.255	2.601	-.490	.265	.613
Employment status						
Part-time	.721***	.145	2.056	-.615***	.160	.541
Other	.956***	.126	2.471	-.693***	.139	.500
Motivation						
Money (less important)	.005	.127	1.005	.066	.138	1.069
Self-determination	.141	.185	1.152	.280	.211	1.323
Self-improvement	.363	.225	1.438	-.256	.232	.774
MTurk worker	.136	.152	1.146	.237	.167	1.267
UHRS worker	.319	.177	1.376	-.188	.188	.829
LeadGenius worker	.307	.201	1.359	.100	.214	.905
Amara worker	-.492	.256	.612	.232	.267	1.261
	X^2=137.40, df=16			X^2=82.28, df=16		

*Note: (1) The odds ratio of age is presented in the units of a standard deviation. (2) *p<.05, **p<.01, ***p<.001*

work scheduling patterns, workers of the four different platforms show no significant difference regarding working during the daytime and the nighttime.

Conclusion

By analyzing the correlation between worker demographics and motivations we show how workers fit on-demand work into their lives. More specifically, demographics help make sense of the patterns we see in who participates in this labor market and how workers engage this type of work. For example, we could not detect any correlation between gender and the importance of earning money suggesting that women and men equally value earning money and feel comparable structural pressures to participate in the global economy. The interplay of gender and scheduling also illustrate the real-world constraints that people face entering labor markets. We found that men are more likely to work during the nights and weekends, perhaps because they were more likely to work outside the home during the week. Women are more likely to work during the day and less on the weekends, perhaps because they are more likely to work inside the home during the week. This is an example of an offline constraint dictating when a worker can do online work.

We saw another example of a demographics structuring workers' motivations in that workers who have fewer outside options to earn money, whether that's because they had fewer income streams, were older or less educated, or were more likely to do on-demand work for pay. In this example workers with fewer earning options, due to various socioeconomic constraints, placed a higher importance on earning money via on-demand work. And a workers' employment status and capacity to earn correlates to when people do on-demand work but not how many hours they take on any given week.

Demographics also influence how workers do on-demand work, influencing which platforms workers choose to work on. For example, MTurk workers are primarily motivated by money whereas UHRS and Amara workers are not primarily motivated by money. We cannot conclude, from our observational data, whether MTurk, for example, attracts workers who prioritize earning money, or if workers who prioritize earning money choose MTurk or both. We leave that research question to future work. The associations among workers' demographics, motivations and choices of platforms demonstrate that each on-demand work platform may attract a group of people, forming a worker population with specific characteristics. Thus, task requesters and scientific researchers who employ this online labor market to fulfill their needs may reach very different worker populations, depending on which platform they choose to use.

At first glance one might think that on-demand labor platforms offer people of any walk of life and in any location a chance to earn, improve themselves, and control their own schedules. But, what unifies all of our results is that there are social dimensions such as how many outside options one has to earn, the timing of home and work responsibilities, and geographic location which are all correlated with who does on-demand work and when and why they do it. In fact, some of these social dimensions that stem from the offline world are carried into the online world of on-demand work.

There are several implications of our results. First, an online labor platform where tasks are typically posted during the day in the U.S. implicitly biases which workers can and will do the tasks. That is, the available pool of on-demand workers is constantly changing in different time buckets. Second, platform operators and task requesters should be aware that distinct groups of on-demand workers may influence who does the work; moreover, the different pools of on-demand workers may lead the system to produce potentially biased content. While task requesters and researchers benefit from the convenience of online labor platforms and workers, it is important to realize that they may reach very different groups of on-demand workers with dissimilar characteristics, depending on how the tasks are designed and when the tasks are available. In addition, researchers should be aware the different platforms attract workers with different motivations. A study done on one platform may not generalize to another platform with a different workforce. Lastly, this research suggests that each platform's design offers different technological affordances that work with or dampen workers' different motivations. With this in mind and a baseline assumption that part of the motivation for paid crowdwork is the money, we aimed to illustrate how financial motivations fail to explain who's incented to participate and how they decide when to do this work. To be clear, we are not arguing that motivation should determine pricing. A fair wage is integral to dignified, paid work. That said, our findings suggest that pricing can be augmented with other incentives that account for what else might be in play for workers, beyond a price point.

References

Antin, J., and Shaw, A. 2012. Social desirability bias and self-reports of motivation: A study of Amazon Mechanical Turk in the US and India. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2925–2934). New York, NY, USA: ACM.

Berg, J. 2015. Income security in the on-demand economy: Findings and policy lessons from a survey of crowdworkers. *Comparative Labor Law & Policy Journal*, *37*, 543–576.

Brewer, R.; Morris, M. R.; and Piper, A. M. 2016. "Why would anybody do this?": Understanding older adults' motivations and challenges in crowd work. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (pp. 2246–2257). New York, NY, USA: ACM.

Chandler, J.; Mueller, P.; and Paolacci, G. 2014. Nonnaïveté among Amazon Mechanical Turk workers: Consequences and solutions for behavioral researchers. *Behavior Research Methods*, *46*(1), 112–130.

Difallah, D.; Filatova, E.; and Ipeirotis, P. 2018. Demographics and dynamics of Mechanical Turk workers.

Gupta, N.; Martin, D.; Hanrahan, B. V.; and O'Neill, J. 2014. Turk-life in India. In *Proceedings of the 18th International Conference on Supporting Group Work* (pp. 1–11). New York, NY, USA: ACM.

Hara, K.; Adams, A.; Milland, K.; Savage, S.; Callison-Burch, C.; and Bigham, J. P. 2018. A data-driven analysis of workers' earnings on Amazon Mechanical Turk. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (pp. 449:1–449:14). New York, NY, USA: ACM.

Hochschild, A., and Machung, A. 2012. *The second shift: Working families and the revolution at home*. Penguin.

Hossain, M. 2012. Users' motivation to participate in online crowdsourcing platforms. In *2012 International Conference on Innovation Management and Technology Research* (pp. 310–315).

Ipeirotis, P. G. 2010. *Demographics of Mechanical Turk* (SSRN Scholarly Paper No. ID 1585030). Rochester, NY: Social Science Research Network.

Kaufmann, N.; Schulze, T.; and Veit, D. 2011. More than fun and money. Worker motivation in crowdsourcing - A study on Mechanical Turk. In *AMCIS* (Vol. 11, pp. 1–11).

Long, J. S., and Freese, J. 2014. *Regression models for categorical dependent variables using Stata* (Third Edition). Stata press.

Martin, D.; Hanrahan, B. V.; O'Neill, J.; and Gupta, N. 2014. Being a Turker. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing* (pp. 224–235). New York, NY, USA: ACM.

Martin, D.; O'Neill, J.; Gupta, N.; and Hanrahan, B. V. 2016. Turking in a global labour market. *Computer Supported Cooperative Work (CSCW)*, *25*(1), 39–77.

Naderi, B.; Wechsung, I.; Polzehl, T.; and Möller, S. 2014. Development and validation of extrinsic motivation scale for crowdsourcing micro-task platforms. In *Proceedings of the 2014 International ACM Workshop on Crowdsourcing for Multimedia* (pp. 31–36). New York, NY, USA: ACM.

Paolacci, G., and Chandler, J. 2014. Inside the Turk: Understanding Mechanical Turk as a participant pool. *Current Directions in Psychological Science*, *23*(3), 184–188.

Posch, L.; Bleier, A.; and Strohmaier, M. 2017. Measuring motivations of crowdworkers: The multidimensional crowdworker motivation scale. *ArXiv:1702.01661*.

Ross, J.; Irani, L.; Silberman, M. S.; Zaldivar, A.; and Tomlinson, B. 2010. Who are the crowdworkers?: Shifting demographics in Mechanical Turk. In *CHI '10 Extended Abstracts on Human Factors in Computing Systems* (pp. 2863–2872). New York, NY, USA: ACM.

Smith, A. 2016, November 17. Gig work, online selling and home sharing. Retrieved March 5, 2018, from http://www.pewinternet.org/2016/11/17/gig-work-online-selling-and-home-sharing/

Teodoro, R.; Ozturk, P.; Naaman, M.; Mason, W.; and Lindqvist, J. 2014. The motivations and experiences of the on-demand mobile workforce. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing* (pp. 236–247). New York, NY, USA: ACM.