http://pubsonline.informs.org/journal/isre

INFORMATION SYSTEMS RESEARCH
Articles in Advance, pp. 1–22
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

The Hidden Costs and Benefits of Monitoring in the Gig Economy

Chen Liang,[a,*] Jing Peng,[a] Yili Hong,[b] Bin Gu[c]

[a] School of Business, University of Connecticut, Storrs, Connecticut 06269; [b] Miami Herbert Business School, University of Miami, Coral Gables, Florida 33146; [c] Questrom School of Business, Boston University, Boston, Massachusetts 02215
*Corresponding author

Contact: chenliang@uconn.edu, https://orcid.org/0000-0002-8444-8050 (CL); jing.peng@uconn.edu, https://orcid.org/0000-0001-5490-6228 (JP); khong@miami.edu, https://orcid.org/0000-0002-0577-7877 (YH); bgu@bu.edu, https://orcid.org/0000-0002-0396-8899 (BG)

Received: December 24, 2019
Revised: January 18, 2021; November 3, 2021; February 26, 2022
Accepted: March 15, 2022
Published Online in Articles in Advance: April 26, 2022

https://doi.org/10.1287/isre.2022.1130

Abstract. Monitoring, a digital surveillance technology that allows employers to track the activities of workers, is ubiquitous in the gig economy wherein the workforce is geographically dispersed. However, workers are often reluctant to be monitored because of privacy concerns, resulting in a hidden economic cost for employers as workers tend to demand higher wages for monitored jobs. To help employers make informed decisions on whether they should adopt monitoring and how to design monitoring policies, we investigate how three common dimensions of monitoring affect workers' willingness to accept monitored jobs as well as the underlying mechanisms through online experiments on two gig economy platforms (Amazon Mechanical Turk (AMT) and Prolific). The three dimensions of monitoring are *intensity* (how much information is collected), *transparency* (whether the monitoring policy is disclosed to workers), and *control* (whether workers can remove sensitive information). We find that, as the monitoring intensity increases, workers become less willing to accept monitoring because of elevated privacy concerns. Furthermore, we find that being transparent about the monitoring policy increases workers' willingness to accept monitoring only when the monitoring intensity is low. Transparent disclosure does not reduce privacy concerns over high-intensity monitoring. Interestingly, providing control over high-intensity monitoring does not significantly reduce workers' privacy concerns either, rendering this well-intentioned policy ineffective. Finally, females are more willing to accept monitored jobs than males as they perceive higher payment protection from monitoring and have lower privacy concerns. On average, we estimate that the compensations required for workers to accept monitoring are \$1.8/hour for AMT workers and \$1.6/hour for Prolific workers, which translate to roughly 37.5% and 28.6% of their average hourly wages, respectively.

History: Alessandro Acquisti, Senior Editor; Idris Adjerid, Associate Editor.
Funding: This work was supported by National Science Foundation Doctoral Dissertation Research [Grant 1824432].
Supplemental Material: The online appendix is available at https://doi.org/10.1287/isre.2022.1130.

Keywords: monitoring • gig economy • privacy concern • payment protection • gender • willingness to accept

1. Introduction

The gig economy has witnessed tremendous growth in the past decade (Huang et al. 2020). The COVID-19 pandemic accelerated the growth as business closures drove unemployed workers into the gig economy. For example, Upwork reported a 50% increase in sign-ups since the pandemic began,[1] and Instacart hired 300,000 new gig workers in just one month.[2] On the demand side, firms struggling during the pandemic also increased their reliance on gig workers rather than hiring full-time employees.[3]

Despite the rapid growth of the gig economy, major challenges linger in this market. On the demand side, employers have little control over gig workers, making it difficult to manage workers' progress and evaluate their performance on the job. On the supply side, gig workers are frustrated about frequently having their work output rejected for unjustifiable reasons or even no reason at all (Benson et al. 2020). According to a survey conducted by the International Labor Organization on 3,500 gig workers across various gig platforms, nearly 90% of workers have experienced work rejections, and only 12% of workers stated that all their rejections were justifiable (Berg et al. 2018). It is estimated that, on average, the loss resulting from unpaid work amounts to 13% of gig workers' annual income.[4]

These challenges facing employers and workers in the gig economy largely result from asymmetric information between the two parties. To mitigate the potential moral hazard problem resulting from information asymmetry, employers usually use efficiency wages to discourage workers from shirking (Akerlof 1984, Stiglitz 1987). Nevertheless, an efficiency wage may not pay off to employers because the decrease in shirking may not offset the efficiency wage premium (Cappelli and Chauvin 1991). Recently, with advancements in digital surveillance technologies, monitoring has become an attractive alternative to address the information asymmetry problem. For instance, Upwork provides a desktop app that can automatically take screenshots and track workers' activities on hourly projects.[5] From the perspective of employers, monitoring allows them to track workers' progress and intervene when necessary (Möhlmann et al. 2021). Prior studies show that monitoring can improve workers' productivity (Hubbard 2000, Duflo et al. 2012). From the perspective of workers, the information recorded by monitoring systems, such as working hours and computer screenshots, can serve as proof of their work and protect them from unjustified rejections. Such payment protection is often featured by gig economy platforms (e.g., Upwork and Freelancer) to encourage workers to use their monitoring apps. Therefore, monitoring has the potential to overcome the aforementioned challenges facing employers and workers.

However, because monitoring systems operate by continuously collecting information (e.g., working hours, computer screenshots, or moving routes) from workers, they often lead to serious privacy concerns. As a result, workers may be reluctant to take jobs that are monitored by employers. For example, Uber's monitoring system was considered intrusive by some drivers, and some even filed a lawsuit against Uber to protect their privacy.[6] In theory, workers' privacy concerns over monitoring may be influenced by multiple factors, such as how much information is collected (i.e., *intensity*), whether the information collection policy is fully disclosed to workers (i.e., *transparency*), and whether workers have control over the collected information (i.e., *control*). Specifically, higher intensity monitoring may lead to stronger privacy concerns as privacy concerns increase with the amount of information collected (Gandy 1993, Malhotra et al. 2004). In contrast, being transparent about the information-collection process can increase the perceived fairness and appropriateness of monitoring, which reduces workers' privacy concerns (Culnan and Armstrong 1999). Similarly, a monitoring system that provides workers with certain control over the information being collected (e.g., allowing workers to remove sensitive computer screenshots captured by the monitoring system) may alleviate workers' privacy concerns because such a monitoring policy is more likely to be considered fair and appropriate (Culnan and Armstrong 1999).

Aligned with the aforementioned three dimensions of monitoring policy (i.e., intensity, transparency, and control), three corresponding industry practices are used to alleviate workers' privacy concerns and lower their resistance against monitoring. The first practice is to lower the intensity of monitoring. For example, although many third-party monitoring apps record workers' working hours and computer screenshots (e.g., EmpMonitor, StaffCop), some other monitoring apps only track working hours (e.g., Harvest, WorkTime). The second practice is to increase the transparency of monitoring by informing workers how they will be monitored. For instance, unlike many monitoring apps that do not disclose to workers the details on what information is collected, TimeDoctor allows workers to inspect the monitored records.[7] The third practice is to provide workers control over the information recorded. Toward that end, some monitoring apps (e.g., Screenmeter) allow workers to delete a few screenshots that contain sensitive information or those they are uncomfortable sharing. Notably, the latter two practices are advocated by government agencies (e.g., the White House and Federal Trade Commission)[8] and academic scholars (e.g., Malhotra et al. 2004, Adjerid et al. 2013).

Despite the practical interest in the design of monitoring policies, whether and to what extent they can alleviate privacy concerns are still open questions. Moreover, the design of the monitoring policy may also influence workers' perceived payment protection from monitoring, which is considered a key benefit for gig workers. For example, low monitoring intensity may make monitoring logs less effective in protecting workers from unjustified rejections (Moore and Hayes 2018). On the contrary, when the monitoring intensity is high, being transparent about the monitoring policy may increase workers' perceived payment protection from monitoring. Considering the potential countervailing roles of these two mechanisms (privacy concerns and payment protection), how different monitoring policies affect workers' resistance against monitored jobs is not clear.

Notably, workers' privacy concerns over and perceived payment protection from monitoring may vary across gender based on the literature on the gender differences in privacy concerns and risk attitudes. Prior literature has mixed findings on the potentially gender-specific differential effects of monitoring on privacy concerns. On the one hand, females are more likely to disclose their personal information than males (Kays et al. 2012, Hollenbaugh and Everett 2013). On the other hand, females tend to worry about their privacy more than males when evaluating the potential risk of privacy invasion (Sheehan 1999, Hoy and Milne 2010). Because the privacy concerns over monitoring depend on both the willingness to disclose information and the evaluation of potential negative consequences resulting from privacy invasion, it is unclear whether males or females have stronger privacy concerns in the presence of monitoring. In addition to privacy concerns, the perceived payment protection from monitoring may also vary across gender. Compared with males, females are more risk-averse in making economic decisions (Fellner and Maciejovsky 2007, Croson and Gneezy 2009). Therefore, females may value the payment protection from monitoring more than males, making them more open to monitoring.

To help employers and platforms make informed decisions regarding the design of monitoring policies, it is important to understand how different monitoring policies influence workers' perception and acceptance of monitoring. To that end, we seek to address the following research questions in this study:

1. How do different dimensions of monitoring policy (i.e., intensity, transparency, and control) affect workers' choices between monitored jobs and unmonitored jobs?
2. How do different dimensions of monitoring policy (i.e., intensity, transparency, and control) affect workers' privacy concerns over monitoring and perceived payment protection from monitoring?
3. Is there a gender difference in the perception and acceptance of monitoring?
4. What is the compensation required for workers to choose a monitored job over an unmonitored (but otherwise identical) job?

To answer the first three research questions, we conduct two online experiments in the job-screening process for an image-labeling task on two major gig economy platforms, that is, Amazon Mechanical Turk (AMT) and Prolific. Gig workers participating in our experiments are randomly assigned to four groups with different monitoring policies along the three design dimensions: (a) the *only_time* group, in which only workers' working hours are tracked (a common monitoring policy adopted by many gig platforms and monitoring apps, such as AMT and Harvest); (b) the *all_screenshots* group, in which both working hours and computer screenshots are tracked (a high-intensity monitoring policy adopted by monitoring apps such as EmpMonitor and StaffCop); (c) the *no_disclosure* group, in which workers are aware of monitoring but *not* informed how they will be monitored (a monitoring policy without transparency such as the one employed by Uber);[9] and (d) the *controlled_screenshots* group, in which both working hours and computer screenshots are recorded but workers have the option to remove some screenshots (a monitoring policy offered by Freelancer and Screenmeter).

Because the compensation required for an individual to accept certain negative utility is also known as the willingness to accept (WTA) compensation (Martín-Fernández et al. 2010), our last research question boils down to measuring the WTA for monitoring. The current best practice to measure individuals' willingness to pay or accept is discrete choice experiments (Martín-Fernández et al. 2010, Mas and Pallais 2017, Hedegaard and Tyran 2018). For instance, Hedegaard and Tyran (2018) measure workers' willingness to pay for discrimination based on their choices between two jobs with a same- versus different-ethnic coworker. Mas and Pallais (2017) estimate workers' willingness to pay for alternative work arrangements by offering each worker two job options at different wages: one with a standard schedule and the other with a flexible schedule. Following this practice, we estimate workers' WTA for monitoring by randomizing the wage difference between a monitored job and an unmonitored job and observing workers' choice between the two jobs at different levels of wage differences under different monitoring policies. We further measure workers' privacy concerns over and perceived payment protection from monitoring in different monitoring policy groups.

Several findings emerge from our experiments: (a) increasing monitoring intensity reduces workers' willingness to accept monitoring by increasing their privacy concerns; (b) when the monitoring intensity is *low*, being transparent about the monitoring policy can increase workers' willingness to accept monitoring by reducing their *privacy concerns*. Conversely, when the monitoring intensity is *high*, being transparent about the monitoring policy does not significantly affect workers' willingness to accept monitoring though it can increase their perceived *payment protection*. And (c), notably, when the monitoring intensity is high, providing control over monitored information has no significant effect on either privacy concerns or perceived payment protection, rendering this policy ineffective. Finally, (d) compared with males, females are more willing to accept monitored jobs because they perceive lower privacy concerns over and higher payment protection from monitoring. Our further analyses show that the compensation required for gig workers to accept monitoring is \$1.6~\$1.8 per hour (\$1.4~\$1.7 per hour for females and \$1.9~\$2.0 per hour for males), which is a nonnegligible economic cost for employers.

Our study contributes to several streams of literature and provides important implications in the design of monitoring policies for employers on gig economy platforms. First, our study advances the extant literature on monitoring (Hubbard 2000, Duflo et al. 2012) by quantifying the effect of monitoring on wage cost in the gig economy context. Second, our study also contributes to the privacy literature. Although prior studies show that workers are uncomfortable with monitoring because of privacy concerns (Townsend and Bennett 2003, Brandimarte et al. 2013), it is unknown whether and to what extent they need to be compensated to accept monitoring given the well-documented discrepancy between privacy-related attitude and behavior (Acquisti et al. 2015). Third, our study provides important insights into the optimal design of monitoring policies for both employers and workers, in terms of intensity, transparency, and control. Finally, the heterogeneity in workers' WTAs for monitoring across gender advances our understanding of the heterogeneous compensation differentials for nonwage job amenities (Mas and Pallais 2017, Wiswall and Zafar 2018).

2. Theoretical Background

According to the privacy calculus theory (Culnan and Armstrong 1999, Jiang et al. 2013), workers' willingness to accept monitoring should depend on the trade-off between the perceived cost (i.e., privacy concerns) and benefit (i.e., payment protection). In this section, we draw on the literature and discuss how the intensity, transparency, and control of a monitoring policy may influence privacy concerns, perceived payment protection, and ultimately, workers' acceptance of monitoring.

2.1. Intensity

The intensity of monitoring refers to the volume and sensitivity of the information that is collected by the monitoring system. The intensity of monitoring may influence both privacy concerns and the perceived payment protection of workers as elaborated herein.

2.1.1. Intensity and Privacy Concerns. As the monitoring system collects more information from workers, especially sensitive information, the monitoring intensity increases. For instance, a monitoring policy that only tracks time is often considered low-intensity monitoring as it only records some basic, nonsensitive information. In contrast, monitoring that captures computer screenshots in addition to tracking time is often considered high-intensity monitoring as the screenshots may contain sensitive information about workers. When the monitoring system collects more (sensitive) information, individuals tend to have a stronger concern about their privacy being invaded (Gandy 1993). Moreover, individuals may perceive a higher vulnerability (Martin et al. 2017) because of the potential misuse of their data, such as personal data leakage, unauthorized secondary usage, or improper access of workers' private information. As such, workers' privacy concerns are likely to increase with the intensity of monitoring.

2.1.2. Intensity and Payment Protection. Monitoring is usually touted as a feature that offers payment protection by gig economy platforms, and gig workers generally share this point of view. According to a survey on participants from 25 different organizations by Stanton and Weiss (2000), some participants believed that monitoring helps ensure that their working hours are 100% billable. The level of workers' perceived payment protection depends on the extent and amount of recorded information that can serve as evidence of their work. When more detailed information is collected by the monitoring system, workers are likely more confident that the monitoring system records sufficient information to protect them from potential payment disputes (Moore and Hayes 2018). Therefore, the perceived payment protection is also expected to increase with the intensity of monitoring.

Given that both workers' privacy concerns and perceived payment protection are expected to increase with the intensity of monitoring, the impact of monitoring intensity on workers' overall attitude toward monitoring is unclear. Whether workers are more likely to accept monitored jobs when the intensity of monitoring increases depends on how workers trade off privacy concerns and perceived payment protection and the extent to which each perception changes with the increasing intensity of monitoring.

2.2. Transparency

Karwatzki et al. (2017, p. 372) argue that "transparency features give an overview and thus enhance the sense of which information is collected and how it could be used by organizations in an accessible and understandable way." In the context of monitoring, transparency refers to the disclosure of what information is collected and how it is collected. We discuss how transparency may influence workers' privacy concerns and perceived payment protection.

2.2.1. Transparency and Privacy Concerns. In the absence of transparency, workers face uncertainty regarding what and how data are collected, which may lead them to expect the worst (Friedland 1982). That is, when the monitoring policy is not disclosed, risk-averse workers tend to assume the intensity of the monitoring system to be high, elevating their privacy concerns. Therefore, the impact of transparency on workers' privacy concerns depends on the monitoring intensity. Specifically, when the monitoring intensity is low, being transparent about the monitoring policy can resolve unnecessary privacy concerns resulting from uncertainty about the monitoring policy. However, when the monitoring intensity is high, although a transparent monitoring policy resolves workers' uncertainty, it simply confirms workers' expectation of intense monitoring and, hence, may not be effective in alleviating their privacy concerns.

In addition to reducing uncertainty, transparency can also attenuate workers' privacy concerns by increasing the perceived procedural fairness of the monitoring policy. As suggested by Culnan and Armstrong (1999), the disclosure of data-collection practices (termed "notice") lies at the core of procedural fairness. The transparent disclosure of a monitoring policy, therefore, increases the perceived procedural fairness of the monitoring policy. Prior work shows that individuals tend to express lower privacy concerns when a data-collection practice is considered fair (Culnan and Armstrong 1999). As such, workers' privacy concerns may decrease with the transparency of the monitoring policy. However, it should be noted that workers' perception of procedural fairness also depends on whether they believe the information collected or used by the monitoring system is relevant, necessary, and appropriate (Alge 2001). When the information collected by the monitoring system is excessive or overly sensitive (i.e., when the monitoring intensity is high), transparency is not sufficient to justify the procedural fairness of the monitoring policy. Therefore, a transparent monitoring policy is expected to be more effective in alleviating privacy concerns when the monitoring intensity is low.

2.2.2. Transparency and Payment Protection. When the monitoring policy is opaque, workers are uncertain about what information is collected. Accordingly, they may be skeptical about whether the information recorded by the monitoring system can be used as evidence of their work, thereby leading to uncertainty of their compensation (Möhlmann et al. 2021). Conversely, a transparent monitoring policy provides workers the necessary information to evaluate whether the recorded information can protect them from payment disputes (Karwatzki et al. 2017). In particular, when the monitoring intensity is high, transparent disclosure can assure workers that the collected information is detailed enough to prevent unjustifiable rejection of their work. In this sense, workers may perceive stronger payment protection from a transparent monitoring policy than anontransparent one. However, when the monitoring intensity is low, being transparent is unlikely to increase the perceived payment protection because of the limited information tracked by the monitoring system. Therefore, transparency may only increase workers' perceived payment protection when the monitoring intensity is high.

Based on this discussion, the transparency of a monitoring policy may influence workers' acceptance of monitoring through two distinct and nuanced mechanisms. Specifically, when the monitoring intensity is high, the monitoring policy's transparency increases workers' perceived payment protection and, hence, increases their willingness to accept monitored jobs. When the monitoring intensity is low, the reduced uncertainty and improved procedural fairness resulting from transparency can effectively alleviate workers' privacy concerns, making workers more willing to accept monitored jobs.

2.3. Control

2.3.1. Control and Privacy Concerns. In the monitoring context, control means whether individuals have the "ability to modify characteristics of or eliminate the occurrence of monitoring" (Stanton 2000, p. 96). The provision of control allows workers to remove certain collected information that they are uncomfortable sharing with others, such as screenshots containing sensitive information. Building on the extant literature, we argue that providing control can alleviate workers' privacy concerns. First, the provision of control allows workers to remove information they are not willing to share with employers, which can greatly alleviate their concerns over the sharing of sensitive information. Second, psychologically, the provision of control also gives workers a sense of autonomy. With the autonomy to control the collection of their personal information, workers are less likely to perceive vulnerability (Martin et al. 2017), lowering their privacy concerns. Third, the provision of control can increase the perceived procedural fairness of the monitoring policy (Culnan and Armstrong 1999), which subsequently leads to lower privacy concerns (Alge 2001).

2.3.2. Control and Payment Protection. The provision of control may lower workers' perceived payment protection from monitoring because the removed information cannot be used as evidence of work. In addition, employers may become more skeptical about the monitoring records when workers have the right to cherry-pick the records to submit, which may also weaken workers' perceived payment protection. Nonetheless, the negative effect of control on payment protection, if any, is not expected to be particularly strong because workers have the right to keep any relevant information that can help them win potential disputes.

As the provision of control has the potential to reduce both privacy concerns and perceived payment protection, it is unclear whether and how control affects workers' acceptance of monitoring.

2.4. Gender Differences

Males and females may respond to monitoring differently because of gender differences in privacy concerns and perceived payment protection. The gender difference in privacy concerns is well-documented in the literature, albeit the findings vary across attitudes and behavior, which is also known as the privacy paradox (Acquisti et al. 2015). Specifically, when responding to hypothetical questions regarding privacy invasion, females are known to express higher privacy concerns than males (Hoy and Milne 2010). However, in terms of actual behavior, females are shown to disclose more private information than males on online platforms (Sheehan 1999, Hollenbaugh and Everett 2013) and online surveys (Kays et al. 2012). One potential explanation for the latter finding is that females tend to be more compliant than males (Sheehan 1999). Given that employers and workers may both potentially benefit from monitoring, it is possible that females may evaluate monitoring from a practical perspective of whether they should comply with monitoring and, hence, express lower privacy concerns over monitoring than males.

The potential gender difference in perceived payment protection depends on the gender difference in risk attitudes. Prior research suggests that females are more risk-averse than males in general (Fellner and Maciejovsky 2007, Croson and Gneezy 2009), especially when there is a safe option (Filippin and Crosetto 2016). Given that it is common for gig workers to get rejected for their work, the payment protection provided by monitoring may be perceived as a safe option that can protect them from potential payment disputes. As a result, females who are generally more risk-averse than males may perceive a higher level of payment protection from monitoring.

Because job choices reflect more about one's behavior than attitude, we expect the gender difference in behavior to play a larger role in gig workers' choices between monitored and unmonitored jobs, suggesting that females may be less concerned about monitoring policies. Considering that females may also perceive a higher level of payment protection from monitoring because of their stronger risk aversion, we expect that females are more likely to accept monitored jobs than males.

Table 1 summarizes how the perception and acceptance of monitoring may be influenced by the intensity, transparency, and control of monitoring policies as well as workers' gender.

3. Experimental Design

To answer our four research questions, we conduct two online experiments, one on AMT (https://www.mturk.com/) and one on Prolific (https://www.prolific.co/), using a realistic job screening process for an image-labeling task as the research context.[10] Gig economy platforms such as AMT and Prolific are ideal settings for this experiment because the subjects are real gig workers who receive compatible incentives in a realistic scenario (Chen and Horton 2016), and this allows us to accurately estimate the WTA for monitoring within this setting. We post a job screening survey on AMT/Prolific so that workers interested in the image-labeling task can take this survey, in which we ask them to choose between monitored and unmonitored image-labeling jobs at different wages. To investigate how workers' acceptance of monitoring varies with the design of the monitoring policy, we manipulate the monitoring policy in three dimensions. Next, we elaborate on how we manipulate the monitoring policy and the job wages as well as the overall design of the experiment.

3.1. Manipulation of Monitoring Policy

We manipulate the intensity, transparency, and control of monitoring and study how they affect workers' perception and acceptance of monitoring. Ideally, we would consider a 2 (high versus low intensity) × 2 (with versus without transparency) × 2 (with versus without control) full factorial design. However, some of the combinations are either infeasible or impractical. First, when the intensity of monitoring is relatively low (e.g., only working hours are tracked), it is impractical to provide control over the limited information collected (e.g., removing tracked hours is typically not an option to workers). Second, because the monitoring policy is not disclosed to workers in the no transparency condition, the level of monitoring intensity and the availability of control simply cannot be manipulated. Therefore, our experiments include four feasible monitoring conditions: without transparency, with transparency × low intensity × without control, with transparency × high intensity × without control, and with transparency × high intensity × with control.

Our experiments adopt a between-subjects discrete choice experimental design by randomly assigning workers to one of the four groups in our experiment: (a) the *no_disclosure* group, in which workers are *not* informed how they will be monitored; (b) the *only_time* group, in which workers are informed that their working hours are tracked but no computer screenshots are taken; (c) the *controlled_screenshots* group, in which workers are informed that both working hours and computer screenshots are recorded, but workers have the option to remove some screenshots; and (d) the *all_screenshots* groups, in which workers are informed that both working hours and computer screenshots are tracked and recorded screenshots cannot be removed. Table 2 shows how these four groups map to the four feasible monitoring conditions in the factorial design as well as the exemplary firms, institutions, or third-party monitoring apps that adopt each policy.

Before asking a worker to choose between a monitored and unmonitored job, we provide a tutorial

Table 1. Summary of Theoretical Predictions

Dimension	Privacy concerns	Payment protection	Job choice
Intensity	Increasing intensity can increase privacy concerns because a) Workers become more concerned about their privacy being invaded (Gandy 1993). b) Workers perceive a higher vulnerability (Martin et al. 2017) related to data misuse.	Increasing intensity can increase workers' perceived payment protection because a) More information that can serve as proof of work gets recorded (Moore and Hayes 2018).	a) Increasing the intensity of monitoring *decreases* workers' willingness to accept monitoring by increasing their privacy concerns. b) Increasing the intensity of monitoring *increases* workers' willingness to accept monitoring by increasing their perceived payment protection.
Transparency	The impact of transparency on privacy concerns depends on the monitoring intensity. a) When the intensity is *low*, transparency can alleviate privacy concerns because it can (i) avoid unnecessary privacy concerns resulting from uncertainty and (ii) increase the perceived procedural fairness of monitoring. b) When the intensity is *high*, transparency is not expected to alleviate privacy concerns because (i) the transparent disclosure confirms workers' concern about intense information collection, and (ii) transparency is not sufficient to justify the procedural fairness of intense monitoring.	The impact of transparency on perceived payment protection depends on the monitoring intensity. a) When the intensity is *high*, transparency can assure workers that the collected information is sufficient to protect them from payment disputes. b) When the intensity is *low*, transparency may not increase the perceived payment protection as only limited information is recorded as potential evidence.	a) When the monitoring intensity is *low*, being transparent about the monitoring policy *increases* workers' willingness to accept monitoring by reducing their privacy concerns. b) When the monitoring intensity is *high*, being transparent about the monitoring policy *increases* workers' willingness to accept monitoring by increasing their perceived payment protection.
Control	Providing control can reduce privacy concerns because a) It allows workers to remove sensitive information. b) It increases the perceived procedural fairness of monitoring (Culnan and Armstrong 1999, Alge 2001). c) Workers have a sense of autonomy (Martin et al. 2017).	Providing control can reduce workers' perceived payment protection because a) The removed information cannot be used as proof of work anymore. b) Employers may become more skeptical about the selective monitoring logs submitted by workers.	a) The provision of control *increases* workers' willingness to accept monitoring by reducing their privacy concerns. b) The provision of control *decreases* workers' willingness to accept monitoring by reducing their perceived payment protection.
Gender	Females may have *stronger* privacy concerns over monitoring than males because a) Females are more sensitive to potential privacy invasion (Sheehan 1999, Hoy and Milne 2010). Females may have *weaker* privacy concerns over monitoring than males because a) Females are more willing to disclose information on online platforms (Sheehan 1999, Hollenbaugh and Everett 2013). b) Females are more compliant (Sheehan 1999).	Females may perceive *stronger* payment protection from monitoring than males because a) Females tend to be more risk-averse (Fellner and Maciejovsky 2007, Croson and Gneezy 2009)	Females are *more* likely to accept monitoring than males because a) Females are more willing to disclose information on online platforms (Sheehan 1999, Hollenbaugh and Everett 2013). b) Females are more compliant (Sheehan 1999). c) Females may perceive stronger payment protection from monitoring.

Table 2. Design of Monitoring Policy Manipulations

		Without control	With control
With transparency	Low intensity	*only_time* (e.g., AMT, Harvest)	*N/A*
	High intensity	*all_screenshots* (e.g., EmpMonitor, StaffCop)	*controlled_screenshots* (e.g., Freelancer, Screenmeter)
Without transparency		*no_disclosure* (e.g., Uber, Food and Drug Administration[a])	

[a]See https://www.washingtonpost.com/world/national-security/fda-staffers-sue-agency-over-surveillance-of-personal-e-mail/2012/01/23/gIQAj34DbQ_story.html.

about the monitoring system that will be used for the image-labeling job. The tutorial is customized for each group. Table 3 summarizes how we introduce the monitoring system to workers randomly assigned to each group. The screenshots of different versions of tutorials used in the experimental interface are provided in Online Appendix A. To ensure that workers fully understand how the monitoring system works, at the bottom of the tutorial page, we added a question with statements about the monitoring policies to which they are assigned (e.g., "the monitoring app takes screenshots of your computer") and ask the workers to choose all correct statements except for workers in the *no_disclosure* group. Workers need to examine the correct answers before they can move to the next step. This step is designed to reduce the potential effect of any preexisting misconception regarding how a monitoring system works.

3.2. Manipulation of Wage Premium for Monitoring

We use a discrete choice experimental design to estimate workers' WTA (Mas and Pallais 2017, Hedegaard and Tyran 2018). Specifically, we ask the workers to choose between a monitored and an unmonitored job with different wage premiums for the monitored job. Note that the monitoring policy for the monitored job is randomly assigned independent of the wage premium. Following the wage difference randomization approach of Mas and Pallais (2017), we fix the hourly wage for the higher paid job and randomize the wage premium for monitoring by varying the hourly wage assigned to the lower paid job. The fixed wage for the higher paid job is called the maximum hourly wage. Assuming that the maximum hourly wage is \$10, to obtain a condition with a \$2 (−\$2) wage premium for monitoring, the hourly wages for the monitored and unmonitored jobs are set to \$10 (\$8) and \$8 (\$10), respectively. We discuss the maximum hourly wages used in our experiments in Section 3.3.

The wage premium for monitoring is randomly chosen from the range of −\$2 to \$5 at an interval of \$0.5. We allow the wage premium to be negative because highly risk-averse workers may prefer monitored jobs over unmonitored jobs because of the payment protection of monitoring. Ruling out the existence of such workers a priori could possibly render the estimated WTA unrepresentative of the whole population of workers. To assess whether this range covers the WTAs of most workers, we conducted a pilot test on 280 AMT workers. Among the 19 workers who were assigned to the condition with a \$5 wage premium for monitoring, all of them chose the monitored job, suggesting that the \$5 wage premium is high enough to ensure that all workers are willing to accept monitoring. Among the 21 workers who received a wage premium of −\$2 for the monitored job, only one worker chose the monitored job. This

Table 3. Operationalization of Different Monitoring Policies

Treatment group	Description of the monitoring system
no_disclosure	None
only_time	The monitoring system only tracks how long the employee works for the project. It does not take screenshots of the employee's computer.
controlled_screenshots	The monitoring system tracks how long the employee works for the project. Meanwhile, it takes screenshots of the employee's computer at regular or irregular time intervals when the employee is working. To protect the privacy of the employee, the employee may delete a few screenshots the employee does not feel comfortable to upload.
all_screenshots	The monitoring system tracks how long the employee works for the project. Meanwhile, it takes screenshots of the employee's computer at regular or irregular time intervals when the employee is working. Once those screenshots are taken, the employee cannot delete any screenshots.

finding suggests that −\$2 is an appropriate lower bound for WTA for monitoring.

Figure 1 provides an example of two job positions presented to a prospective worker with a zero wage premium for the monitored job. The order of monitored and unmonitored jobs is randomized to reduce the potential anchoring effect of the first option (Strack and Mussweiler 1997). To ensure that workers accurately report their job preferences, we inform them that their job preferences over monitored or unmonitored jobs will not affect their chances of being hired. In addition, the job preference question is designed to be a text entry question in which each worker needs to fill in the four-digit number of the worker's preferred position instead of a multichoice question. This design can help reduce the number of inattentive responses (Mas and Pallais 2017). As an additional attention check, we further ask workers whether they have chosen a monitored job at the end of the survey.

3.3. Overall Design

3.3.1. Study 1 on AMT. We now discuss the overall design and flow of our experiment. As shown in Figure 2, the job screening survey includes seven major steps. In the beginning, we collect demographic information about the prospective workers, including gender, race, education, work experience, and their average hourly wage from AMT. After that, we ask them to label a small sample of images and record their labeling speed and accuracy. The monitoring policy is manipulated in step 3 in which workers are randomly shown one of the four versions of the monitoring system tutorials listed in Table 3. After the monitoring tutorial, we ask workers whether they have been monitored at work in the past. In step 4, we ask workers to choose between a monitored job and an unmonitored job wherein the wage premium of the monitored job over the unmonitored job is randomly chosen from the range of −\$2 to \$5. Given that the median hourly wage of AMT workers is between approximately \$4 and \$5 (Adams and Berg 2017), we set the maximum hourly wage (i.e., the hourly wage for the higher paid job) to \$9. This ensures that, when the wage premium for the monitored job is at its maximum (\$5), the lower paid unmonitored job still receives \$4 per hour.

To investigate the mechanisms underlying the workers' choices between monitored and unmonitored jobs, we further ask the workers to answer a few questions regarding their privacy concerns over and perceived payment protection from the monitoring system in step 5. The set of items used to measure privacy concerns are adapted from the Global Information Privacy Concern Scale (Malhotra et al. 2004). Please refer to Online Appendix C for more details. To measure workers' perceived payment protection from monitoring, we ask workers to indicate to what extent they agree with the statement "Monitoring system can provide evidence of my effort" on a seven-point Likert scale.

Because the measurement of privacy concerns is highly sensitive to information cues (John et al. 2010, Acquisti et al. 2017), it is possible that workers' job choices in step 4 may influence their reported privacy concerns in step 5. To rule out the potential reverse causality between privacy concerns and job choices, we randomize the order of the job choice question and the privacy concern questions, which is known as a counterbalance design for serial order effects (Brooks 2012). In other words, the privacy concern is measured before the job choice for half of the workers and after the job choice for the other half; this allows us to rule out the concern that our findings are an artifact of potential serial order effects.

In step 6, workers are asked to finish a general cognitive ability test composed of four questions from ACT Work Keys,[11] a test commonly used to assess workers' cognitive capability in the workplace. In the last step, we ask workers to report whether they chose a monitored/unmonitored job as an attention check.

Figure 1. (Color online) An Example of Job Preference Question in Study 1

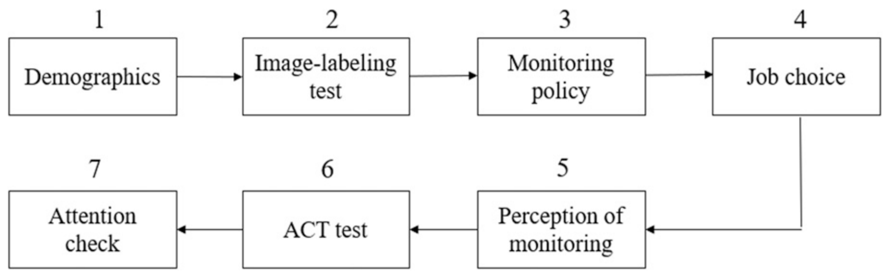
Suppose you are offered two positions described below, which one would you prefer?
It is crucial that you carefully read both job descriptions and correctly indicate your preference.

Administrative Assistant Position #1738
This is a part-time job. You may work from home with a flexible schedule of your own choice. You will be monitored while working on this job. This work pays 9 dollars per hour.

Administrative Assistant Position #1359
This is a part-time job. You may work from home with a flexible schedule of your own choice. You will NOT be monitored while working on this job. This work pays 9 dollars per hour.

Please specify your preferred position number (four digits) in the box below.

Figure 2. The Flow of the Experiment



In Online Appendix A, we provide screenshots for each step of the experiment.

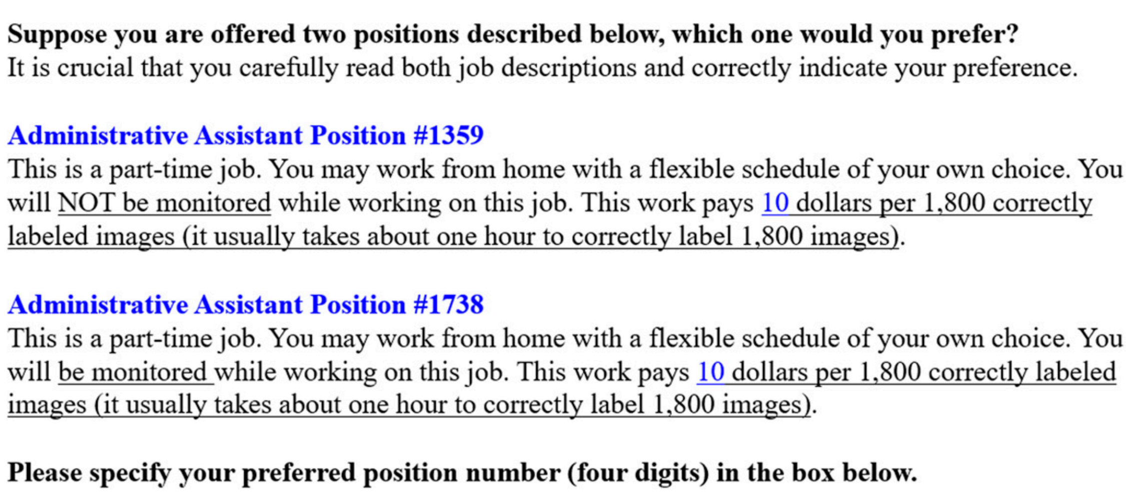
The WTA for monitoring may vary across countries because workers in different economic and cultural environments may have very different perceptions of monitoring. In this study, we seek to measure the WTA of workers in the United States. Therefore, we only allow workers from the United States to participate in the job screening survey. For quality control, we focus on workers who have finished more than 1,000 tasks on AMT and have an approval rate higher than 98%. Each worker can only participate in this survey once and receives \$0.80 as compensation for completing the survey.

Study 1 on AMT provides us evidence for how the three dimensions of the monitoring policy affect job choice and the mechanisms underlying those choices. After conducting Study 1, we seek to evaluate the replicability and generalizability of the findings to other platforms. Further, according to the prior literature on monitoring and moral hazard (Hubbard 2000, Duflo et al. 2012), different monitoring policies may affect workers' perception of how much effort is required to complete a monitored job, which may be a potential confounder. Therefore, in Study 2, we further investigate whether we find consistent results in a non-AMT platform after excluding the potential confounding effect of workers' perceived effort requirement.

3.3.2. Study 2 on Prolific. To replicate Study 1 and to establish the external validity of our findings, we conduct Study 2 on Prolific. Prolific is a popular gig platform for psychological and behavioral research and is recommended by many scholars (e.g., Peer et al. 2017, Palan and Schitter 2018). As suggested by Peer et al. (2017), workers on Prolific tend to be more diverse, naïve, and honest than those on AMT.

The design of Study 2 is similar to that of Study 1. Notably, however, to eliminate the concern that monitoring policies may affect workers' perceived effort required to complete a job, this second experiment on Prolific focuses on image-labeling jobs paid by outcome (i.e., the number of correctly labeled images) rather than by working hours. Figure 3 provides an example of the job preference question in Study 2. To ensure that the estimated WTA for monitoring from Study 2 can also be interpreted based on hourly wages, the jobs in Study 2 are described in a way that

Figure 3. (Color online) An Example of Job Preference Question in Study 2



Suppose you are offered two positions described below, which one would you prefer?
It is crucial that you carefully read both job descriptions and correctly indicate your preference.

Administrative Assistant Position #1359
This is a part-time job. You may work from home with a flexible schedule of your own choice. You will NOT be monitored while working on this job. This work pays 10 dollars per 1,800 correctly labeled images (it usually takes about one hour to correctly label 1,800 images).

Administrative Assistant Position #1738
This is a part-time job. You may work from home with a flexible schedule of your own choice. You will be monitored while working on this job. This work pays 10 dollars per 1,800 correctly labeled images (it usually takes about one hour to correctly label 1,800 images).

Please specify your preferred position number (four digits) in the box below.

is straightforward for workers to infer the effective hourly wages (e.g., the effective hourly wages of the two jobs in Figure 3 are both \$10).

We further optimize a few aspects of the experimental design for Prolific. We first narrow the range of wage premium of the monitored job over the unmonitored job to be between −\$1 and \$5 after learning from the AMT experiment that a rather small share of workers chose the monitored job when the wage premium for monitoring is negative. Further, given that the average hourly wage of Prolific workers is roughly \$1 higher than that of AMT workers, we increase the maximum hourly wage to \$10. Moreover, because our counterbalance design pertaining to the order of the privacy concern questions and the job choice questions in Study 1 suggests that our findings are not sensitive to the order of these two questions, we drop the counterbalance design in Study 2 and consistently measure the privacy scale after the job choice question. Similar to Study 1, we focus on U.S. workers who have finished more than 100 tasks on Prolific and have an approval rate higher than 98%.

We use the same set of questions as Study 1 to measure workers' privacy concerns. However, for perceived payment protection, because workers in Study 2 are paid by the number of correctly labeled images rather than working hours or other proxies of efforts, we instead ask the workers to indicate to what extent they agree with the statement "If I am monitored while working on the job, the information recorded by the monitoring system may help me on a potential dispute" on a seven-point Likert scale.

4. Empirical Models

4.1. Effects of Monitoring Policies on Job Preferences

We use a linear regression model to identify workers' trade-offs in selecting between an unmonitored job and a monitored job with randomly assigned wage premiums for monitoring and a randomly assigned monitoring policy. Equation (1) provides the estimation model on how the wage premium and monitoring policy affect workers' decisions to accept monitoring (or not).

$$choice_i = \beta_0 + \beta_1 wage\_premium_i + \beta_2 monitoring\_policy_i + \alpha \boldsymbol{X}_i + \varepsilon_i. \quad (1)$$

Here, we use i to index workers. The dependent variable $choice_i$ equals one if worker i chooses the monitored job and zero otherwise. The variable $monitoring\_policy_i$ denotes the monitoring policy for worker i and is represented by a set of dummies. The term $\boldsymbol{X}_i$ represents the demographic attributes of worker i, including gender, race, education, working experience, and average hourly wage on AMT/Prolific.

The linear regression model given by Equation (1) is usually referred to as a linear probability model (LPM) in that the dependent variable is binary. In addition to the LPM, we also consider a probit model to account for the binary nature of the dependent variable. As we show next, the probit model also allows us to estimate the economic cost of monitoring (i.e., WTA for monitoring).

4.2. WTA for Monitoring

In this section, we show how workers' WTA for monitoring can be estimated using a probit model. Given that workers' WTA for monitoring may depend on various factors, without loss of generality, we formulate the WTA of worker i as

$$WTA_i = \gamma \boldsymbol{X}_i + v_i, \quad (2)$$

where the random variable v_i represents the baseline WTA of worker i and $\boldsymbol{X}_i$ represents the set of variables that may affect the worker's WTA, including the monitoring policy assigned to worker i and demographic attributes of worker i.

A worker chooses the monitored job when the wage premium for the monitored job exceeds the worker's WTA for monitoring. Specifically, the probability that worker i chooses the monitored job is given by

$$P(choice_i = 1) = \Pr(wage\_premium_i - WTA_i > 0), \quad (3)$$

where WTA_i is given by Equation (2). Following the distributional assumption on v_i (i.e., $v_i \sim N(\mu, \sigma^2)$),

$$\begin{aligned} P(choice_i = 1) &= \Pr(wage\_premium_i - \gamma \boldsymbol{X}_i - v_i > 0) \\ &= \Phi\left(\frac{wage\_premium_i - \gamma \boldsymbol{X}_i - \mu}{\sigma}\right), \end{aligned} \quad (4)$$

where $\Phi(\cdot)$ represents the cumulative distribution function of the standard normal distribution.

Letting $\beta_1 = 1/\sigma$, $\beta_2 = -\gamma\beta_1$, and $\beta_0 = -\mu\beta_1$, we have

$$P(choice_i = 1) = \Phi(\beta_0 + \beta_1 wage\_premium_i + \beta_2 \boldsymbol{X}_i). \quad (5)$$

The set of parameters $\{\beta_0, \beta_1, \beta_2\}$ in Equation (5) can be estimated using a probit model, from which we can infer $\{\mu, \sigma, \gamma\}$. The latter set of parameters characterizes workers' WTA for monitoring. Therefore, these results suggest that we can infer the WTA for monitoring by estimating how the wage premium, monitoring policy, and demographic attributes affect workers' job choices.

5. Data and Results

5.1. Data Description

Our experiments on AMT and Prolific obtained 1,895 and 1,882 responses, respectively, after standard data processing steps.[12] Table 4 summarizes the descriptive

Table 4. Definition and Summary Statistics of Variables

		AMT				Prolific			
Variable	Definition	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum
choice	Dummy variable that equals one if the monitored job is chosen by the worker	0.46	0.50	0.00	1.00	0.55	0.50	0.00	1.00
no_disclosure	Dummy variable that equals one if the data-collection policy of the monitoring system is not disclosed	0.24	0.43	0.00	1.00	0.25	0.43	0.00	1.00
only_time	Dummy variable that equals one if the monitoring system only tracks time	0.26	0.44	0.00	1.00	0.25	0.43	0.00	1.00
controlled_screenshots	Dummy variable that equals one if the monitoring system tracks time and selective screenshots that workers are comfortable sharing	0.25	0.43	0.00	1.00	0.25	0.43	0.00	1.00
all_screenshots	Dummy variable that equals one if the monitoring system tracks time and all screenshots	0.25	0.43	0.00	1.00	0.25	0.43	0.00	1.00
male	Dummy variable that equals one if the worker is male	0.44	0.50	0.00	1.00	0.48	0.50	0.00	1.00
wage_premium	The wage premium of the monitored job over the unmonitored job	1.49	2.16	−2.00	5.00	1.94	1.82	−1.00	5.00
hourly_wage	The average hourly wage when working on AMT/Prolific	4.83	2.82	0.60	15.00	5.61	3.08	0.00	15.00
privacy	The average score in the privacy concern scale (measured on a seven-point Likert scale)	4.83	1.43	1.00	7.00	4.98	1.38	1.00	7.00
protection	To what extent the worker agrees that monitoring can provide payment protection (measured on a seven-point Likert scale)	5.50	1.36	1.00	7.00	5.25	1.34	1.00	7.00

Notes. As shown in Online Appendix D, the demographic distribution of AMT workers recruited by us closely resembles that of the AMT worker population in the United States. Randomization checks and the number of observations in each experiment group are provided in Online Appendix E.

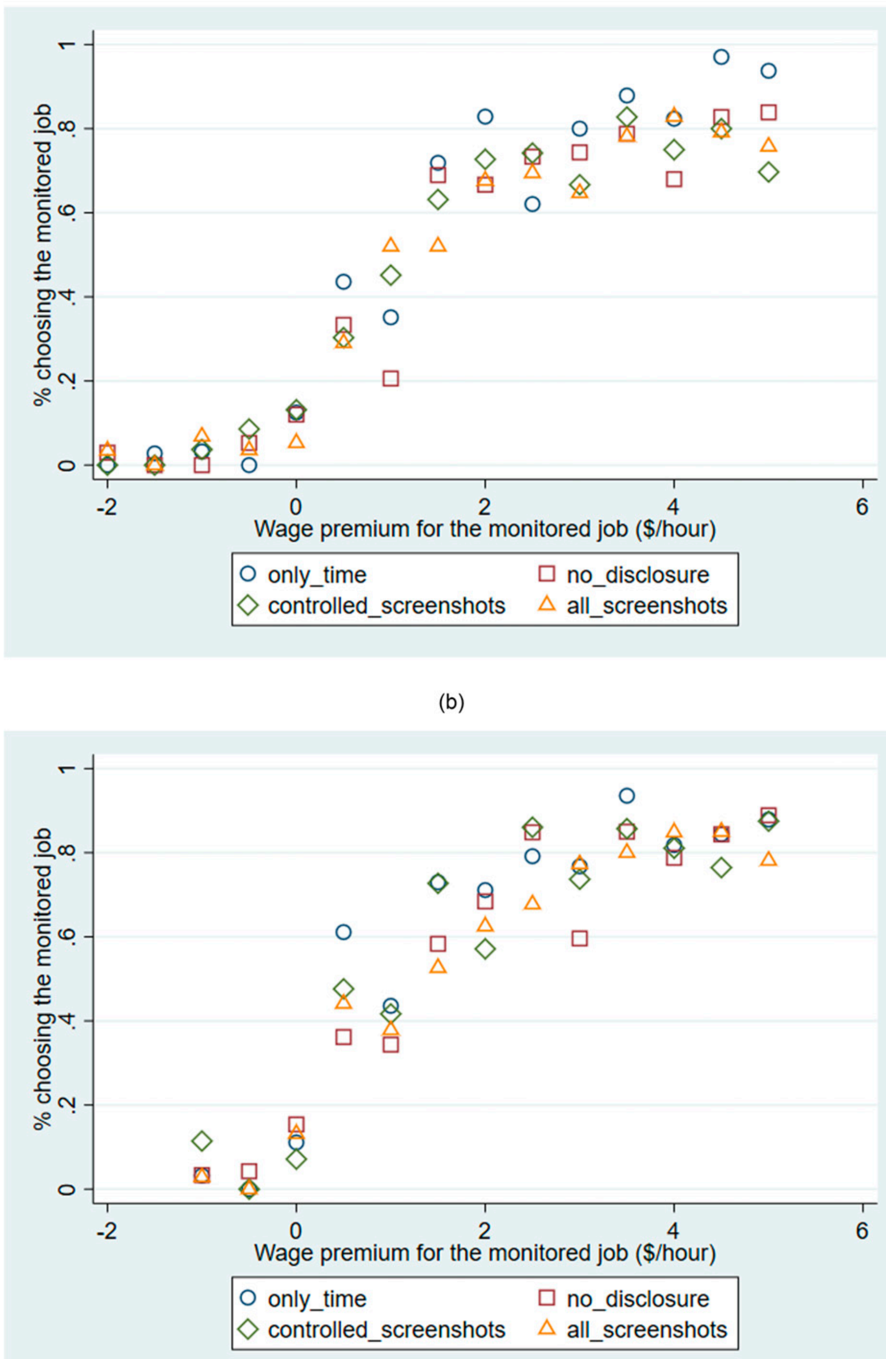
statistics of workers' job choices, the treatment variables (i.e., monitoring policy dummies), the wage premium for monitoring, the privacy concerns of the workers, the perceived payment protection of the workers, and several key demographic attributes of the workers.

Figure 4 shows how the percentage of workers choosing the monitored job varies with the wage premium of the monitored job under different monitoring policies on the two gig economy platforms.

As shown in Figure 4, (a) and (b), when the wage premium for the monitored job is negative, only a very small proportion of workers are willing to be monitored, indicating few workers value payment protection more than privacy concerns. When the

Figure 4. (Color online) Model-Free Evidence of the Impact of Monitoring Policy on Job Choices

(a)



Notes. (a) AMT. (b) Prolific.

wage premium for the monitored job is zero, roughly 10% of workers chose the monitored job on both AMT and Prolific. As the wage premium for the monitored job further increases, the percentage of workers choosing monitored jobs increases quickly with 73% (65%) of AMT (Prolific) workers choosing the monitored job at a wage premium of \$2/hour.

5.2. Treatment Effects

To examine the effects of intensity, transparency, and control on acceptance of monitoring, we contrast the four monitoring groups on different dimensions. Specifically, to understand the effect of intensity, we compare the *only_time* group that only tracks hours with the *all_screenshots* group that further takes screenshots. In addition, to study the effect of transparency under different monitoring intensities, we compare the *no_disclosure* group with two groups with transparent disclosure of the monitoring policy at low and high intensities, namely, the *only_time* and *all_screenshots* groups. Finally, to investigate the effect of control, we compare the *controlled_screenshots* group with the *all_screenshots* group. The only difference between these two groups is that the former gives workers control over the monitored records. Table 5 summarizes our strategy to estimate the effects of different dimensions of monitoring policies.

Next, we estimate the impact of each dimension of monitoring policy on workers' job choices using the LPM model given by Equation (1). As we estimate the effect of each dimension, we focus on the groups that are used for comparison.

5.2.1. Intensity. To investigate the effect of intensity on workers' acceptance of monitoring, we focus on workers in the *only_time* and *all_screenshots* groups, using the former as the reference group as it is the monitoring policy employed by popular gig platforms, such as AMT and Prolific. The LPM estimates, as specified in Equation (1), are reported in Table 6 for both the AMT and Prolific samples. Because the findings on both samples are highly consistent, our following discussion primarily focuses on the AMT sample.

As shown in column (1) of Table 6, workers are more willing to choose the monitored job as the wage premium increases. Moreover, all else equal, workers in the *all_screenshots* group are significantly less likely to choose the monitored job than those in the *only_time* group, suggesting that workers are less likely to choose monitored jobs as the intensity of monitoring increases. The effect of intensity on acceptance of monitoring is not only statistically significant, but also economically significant. Taking the AMT sample as an example, when working hours are tracked, further taking computer screenshots decreases the probability of workers choosing the monitored job by 6.7%, which needs to be compensated by a \$0.45/hour increase in the wage premium for the monitored job ($-0.067/0.150 = -0.45$, where -0.067 and 0.150 are the coefficients of *all_screenshots* and *wage_premium* in column (1) of Table 6). That is, workers demand \$0.45/hour more for them to accept a monitored job with a higher intensity. Similarly, in the Prolific sample, the effect of taking computer screenshots needs to be compensated by a \$0.48/hour increase in the wage premium for the monitored job ($-0.072/0.149 = -0.48$).

To delve into the mechanisms underlying the treatment effect of intensity, we examine how intensity influences workers' privacy concerns and perceived payment protection. To that end, we estimate two linear regression models similar to Equation (1) except that we replace the dependent variable with workers' privacy concerns and perceived payment protection, respectively. The results from these two models are reported in columns (2) and (3) of Table 6 for the AMT sample and columns (6) and (7) for the Prolific sample. The coefficients of *all_screenshots* in these columns suggest that increasing intensity significantly increases workers' privacy concerns but not their perceived payment protection. This finding is consistent with our argument that privacy concerns increase with intensity but do not support the expectation that workers' perceived payment protection increases with intensity.

To investigate whether privacy concerns and perceived payment protection mediate the effects of monitoring policies on workers' acceptance of monitoring as discussed in Section 2, we further estimate an LPM that controls for workers' privacy concerns and perceived payment protection. The results of this model on the AMT and Prolific samples are reported in columns (4) and (8) of Table 6, respectively. In line with

Table 5. Monitoring Groups Used to Estimate the Effects of Intensity, Transparency, and Control

Dimension of monitoring	Groups used for comparison
Intensity	*only_time* versus *all_screenshots*
Transparency	*no_disclosure* versus *only_time* (low intensity)
	no_disclosure versus *all_screenshots* (high intensity)
Control	*all_screenshots* versus *controlled_screenshots*

Notes. We perform a manipulation check on Prolific, which demonstrates that workers' perception of monitoring in the groups used for comparison differs on the corresponding dimension of monitoring. The details are reported in Online Appendix B.

Table 6. Effects of Intensity on Perception and Acceptance of Monitoring

	AMT				Prolific			
	Choice (1)	Privacy (2)	Protection (3)	Choice (4)	Choice (5)	Privacy (6)	Protection (7)	Choice (8)
all_screenshots	−0.067***	0.194**	0.099	−0.055**	−0.072***	0.204**	0.065	−0.053**
	(0.025)	(0.092)	(0.089)	(0.023)	(0.027)	(0.091)	(0.086)	(0.024)
male	−0.071***	0.275***	−0.109	−0.043*	−0.070***	0.115	−0.173**	−0.048*
	(0.025)	(0.094)	(0.091)	(0.023)	(0.027)	(0.092)	(0.087)	(0.024)
wage_premium	0.150***	−0.083***	0.024	0.142***	0.149***	−0.029	0.025	0.145***
	(0.006)	(0.021)	(0.021)	(0.005)	(0.007)	(0.025)	(0.024)	(0.007)
privacy				−0.084***				−0.111***
				(0.008)				(0.009)
protection				0.044***				0.054***
				(0.008)				(0.009)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	966	966	966	966	941	941	941	941
R^2	0.440	0.076	0.032	0.525	0.334	0.038	0.040	0.464

Notes. The reference group is *only_time*. The control variables include workers' education, race, working experience, average hourly wage on the platform, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we exclude worker-level control variables or when we use probit instead of LPM models for workers' job choices.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

our expectation, we find that privacy concerns have a negative effect on the acceptance of monitoring, whereas perceived payment protection has a positive effect. To better understand the mediation roles of privacy concerns and payment protection, we use the bootstrap approach with a bias-corrected 95% confidence interval (CI) to estimate mediation effects (Hayes and Scharkow 2013). The bias-corrected CI accounts for the bias (the median of bootstrap estimates can be a biased estimate of population median) and skewness of bootstrap estimates. This approach is recommended to test mediation effects when power is the utmost concern (Hayes and Scharkow 2013). We report the results in Table 7, and they suggest that only privacy concerns play a statistically significant mediation role. The mediation effect of perceived payment protection is not significantly likely because the effect of intensity on perceived payment protection is not significant in columns (3) and (7) of Table 6. It is worth noting that, because workers' privacy concerns and perceived payment protection are both measured posttreatment, the estimated mediation effects may not be causal.

5.2.2. Transparency. As indicated in Table 5, to estimate the effect of transparency on workers' perception and acceptance of monitoring, we focus on workers in three groups: *no_disclosure*, *only_time*, and *all_screenshots*. We use *no_disclosure* as the reference group as the other two groups both presume transparent disclosure of the monitoring policy. The regression results on the transparency dimension are summarized in Table 8, and they are structured in a similar way as the results on the intensity dimension. The positive and significant coefficient of *only_time* in columns (1) and (5) of Table 8 suggests that, when the monitoring intensity is low, disclosing the monitoring policy transparently can increase workers' propensity to choose monitored jobs. However, the insignificant coefficient of *all_screenshots* in these two columns suggests that transparent disclosure does not significantly increase workers' willingness to accept monitored jobs when the monitoring intensity is high. These findings confirm our expectation that transparency increases the acceptance of monitoring only when the monitoring intensity is low. This analysis shows that the effectiveness of transparency is nuanced, contingent on monitoring intensity, which extends prior studies that show the general desirability of the transparency of companies' data practices and information policies to workers (Foxman and Kilcoyne 1993, Acquisti et al. 2015).

The coefficients of *only_time* and *all_screenshots* in columns (2) and (6) show that transparency significantly reduces privacy concerns when the monitoring intensity

Table 7. Mediation Analysis on Intensity

	AMT		Prolific	
	Estimate	Bias-corrected bootstrap 95% CI	Estimate	Bias-corrected bootstrap 95% CI
Mediation effect through privacy	−0.016	(−0.033, −0.001)	−0.022	(−0.044, −0.003)
Mediation effect through protection	0.004	(−0.003, 0.014)	0.003	(−0.005, 0.013)

Table 8. Effects of Transparency on Perception and Acceptance of Monitoring

	AMT				Prolific			
	Choice (1)	Privacy (2)	Protection (3)	Choice (4)	Choice (5)	Privacy (6)	Protection (7)	Choice (8)
only_time	0.065***	−0.259***	0.059	0.038*	0.068**	−0.236***	0.199**	0.033
	(0.025)	(0.092)	(0.088)	(0.023)	(0.027)	(0.089)	(0.087)	(0.024)
all_screenshots	0.002	−0.064	0.155*	−0.010	−0.004	−0.040	0.264***	−0.022
	(0.025)	(0.093)	(0.088)	(0.023)	(0.027)	(0.090)	(0.088)	(0.024)
male	−0.054***	0.188**	−0.168**	−0.029	−0.092***	0.081	−0.146**	−0.076***
	(0.021)	(0.076)	(0.073)	(0.019)	(0.022)	(0.074)	(0.072)	(0.020)
wage_premium	0.149***	−0.079***	0.035**	0.140***	0.152***	−0.054***	0.022	0.145***
	(0.005)	(0.017)	(0.017)	(0.004)	(0.006)	(0.020)	(0.020)	(0.005)
privacy				−0.094***				−0.108***
				(0.007)				(0.007)
protection				0.044***				0.050***
				(0.007)				(0.008)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,422	1,422	1,422	1,422	1,407	1,407	1,407	1,407
R^2	0.430	0.061	0.041	0.527	0.340	0.035	0.027	0.456

Notes. The reference group is *no_disclosure*. The control variables include workers' education, race, working experience, average hourly wage on the platform, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we exclude worker-level control variables or when we use probit instead of LPM models for workers' job choices.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

is low but not when the intensity is high. This finding confirms our earlier arguments that transparency is effective in alleviating privacy concerns only when the monitoring intensity is low. In addition, the significant and positive coefficients of *all_screenshots* in columns (3) and (7) suggest that, when the monitoring intensity is high, being transparent can increase workers' perceived payment protection. Nevertheless, when the monitoring intensity is low, the effects of transparency on perceived payment protection are mixed and inconclusive, that is, insignificant on AMT and significant on Prolific. Overall, the differential effects of transparency on the perception and acceptance of monitoring under low and high monitoring intensities are consistent with our expectations.

Table 9 reports the estimated mediation effects of privacy concerns and perceived payment protection with bias-corrected bootstrap CIs. When the monitoring intensity is low, transparency significantly increases workers' willingness to accept monitored jobs by lowering their privacy concerns. Meanwhile, when the monitoring intensity is high, transparency significantly increases workers' propensity to choose monitored jobs through increasing their perceived payment protection. These two mediation patterns demonstrate that the effects of transparency on workers' acceptance of monitoring are governed by different mechanisms for low- and high-intensity monitoring as summarized in Table 1.

The mediation analyses in Tables 7 and 9 show that the mediation effect of privacy concerns is generally much larger than that of payment protection. This finding suggests that privacy concerns may play a more pronounced mediation role than perceived payment protection in influencing workers' job choices.

5.2.3. Control. To examine the effect of providing control on workers' perception and acceptance of monitoring, we focus on the *all_screenshots* and *controlled_-screenshots* groups. We use the *all_screenshots* group as the reference group, which does not offer control. Table 10 summarizes the effects of control on workers' perception and acceptance of monitoring. Notably, although there are many reasons to believe that providing control over monitored information can lower workers' privacy concerns (e.g., the ability to remove sensitive information, the sense of autonomy, and the

Table 9. Mediation Analysis on Transparency

		AMT		Prolific	
		Estimate	Bias-corrected bootstrap 95% CI	Estimate	Bias-corrected bootstrap 95% CI
Low intensity	Mediation effect through privacy	0.024	(0.007, 0.043)	0.025	(0.006, 0.043)
	Mediation effect through protection	0.003	(−0.006, 0.010)	0.010	(0.002, 0.020)
High intensity	Mediation effect through privacy	0.006	(−0.010, 0.023)	0.004	(−0.014, 0.024)
	Mediation effect through protection	0.007	(0.0001, 0.016)	0.013	(0.004, 0.023)

Table 10. Effects of Control on Perception and Acceptance of Monitoring

	AMT				Prolific			
	Choice (1)	Privacy (2)	Protection (3)	Choice (4)	Choice (5)	Privacy (6)	Protection (7)	Choice (8)
controlled_screenshots	0.004	0.093	−0.125	0.019	0.035	−0.101	−0.105	0.029
	(0.026)	(0.092)	(0.088)	(0.024)	(0.027)	(0.092)	(0.087)	(0.024)
male	−0.055**	0.137	−0.128	−0.036	−0.068**	0.229**	−0.243***	−0.028
	(0.026)	(0.091)	(0.088)	(0.024)	(0.027)	(0.092)	(0.088)	(0.025)
wage_premium	0.137***	−0.027	0.017	0.133***	0.153***	−0.066***	−0.016	0.146***
	(0.006)	(0.021)	(0.020)	(0.006)	(0.007)	(0.025)	(0.024)	(0.007)
privacy				−0.095***				−0.115***
				(0.009)				(0.009)
protection				0.047***				0.054***
				(0.009)				(0.009)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	948	948	948	948	941	941	941	941
R^2	0.369	0.056	0.041	0.470	0.324	0.035	0.033	0.465

Notes. The reference group is *all_screenshots*. The control variables include workers' education, race, working experience, average hourly wage on the platform, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we exclude worker-level control variables or when we use probit instead of LPM models for workers' job choices.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

perceived procedural fairness), the estimated effect is not significant on either platform. One likely reason for this insignificant finding is that the option to remove sensitive screenshots also reminds workers that the monitoring system may collect sensitive information, which is known as the cueing effect (John et al. 2010, Acquisti et al. 2017). An alternative reason is that the level of control offered by the option to remove sensitive screenshots may not be sufficient to alleviate privacy concerns. To empirically test these two explanations, we conduct a supplementary experiment on AMT and randomly assign workers into the *controlled_screenshots* or *all_screenshots* group. The supplementary experiment follows an identical design as our main experiment on AMT except that we add additional questions regarding workers' perceived monitoring intensity, transparency, and control. The results lend support to the first explanation that the cueing effect cancels out the negative effect of control on privacy concerns. Although workers perceive a significantly higher level of control in the *controlled_screenshots* group, they also report a significantly higher level of privacy concerns after accounting for the impact of perceived control. The details of the supplementary experiment are reported in Online Appendix G.

The coefficients of *controlled_screenshots* in columns (3) and (6) show that the provision of control has no significant effect on workers' perceived payment protection either. This finding is not particularly surprising as the provision of control does not deprive workers' rights to retain relevant information that can help them in potential payment disputes. Given that the provision of control has no significant effects on either privacy concerns or payment protection, it is understandable that the effect of control on workers' job choices is also not significant.

5.2.4. Comparison of Monitoring Policies. To facilitate the comparison of different monitoring policies, Figure 5 visualizes the predicted probabilities for a worker with average characteristics to choose the monitored job at a $2/hour wage premium for monitoring (the average wage premium in Study 2) under different monitoring policies. Because we use an LPM, the difference in the predicted probabilities for any two groups is the same as the difference in average treatment effects of the two groups. A higher predicted probability to choose the monitored job indicates a higher level of acceptance for a particular monitoring policy. Figure 5 shows that workers' relative acceptance levels of different monitoring policies are consistent across AMT and Prolific. In addition to estimating the effects of monitoring policy dimension by dimension, as summarized in Table 5, we also estimate the effects of different monitoring policies using a full sample analysis on all four monitoring policies. This analysis yields identical findings, and the detailed results are reported in Online Appendix F.

5.3. Gender Differences

Given the mixed findings regarding gender differences in privacy concerns in the literature, we conduct several additional analyses to examine the gender differences in workers' perception and acceptance of monitoring. As reported in Table 11, on average, males are less likely to accept monitoring than females

Table 11. Gender Difference in Perception and Acceptance of Monitoring

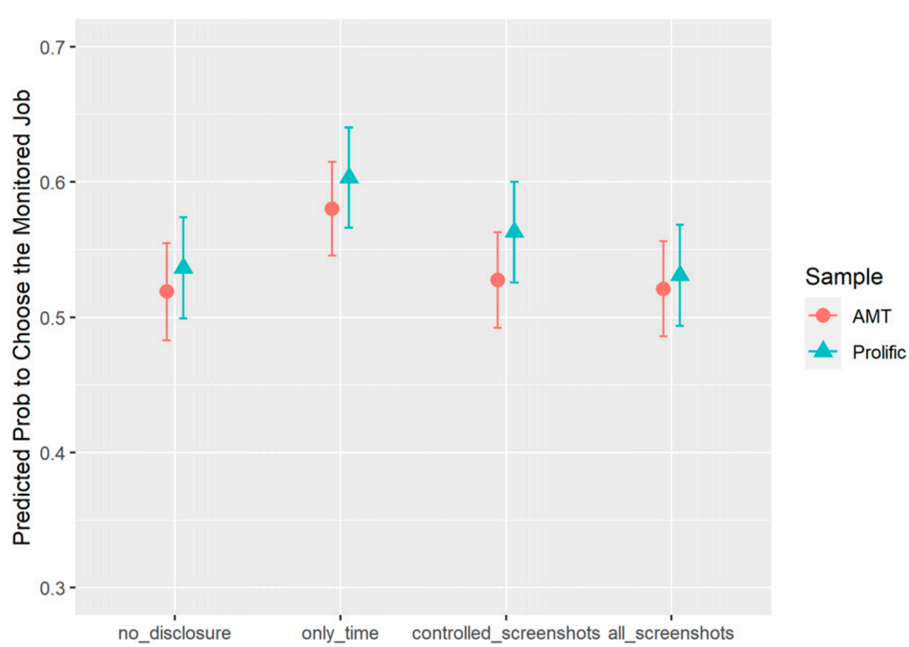
	AMT				Prolific			
	Choice (1)	Privacy (2)	Protection (3)	Choice (4)	Choice (5)	Privacy (6)	Protection (7)	Choice (8)
male	−0.037**	0.119*	−0.120*	−0.019	−0.081***	0.124*	−0.172***	−0.058***
	(0.018)	(0.066)	(0.063)	(0.017)	(0.019)	(0.064)	(0.062)	(0.017)
no_disclosure	−0.061**	0.254***	−0.064	−0.034	−0.067**	0.237***	−0.197**	−0.030
	(0.025)	(0.092)	(0.088)	(0.023)	(0.027)	(0.089)	(0.087)	(0.024)
controlled_screenshots	−0.053**	0.282***	−0.033	−0.024	−0.040	0.094	−0.047	−0.027
	(0.025)	(0.091)	(0.087)	(0.023)	(0.027)	(0.089)	(0.087)	(0.024)
all_screenshots	−0.059**	0.195**	0.092	−0.045**	−0.072***	0.199**	0.063	−0.054**
	(0.025)	(0.090)	(0.087)	(0.023)	(0.027)	(0.089)	(0.087)	(0.024)
wage_premium	0.145***	−0.058***	0.024*	0.139***	0.153***	−0.062***	0.006	0.146***
	(0.004)	(0.015)	(0.014)	(0.004)	(0.005)	(0.017)	(0.017)	(0.005)
privacy				−0.094***				−0.109***
				(0.006)				(0.006)
protection				0.049***				0.054***
				(0.006)				(0.007)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,895	1,895	1,895	1,895	1,882	1,882	1,882	1,882
R^2	0.407	0.053	0.035	0.509	0.329	0.029	0.020	0.452

Notes. The reference group is *only_time*. The control variables include workers' education, race, working experience, average hourly wage on the platform, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we exclude worker-level control variables or when we use probit instead of LPM models for workers' job choices.

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

on both AMT and Prolific. The gender difference in acceptance of monitoring is aligned with the gender differences in privacy concerns and perceived payment protection. Specifically, we find that males report a higher level of privacy concerns than females, which is consistent with males' stronger intention to protect their privacy than females when making actual decisions pertaining to privacy (Sheehan 1999, Hollenbaugh and Everett 2013). In addition, we find that females perceive a higher level of payment protection from monitoring than males, which is consistent with the prior findings that females are generally more risk-

Figure 5. (Color online) Predicted Probability to Choose the Monitored Job by Monitoring Policy



Notes. The predicted probabilities to choose the monitored job by monitoring policy are estimated when the wage premium for monitoring is \$2/hour and all the worker characteristics are set to the sample means. Error bars represent 95% CIs.

averse than males (Fellner and Maciejovsky 2007, Croson and Gneezy 2009). The lower privacy concerns and higher payment protection reported by females well explain why females are more willing to accept monitored jobs than males.

5.4. WTA for Monitoring

To help employers make more informed decisions regarding whether they should adopt monitoring and which monitoring policy to implement, it is important to estimate the economic cost of monitoring, namely, workers' WTA for monitoring. We estimate workers' WTA for monitoring based on the identification strategy discussed in Section 4.2. We report the WTA for each monitoring policy as well as its bootstrap CI in Table 12.

On average, the WTA for the four monitoring policies is \$1.8/hour for AMT workers and \$1.6/hour for Prolific workers, which, respectively, amount to 37.5% and 28.6% of their average hourly wages (\$4.8 for AMT workers and \$5.6 for Prolific workers). Consistent with the earlier findings that increasing transparency (when the intensity is low) and lowering intensity both increase workers' acceptance of monitoring, workers' WTA is the lowest for the *only_time* monitoring policy, which has a low intensity and a high transparency. This finding explains why many popular gig economy platforms (e.g., AMT and Prolific) employ the *only_time* monitoring policy.

The WTA of workers in the *no_disclosure* group is significantly higher than that of workers in the *only_time* group but not significantly different from those of workers in the *controlled_screenshots* and *all_screenshots* groups. Thus, in contrast to the conventional wisdom that improving transparency can lower the resistance to monitoring (Culnan and Armstrong 1999, Karwatzki et al. 2017), we find that transparent disclosure is not helpful when the monitoring intensity is high, albeit it is still beneficial when the monitoring intensity is low.

Moreover, workers' WTA in the *no_disclosure* group is closest to that in the *all_screenshots* group on both AMT and Prolific. One potential explanation is that workers tend to assume the worst when they face ambiguity or uncertainty (Friedland 1982). To verify whether this explanation is plausible, at the end of the experiment in Study 2, we ask all the workers in the *no_disclosure* group how they think they would be monitored if they chose the monitored job, and 51% (83%) of them expected their screenshots (working hours) to be recorded, which suggests that the majority of workers assume intense monitoring in the absence of transparency. Therefore, employers are encouraged to be more transparent about the monitoring policy when the intensity is low.

We further estimate workers' WTAs for monitoring that can be attributed to privacy concerns and perceived payment protection by adding them as two extra regressors in Equation (2). For workers in each group, the WTA explained by privacy concerns (perceived payment protection) is calculated as the difference in predicted WTAs for workers with average and no privacy concerns (perceived payment protection). The WTAs explained by privacy concerns (perceived payment protection) for different groups are reported in the second (third) column of Table 12. Workers' WTA explained by privacy concerns is the lowest in the *only_time* group, in line with the lowest privacy concerns perceived by workers in this group. On the other hand, the WTA explained by perceived payment protection is the highest for workers in the *all_screenshots* group, which is again not surprising as this monitoring policy records more information than other groups.

In line with the finding that females are more likely to choose monitored jobs than males, we find that females have lower WTA for monitoring than males. Among workers on AMT (Prolific), the average WTAs

Table 12. WTA for Monitoring

Sample: AMT	Average WTA	WTA explained by privacy concerns	WTA explained by payment protection
only_time	1.38 (1.13, 1.64)	3.65 (3.21, 4.14)	−2.25 (−2.85, −1.64)
no_disclosure	1.98 (1.72, 2.25)	3.82 (3.36, 4.33)	−2.23 (−2.83, −1.63)
controlled_screenshots	1.87 (1.61, 2.13)	3.86 (3.39, 4.37)	−2.23 (−2.82, −1.62)
all_screenshots	2.00 (1.69, 2.28)	3.81 (3.34, 4.32)	−2.29 (−2.90, −1.66)
Sample: Prolific	Average WTA	WTA explained by privacy concerns	WTA explained by payment protection
only_time	1.22 (0.96, 1.48)	4.01 (3.45, 4.61)	−2.47 (−3.03, −1.94)
no_disclosure	1.73 (1.49, 2.01)	4.21 (3.62, 4.84)	−2.38 (−2.92, −1.87)
controlled_screenshots	1.51 (1.24, 1.77)	4.10 (3.52, 4.71)	−2.45 (−3.00, −1.92)
all_screenshots	1.78 (1.52, 2.04)	4.19 (3.60, 4.81)	−2.50 (−3.07, −1.96)

Notes. 95% CIs based on 1,000 bootstraps are reported in parentheses. Workers' WTA explained by payment protection is negative, implying that payment protection has a positive value for workers. For each monitoring policy, the sums of the values in columns (2) and (3) are slightly different from the value in column (1). Such differences represent the portion of WTA that cannot be explained by privacy concerns or perceived payment protection. The unexplained WTA is not significantly different from zero in any of the four monitoring groups.

for monitoring are \$1.71/hour (\$1.33/hour) for females and \$1.92/hour (\$1.83/hour) for males.

5.5. Robustness Checks

We conduct a series of robustness checks for our analyses. Because of page limits, we report the results of these analyses in the online appendices. First, to rule out the possibility that our findings are driven by inattentive responses, we estimate models that explicitly account for inattention and find that the results are consistent (Online Appendix H). Second, to rule out the potential reverse causality between job choices and privacy concerns, we run a subsample analysis on workers whose privacy concerns are measured before their job choices and find a consistent mediation pattern (Online Appendix I). Third, we show that results are consistent when we use principal component analysis to construct the measure for privacy concerns (Online Appendix J).

6. Discussion and Conclusion

Given the challenge of quantifying the hidden cost of workers' resistance to monitoring, employers may overestimate the benefit of monitoring by primarily focusing on the improvement in worker productivity. To help employers make informed decisions about whether to adopt monitoring and how to design monitoring policies, we make a first attempt to comprehensively investigate how different designs of monitoring policies affect gig workers' perception and acceptance of monitoring as well as to quantify the economic cost of monitoring (i.e., WTA for monitoring) through online experiments on two gig economy platforms (AMT and Prolific).

We consider four monitoring policies that differ in intensity, transparency, and control, and they correspond to three common industry practices to alleviate workers' privacy concerns and lower their resistance against monitoring, respectively. We find that, as the monitoring intensity increases, workers become less likely to accept monitored jobs because of elevated privacy concerns. Furthermore, we find that transparent disclosure of the monitoring policy can increase workers' willingness to accept monitored jobs, but only when the monitoring intensity is low. When the monitoring intensity is high, although transparency can increase workers' perceived level of payment protection, it does not significantly reduce workers' privacy concerns or increase workers' willingness to accept monitored jobs. Interestingly, providing control over monitored information, a policy designed to address workers' concerns over the sharing of sensitive information (Xu et al. 2012, Brandimarte et al. 2013) is not effective in reducing workers' privacy concerns over high-intensity monitoring. As a result, providing control has no significant effect on workers' willingness to accept monitored jobs. Finally, we observe gender differences in the perception and acceptance of monitoring. Specifically, compared with males, females sense stronger payment protection from monitoring and yet have lower privacy concerns over monitoring, rendering them more willing to accept monitored jobs.

Our findings have important managerial implications. First, implementing monitoring can add a nonnegligible labor cost. On average, the hourly wage compensation required for gig workers to accept monitoring is 1.6~1.8 dollars, which amounts to roughly 28.6%~37.5% of their average hourly wage. Therefore, when deciding whether to deploy employee monitoring, employers should take this cost into account. Second, the economic cost associated with monitoring depends on the design of monitoring policies (i.e., the intensity of monitoring, the transparency of the monitoring policy, and workers' control over the monitored records) and the gender composition of gig workers. Finally, employers should carefully weigh these factors when designing a monitoring policy. Our results suggest that (1) increasing the monitoring intensity increases workers' resistance against monitoring; (2) improving transparency is an effective strategy to reduce gig workers' resistance against monitoring but only when the monitoring intensity is low; (3) although the provision of control is strongly advocated by both researchers and practitioners, we do not find it to be useful in reducing gig workers' resistance against monitoring; and (4) to reduce workers' resistance against monitoring, employers should place a stronger emphasis on monitoring policies that alleviate workers' privacy concerns compared with those that increase workers' perceived payment protection as workers' decisions seem to be primarily driven by privacy concerns.

This work has several limitations, which open ample opportunities for future research. First, our study focuses on the monitoring of gig workers. Regular employees in the traditional workplace may react to monitoring differently. On the one hand, they might be more willing to accept monitoring than gig workers as more is at stake. On the other hand, they are generally less wage-sensitive than gig workers and, hence, may be less tolerant of monitoring. Investigating the differences between gig workers and regular employees in terms of their perception and acceptance of monitoring can be a promising future direction. Second, our online experiments are conducted in the image-labeling context, and it is a common and relatively easy task to monitor. Future research can investigate the effect of the monitoring policy on other types of more sophisticated jobs, such as software development, and jobs that involve creative processes, such as graphic design and writing. Third, although the estimated effects of monitoring policies on workers' perception and acceptance of monitoring have causal interpretations, the mediators measured in our experiments could be endogenous because they are measured posttreatment (Peng 2022); therefore, cautions need to be exercised when readers interpret the estimated mediation effects. Finally, there are new advances in monitoring technologies that are not fully reflected in the design of the two experiments reported in this study. For instance, Upwork recently started allowing employers to use webcams to monitor workers in addition to tracking hours and taking computer screenshots. Future studies can investigate how workers react to such highly intrusive monitoring practices.

Acknowledgments

The authors thank the senior editor Alessandro Acquisti, the associate editor Idris Adjerid, and the anonymous reviewers for their constructive comments throughout the review process. The authors also thank Basit Zafar and the participants at the 2019 Conference on Digital Experimentation and the 2019 Conference on Information Systems and Technology for their helpful suggestions.

Endnotes

[1] See https://time.com/5836868/gig-economy-coronavirus/.

[2] See https://www.cnn.com/2020/04/23/tech/instacart-hiring-workers/index.html.

[3] See https://hbr.org/2020/07/gig-workers-are-here-to-stay-its-time-to-give-them-benefits.

[4] See https://www.invoiceberry.com/blog/stiffed-last-time-ensuring-get-paid-freelancer/.

[5] See https://support.upwork.com/hc/en-us/articles/211064038-About-the-Desktop-App.

[6] See https://www.cnbc.com/2019/03/22/uber-faces-fresh-legal-challenge-over-driver-data.html.

[7] See https://www.eff.org/deeplinks/2020/06/inside-invasive-secretive-bossware-tracking-workers.

[8] See more on the White House Consumer Privacy Bill of Rights (https://obamawhitehouse.archives.gov/sites/default/files/privacy-final.pdf) and Federal Trade Commission's Privacy Framework and Implementation Recommendations (https://www.ftc.gov/sites/default/files/documents/reports/federal-trade-commission-report-protecting-consumer-privacy-era-rapid-change-recommendations/120326privacyreport.pdf).

[9] Uber's driver contract states that the company may track drivers' geolocation, but it does not explain exactly what information is collected. See https://www.wsj.com/articles/ubers-app-will-soon-begin-tracking-driving-behavior-1467194404 for more details.

[10] Institutional Review Board approval was obtained before we ran the experiments.

[11] See https://www.act.org/content/act/en/products-and-services/workkeys-for-employers/assessments.html.

[12] Incomplete responses, duplicated responses from the same IP addresses, responses from non-English speakers, and responses with zero image-labeling time were removed from the analyses.

References

Acquisti A, Brandimarte L, Loewenstein G (2015) Privacy and human behavior in the age of information. *Sci.* 347(6221):509–514.

Acquisti A, Adjerid I, Balebako R, Brandimarte L, Cranor LF, Komanduri S, Leon PG, Sadeh N, Schaub F, Sleeper M (2017) Nudges for privacy and security: Understanding and assisting users' choices online. *ACM Comput. Surveys* 50(3):1–41.

Adams A, Berg J (2017) When home affects pay: An analysis of the gender pay gap among crowdworkers. Preprint, submitted October 6, https://dx.doi.org/10.2139/ssrn.3048711.

Adjerid I, Acquisti A, Brandimarte L, Loewenstein G (2013) Sleights of privacy: Framing, disclosures, and the limits of transparency. *Proc. Ninth Sympos. Usable Privacy Security* (Association for Computing Machinery, New York), 1–11.

Akerlof G (1984) Gift exchange and efficiency-wage theory: Four views. *Amer. Econom. Rev.* 74(2):79–83.

Alge BJ (2001) Effects of computer surveillance on perceptions of privacy and procedural justice. *J. Appl. Psych.* 86(4):797–804.

Benson A, Sojourner A, Umyarov A (2020) Can reputation discipline the gig economy? Experimental evidence from an online labor market. *Management Sci.* 66(5):1802–1825.

Berg J, Furrer M, Harmon E, Rani U, Silberman MS (2018) Digital labour platforms and the future of work: Toward decent work in the online world (International Labour Organization, Geneva).

Brandimarte L, Acquisti A, Loewenstein G (2013) Misplaced confidences: Privacy and the control paradox. *Soc. Psych. Personality Sci.* 4(3):340–347.

Brooks JL (2012) Counterbalancing for serial order carryover effects in experimental condition orders. *Psych. Methods* 17(4):600–614.

Cappelli P, Chauvin K (1991) An interplant test of the efficiency wage hypothesis. *Quart. J. Econom.* 106(3):769–787.

Chen DL, Horton JJ (2016) Research note—Are online labor markets spot markets for tasks? A field experiment on the behavioral response to wage cuts. *Inform. Systems Res.* 27(2):403–423.

Croson R, Gneezy U (2009) Gender differences in preferences. *J. Econom. Literature* 47(2):448–474.

Culnan MJ, Armstrong PK (1999) Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. *Organ. Sci.* 10(1):104–115.

Duflo E, Hanna R, Ryan SP (2012) Incentives work: Getting teachers to come to school. *Amer. Econom. Rev.* 102(4):1241–1278.

Fellner G, Maciejovsky B (2007) Risk attitude and market behavior: Evidence from experimental asset markets. *J. Econom. Psych.* 28(3):338–350.

Filippin A, Crosetto P (2016) A reconsideration of gender differences in risk attitudes. *Management Sci.* 62(11):3138–3160.

Foxman ER, Kilcoyne P (1993) Information technology, marketing practice, and consumer privacy: Ethical issues. *J. Public Policy Marketing* 12(1):106–119.

Friedland N (1982) A note on tax evasion as a function of the quality of information about the magnitude and credibility of threatened fines: Some preliminary research. *J. Appl. Soc. Psych.* 12(1):54–59.

Gandy OH Jr (1993) *The Panoptic Sort: A Political Economy of Personal Information*, Critical Studies in Communication and in the Cultural Industries (Westview Press, Boulder, CO).

Hayes AF, Scharkow M (2013) The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter? *Psych. Sci.* 24(10):1918–1927.

Hedegaard MS, Tyran JR (2018) The price of prejudice. *Amer. Econom. J. Appl. Econom.* 10(1):40–63.

Hollenbaugh EE, Everett MK (2013) The effects of anonymity on self-disclosure in blogs: An application of the online disinhibition effect. *J. Comput. Comm.* 18(3):283–302.

Hoy MG, Milne G (2010) Gender differences in privacy-related measures for young adult Facebook users. *J. Interactive Advertising* 10(2):28–45.

Huang N, Burtch G, Hong Y, Pavlou PA (2020) Unemployment and worker participation in the gig economy: Evidence from an online labor market. *Inform. Systems Res.* 31(2):431–448.

Hubbard TN (2000) The demand for monitoring technologies: The case of trucking. *Quart. J. Econom.* 115(2):533–560.

Jiang Z, Heng CS, Choi BCF (2013) Research note—Privacy concerns and privacy-protective behavior in synchronous online social interactions. *Inform. Systems Res.* 24(3):579–595.

John LK, Acquisti A, Loewenstein G (2010) Strangers on a plane: Context-dependent willingness to divulge sensitive information. *J. Consumer Res.* 37(5):858–873.

Karwatzki S, Dytynko O, Trenz M, Veit D (2017) Beyond the personalization–privacy paradox: Privacy valuation, transparency features, and service personalization. *J. Management Inform. Systems* 34(2):369–400.

Kays K, Gathercoal K, Buhrow W (2012) Does survey format influence self-disclosure on sensitive question items? *Comput. Human Behav.* 28(1):251–256.

Malhotra NK, Kim SS, Agarwal J (2004) Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model. *Inform. Systems Res.* 15(4):336–355.

Martin KD, Borah A, Palmatier RW (2017) Data privacy: Effects on customer and firm performance. *J. Marketing* 81(1):36–58.

Martín-Fernández J, del Cura-González MI, Gómez-Gascón T, Oliva-Moreno J, Domínguez-Bidagor J, Beamud-Lagos M, Pérez-Rivas FJ (2010) Differences between willingness to pay and willingness to accept for visits by a family physician: A contingent valuation study. *BMC Public Health* 10(1):236.

Mas A, Pallais A (2017) Valuing alternative work arrangements. *Amer. Econom. Rev.* 107(12):3722–3759.

Möhlmann M, Zalmanson L, Henfridsson O, Gregory RW (2021) Algorithmic management of work on online labor platforms: When matching meets control. *Management Inform. Systems Quart.* 45(4):1999–2022.

Moore S, Hayes LJB (2018) The electronic monitoring of care work—The redefinition of paid working time. *Humans and Machines at Work* (Palgrave Macmillan, Cham, Switzerland), 101–124.

Palan S, Schitter C (2018) Prolific.ac—A subject pool for online experiments. *J. Behav. Experiment. Finance* 17(c):22–27.

Peer E, Brandimarte L, Samat S, Acquisti A (2017) Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *J. Experiment. Soc. Psych.* 70:153–163.

Peng J (2022) Identification of causal mechanisms from randomized experiments: A framework for endogenous mediation analysis. *Inform. Systems Res.*, ePub ahead of print March 4, https://doi.org/10.1287/isre.2022.1113.

Sheehan KB (1999) An investigation of gender differences in on-line privacy concerns and resultant behaviors. *J. Interactive Marketing* 13(4):24–38.

Stanton JM (2000) Reactions to employee performance monitoring: Framework, review, and research directions. *Human Performance* 13(1):85–113.

Stanton JM, Weiss EM (2000) Electronic monitoring in their own words: An exploratory study of employees' experiences with new types of surveillance. *Comput. Human Behav.* 16(4):423–440.

Stiglitz JE (1987) The causes and consequences of the dependence of quality on price. *J. Econom. Literature* 25(1):1–48.

Strack F, Mussweiler T (1997) Explaining the enigmatic anchoring effect: Mechanisms of selective accessibility. *J. Personality Soc. Psych.* 73(3):437–446.

Townsend AM, Bennett JT (2003) Privacy, technology, and conflict: Emerging issues and action in workplace privacy. *J. Labor Res.* 24(2):195–205.

Wiswall M, Zafar B (2018) Preference for the workplace, investment in human capital, and gender. *Quart. J. Econom.* 133(1):457–507.

Xu H, Teo HH, Tan BC, Agarwal R (2012) Research note—Effects of individual self-protection, industry self-regulation, and government regulation on privacy concerns: A study of location-based services. *Inform. Systems Res.* 23(4):1342–1363.