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Gender wage gap in online gig economy and gender differences in job preferences

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Monitoring Policies and Gig Workers' Job Preferences

Abstract

Monitoring, a digital surveillance technology that allows employers to track the activities of workers, is ubiquitous in the gig economy where workforce is distributed. However, workers are often reluctant to be monitored due to 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 about whether to adopt monitoring and what monitoring policy to use, we investigate how three common aspects 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 and Prolific). The three aspects 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 likely to accept monitoring due to 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, as 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/hr for AMT workers and $1.6/hr for Prolific workers, which translate to roughly 37.3% and 28.5% of their average hourly wages, respectively.

Keywords: monitoring, gig economy, privacy concerns, payment protection, gender, willingness to accept (WTA)

A Revised Submission to ***Information Systems Research***

1. Introduction

The gig economy has seen tremendous growth in the past decade (Huang et al. 2020). The COVID-19 pandemic has accelerated the growth as unemployment soars and massive numbers of workers transitioned 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 beyond the contractual requirements, 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 (e.g., AMT and Prolific), nearly 90% of workers have ever had work rejected and only 12% of workers stated that all the rejections were justifiable.[4] It has been estimated that on average, the loss due to unpaid work amounts to 13% of gig workers' annual income.[5]

The above challenges facing employers and workers largely result from the asymmetric information between the two parties. To mitigate the potential moral hazard problem due to 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, especially for gig economy platforms that facilitate transactions between strangers. For instance, Upwork provides a desktop app that can automatically take screenshots and track workers'

[1] https://time.com/5836868/gig-economy-coronavirus/
[2] https://www.cnn.com/2020/04/23/tech/instacart-hiring-workers/index.html
[3] https://hbr.org/2020/07/gig-workers-are-here-to-stay-its-time-to-give-them-benefits
[4] https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/---publ/documents/publication/wcms_645337.pdf
[5] https://www.invoiceberry.com/blog/stiffed-last-time-ensuring-get-paid-freelancer/

activities in hourly projects.[6] From the perspective of employers, monitoring allows them to track workers' progress and intervene when necessary. Prior studies have shown that monitoring can improve workers' productivity (Duflo et al. 2012, Hubbard 2000). 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, since monitoring systems operate by continuously collecting information (e.g., working hours, computer screenshots, or moving routes) from workers, they may 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.[7] 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, monitoring with a higher intensity 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 systems, which reduces workers' privacy concerns (Culnan and Armstrong 1999). Similarly, a monitoring system that provides workers 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 as fair and appropriate (Culnan and Armstrong 1999).

Aligned with the above mentioned three dimensions of monitoring policy (i.e., intensity, transparency, and control), three corresponding industry practices are used to alleviate workers' privacy concerns and

[6] https://support.upwork.com/hc/en-us/articles/211064038-About-the-Desktop-App.
[7] https://www.cnbc.com/2019/03/22/uber-faces-fresh-legal-challenge-over-driver-data.html.

lower their resistance against monitoring. The first practice is to lower the intensity of monitoring. For example, while many third-party monitoring apps record workers' working hours and computer screenshots (e.g., Monitask, StaffCop), some monitoring apps only track working hours (e.g., Harvest Forecast, WorkTime). The second practice is to increase the transparency of monitoring by informing workers how they will be monitored. For instance, unlike monitoring apps that do not disclose the details about what information is monitored to workers, TimeDoctor allows workers to inspect the monitored records.[8] 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 that they feel uncomfortable sharing. Notably, the latter two practices are also advocated by government agencies (e.g., White House and Federal Trade Commission[9]) and academic scholars (e.g., Adjerid et al. 2013, Malhotra et al. 2004).

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, changes in the monitoring policy may also influence workers' perceived payment protection from monitoring, which is considered as a key benefit for gig workers. For example, lowering the monitoring intensity may make the resulting monitoring logs less effective in protecting workers from unjustified rejections (Moore and Hayes 2018). On the contrary, when the monitoring intensity is high, being more transparent about the monitoring policy may increase workers' perceived payment protection from monitoring. Considering the potential countervailing roles of these two mechanisms (privacy concern and payment protection), how different types of 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. Some

[8] https://www.eff.org/deeplinks/2020/06/inside-invasive-secretive-bossware-tracking-workers
[9] See more on White House Consumer Bill of Rights (https://obamawhitehouse.archives.gov/sites/default/files/privacy-final.pdf) and Federal Trade Commission's Privacy Framework (https://www.ftc.gov/sites/default/files/documents/reports/federal-trade-commission-report-protecting-consumer-privacy-era-rapid-change-recommendations/120326privacyreport.pdf)

mixed findings are relevant to the potentially different effects of monitoring on privacy concerns by gender. On the one hand, females are more likely to disclose their personal information than males (Denniston et al. 2010, Hollenbaugh and Everett 2013, Kays et al. 2012). On the other hand, females tend to worry about their privacy more than males when evaluating the potential risk of privacy invasion (Hoy and Milne 2010, Rowan and Dehlinger 2014, Sheehan 1999). Since the privacy concerns over monitoring depend on both the willingness to disclose information and the evaluation of potential negative consequences due to 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. Since females are more risk-averse than males when making economic decisions (Croson and Gneezy 2009, Fellner and Maciejovsky 2007), they may value the payment protection from monitoring more than males, rendering them more open to monitoring.

To help employers and platforms make informed decisions regarding whether they should adopt monitoring and what monitoring policy to employ, it is important to understand how different monitoring policies influence workers' perception and acceptance of monitoring. Toward 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, i.e., AMT and Prolific. Gig workers participating in our experiments are randomly assigned into four groups with different monitoring policies: a) the *only_time* group in which only workers' working hours are tracked (a common monitoring policy adopted by many gig platforms such as AMT and Prolific); b) the *all_screenshots* groups, in which both working hours and computer screenshots are tracked (a high intensity monitoring policy adopted by monitoring apps such as Monitask 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[10]); 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). We further measure workers' privacy concerns over and perceived payment protection from monitoring in different monitoring policy groups.

Since 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 (Hedegaard and Tyran 2018, Martín-Fernández et al. 2010, Mas and Pallais 2017). For instance, Hedegaard and Tyran (2018) measure workers' willingness to pay for discrimination based on their choices between two jobs with a same-ethnic vs. 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' acceptance of the monitored job at different levels of wage differences, under different monitoring policies.

Several findings emerge from our experiments: 1) Increasing the monitoring intensity reduces workers' propensity to accept monitoring by increasing their privacy concerns. 2) When the monitoring intensity is *low*, being transparent about the monitoring policy can increase workers' propensity to accept monitoring by reducing their *privacy concerns*. Conversely, when the monitoring intensity is *high*, being transparent

[10] 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.

about the monitoring policy does not significantly affect workers' propensity to accept monitoring, though it can increase their perceived *payment protection*. 3) 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. 4) Compared to 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 noneligible economic cost for employers. These findings have important implications in the design and deployment of monitoring policies for employers on gig economy platforms.

Our study contributes to several streams of literature. First, our study is among the first to measure the effect of monitoring on recruitment cost, which has been ignored by the prior studies on monitoring (Duflo et al. 2012, Hubbard 2000). Second, our study also contributes to the privacy literature. While some pioneering studies have shown that workers are uncomfortable with monitoring due to 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, in terms of intensity, transparency, and control. Last but not least, the heterogeneity in workers' WTAs for monitoring across gender advances our understanding of the heterogeneous compensation differentials for non-wage job amenities (Mas and Pallais 2017, Wiswall and Zafar 2018).

2. Theoretical Background

Applying the privacy calculus theory (Culnan and Armstrong 1999, Jiang et al. 2013) into the context of monitoring in gig economy platforms, workers' willingness to disclose information to the monitoring system should depend on the tradeoff 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 monitoring policy may influence privacy concerns, the 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 the privacy concerns and the perceived payment protection of workers, as elaborated below.

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 as low-intensity monitoring, as it only records some basic non-sensitive information. In contrast, a monitoring that captures computer screenshots in addition to tracking time is often considered as high-intensity monitoring, as the screenshots may contain sensitive information of 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) due to the potential misuse of their data by others, which can result in 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.

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 respondents 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 to be 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.

Since both the privacy concerns and perceived payment protection of workers 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 workers' tradeoff and weights on 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. Below we discuss how transparency may influence workers' privacy concerns and perceived payment protection.

Transparency and privacy concerns. In the absence of transparency, workers face uncertainty regarding what and how data will be collected, which may lead them to expect the worst (Friedland 1982). That is, when the monitoring policy is not disclosed, workers tend to assume the intensity of the monitoring system to be rather invasive, elevating their privacy concerns. The impact of transparency on workers' privacy concerns may depend on the monitoring intensity. Specifically, when the monitoring intensity is low, being transparent about the monitoring policy can avoid unnecessary privacy concerns due to the uncertainty about the monitoring policy. However, when the monitoring intensity is high, while a transparent monitoring policy resolves workers' uncertainty, it simply confirms workers' expectation of intense monitoring and hence may not be particularly 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 monitoring policy therefore increases the perceived procedural fairness of a monitoring policy. Prior work has shown 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.

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 for their work. 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 justify their work. In this sense, workers may perceive stronger payment protection from a transparent monitoring policy than a non-transparent one. However, when the monitoring intensity is low, being transparent need not increase the perceived payment protection due to the limited information tracked by the monitoring system. Therefore, it is possible that transparency increases the workers' perceived payment protection only when the monitoring intensity is high.

Based on the above discussion, the transparency of monitoring policy may influence workers' acceptance of monitoring through two distinct mechanisms. Specifically, when the monitoring intensity is high, the transparency about monitoring policy may increase workers' perceived payment protection and hence increase their likelihood to choose 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 likely to choose monitored jobs.

2.3. Control

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 some screenshots that contain sensitive information or that they feel uncomfortable sharing with others. Building on the extant literature, we argue that providing control can alleviate workers' privacy concerns for several reasons. First, the provision of control allows workers to remove or withhold 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).

Control and payment protection. The provision of control may lower workers' perceived payment protection from monitoring to some extent because the removed information cannot be used as evidence of work anymore. In addition, employers may become more skeptical about the monitoring records when workers have the right to cherry-pick which of them 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, since 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, whether and how control affects workers' acceptance of monitoring are not clear.

2.4. Gender Differences

Males and females may respond to monitoring differently due to gender differences in privacy concerns and perceived payment protection. The gender difference in privacy concerns has been well-documented in the literature, though the findings vary across attitude and behavior, which is also known as the privacy paradox (Acquisti et al. 2015). Specifically, when responding to hypothetical questions regarding privacy invasion, females tend to express higher privacy concerns than males (Hoy and Milne 2010, Rowan and Dehlinger 2014). However, in terms of actual behavior, females have shown to disclose more private information than males on online platforms (Hollenbaugh and Everett 2013, Sheehan 1999) and online surveys (Denniston et al. 2010, 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 payment protection depends on the gender difference in risk attitudes. Prior research suggests that females are more risk-averse than males in general (Croson and Gneezy 2009, Fellner and Maciejovsky 2007), 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 more risk-averse than males may perceive a higher level of payment protection from monitoring.

Since 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 more willing to comply with monitoring policies. Considering that females may also perceive a higher level of payment protection from monitoring due to 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 the gender of workers.

Table 1. Summary of Theoretical Predictions

Dimension	**Privacy Concerns**	**Payment Protection**	**Job Choice**
Intensity	Increasing intensity can increase privacy concerns because: • Workers become more concerned about their privacy being invaded (Gandy 1993) • Workers perceive a higher vulnerability (Martin et al. 2017) related to data misuse	Increasing intensity can increase workers' perceived payment protection because: • More information that can serve as proof of work gets recorded (Moore and Hayes 2018)	• Increasing the intensity of monitoring *decreases* workers' propensity to accept monitoring by increasing their privacy concerns • Increasing the intensity of monitoring *increases* workers' propensity to accept monitoring by

			increasing their perceived payment protection
Transparency	The impact of transparency on privacy concerns depends on the monitoring intensity. • When the intensity is *low*, transparency can alleviate privacy concerns because it can i) avoid unnecessary privacy concerns due to uncertainty and ii) increase the perceived procedural fairness of monitoring • 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. • When the intensity is *high*, transparency can assure workers that the collected information is sufficient to protect them from payment disputes • When the intensity is *low*, transparency need not increase the perceived payment protection as only limited information is recorded as potential evidence	• When the monitoring intensity is *low*, being transparent about the monitoring policy *increases* workers' propensity to accept monitoring by reducing their privacy concerns • When the monitoring intensity is *high*, being transparent about the monitoring policy *increases* workers' propensity to accept monitoring by increasing their perceived payment protection
Control	Providing control can reduce privacy concerns because: • It allows workers to remove sensitive information • It increases the perceived procedural fairness of monitoring (Alge 2001, Culnan and Armstrong 1999) • Workers have a sense of autonomy (Martin et al. 2017)	Providing control can reduce workers' perceived payment protection because: • The removed information cannot be used as proof of work anymore • Employers may become more skeptical about the selective monitoring logs submitted by workers	• The provision of control *increases* workers' propensity to accept monitoring by reducing their privacy concerns • The provision of control *decreases* workers' propensity to accept monitoring by reducing their perceived payment protection
Gender	Females may have *stronger* privacy concerns over monitoring than males because: • Females are more sensitive to potential privacy invasion (Hoy and Milne 2010, Rowan and Dehlinger 2014, Sheehan 1999) Females may have *weaker* privacy concerns over monitoring than males because: • Females are more willing to disclose information on online platforms (Hollenbaugh and Everett 2013, Sheehan 1999) • Females are more compliant (Sheehan 1999)	Females may perceive *stronger* payment protection from monitoring than males because: • Females tend to be more risk averse (Croson and Gneezy 2009, Fellner and Maciejovsky 2007)	Females are *more* likely to accept monitoring than males because: • Females are more willing to disclose information on online platforms (Hollenbaugh and Everett 2013, Sheehan 1999) • Females are more compliant (Sheehan 1999) • Females may perceive stronger payment protection from monitoring

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.[11] Gig economy platforms like 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 a monitored and unmonitored image-labeling job at different wages. To investigate how workers' acceptance of monitoring varies with the design of monitoring policy, we further manipulate the monitoring policy in multiple dimensions. Next, we elaborate on how we manipulate the monitoring policy and the wages of jobs, 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 vs. low intensity) × 2 (with vs. without transparency) × 2 (with vs. without control) full factorial design. However, some of the combinations are either infeasible or impractical. Specifically, 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). Moreover, since 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, we are left with four feasible monitoring conditions: no transparency, low intensity, high intensity (without control), and high intensity with control. Note that the latter three conditions presume transparency.

To operationalize the four feasible monitoring conditions which are common in practice, we adopt a

[11] Institutional Review Board (IRB) approval was obtained before we ran the experiments.

between-subject discrete choice experimental design by randomly assigning workers into 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' working hours are tracked but no computer screenshots are taken; c) the *controlled_screenshots* group, in which 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 both working hours and computer screenshots are tracked and recorded screenshots cannot be removed. Table 2 shows these four groups as well as the exemplary firms, institutions, or third-party monitoring apps that adopt each type of monitoring policy.

Table 2. Design of Monitoring Policy Manipulations

		Without Control	With Control
With Transparency	Low Intensity	*only_time* (e.g., AMT, Harvest Forecast)	*N/A*
	High Intensity	*all_screenshots* (e.g., Monitask, StaffCop)	*controlled_screenshots* (e.g., Freelancer, Screenmeter)
Without Transparency		*no_disclosure* (e.g., Uber, Food and Drug Administration[12])	

Before asking a worker to choose between a monitored and unmonitored job, we provide a tutorial about the monitoring system that will be used for the image-labeling job. 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 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 they are assigned to (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 pre-existing misconception regarding how a monitoring system works.

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

Table 3. Operationalization of Different Monitoring Policies

Treatment Group	Description of the Monitoring System
no_disclosure	None
only_time	The monitoring system will *only track how long* the employee works for the project. But it will *not take screenshots* of the employee's computer.
controlled_screenshots	The monitoring system will *track how long* the employee works for the project. Meanwhile, it will *take screenshots* of the employee's computer at regular or irregular time intervals while s/he is working. To protect the privacy of the employee, the employee *may delete a few screenshots* s/he does not feel comfortable to upload.
all_screenshots	The monitoring system will *track how long* the employee works for the project. Meanwhile, it will *take screenshots* of the employee's computer at regular or irregular time intervals while s/he is working. Once those screenshots are taken, the employee *cannot delete any screenshots*.

3.2. Manipulation of Wage Premium

Following prior work, we use a discrete choice experimental design to estimate workers' WTA (Hedegaard and Tyran 2018, Martín-Fernández et al. 2010, Mas and Pallais 2017). Specifically, we ask 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 will be 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. 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 finding suggests that $-2 is an appropriate lower bound for WTA for monitoring. We allow the wage premium to be negative since highly risk-averse workers may prefer monitored jobs over unmonitored jobs due to 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.

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 has to type in the four-digit number of his/her preferred position, instead of a multi-choice 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.

Suppose your 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.

Figure 1. An Example of Job Preference Question in Study 1

3.3. Overall Design

3.3.1. Study 1: AMT

We now discuss the overall design of our experiment. As shown in Figure 2, the job screening survey includes seven major steps. At the beginning of the survey, we collect the demographic information about the prospective workers, including gender, race, education, work experience, whether they have been monitored at work before, 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. 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 \$4~\$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 \$5, the lower paid unmonitored job still receives \$4 per hour.

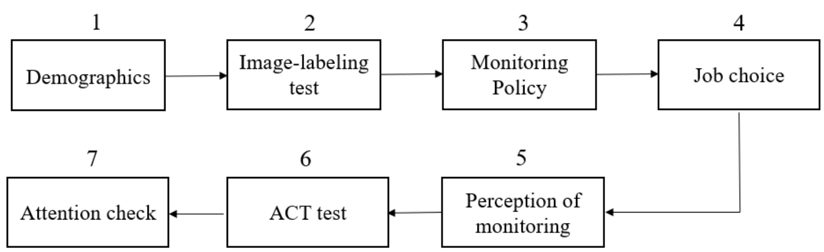


Figure 2. The Flow of the Experiment

To investigate the mechanisms behind the job preference towards monitoring, we further ask workers to answer a few questions regarding their perceptions of the monitoring system (e.g., privacy concerns and perceived payment protection) 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 Appendix B 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 7-point Likert scale (strongly disagree to strongly agree).

Since the measurement of privacy concerns is highly sensitive to information cues (Acquisti et al. 2017, John et al. 2010), 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,[13] 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. In Appendix A, we provide screenshots for each step of the experiment.

The WTA for monitoring may vary across countries since 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 US. Therefore, we only allow workers from the US to participate in the 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 take this survey once. Each worker receives $0.80 as compensation for completing the survey.

Study 1 on AMT provides us evidence for how the three dimensions of 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 (Duflo et al. 2012, Hubbard 2000), different monitoring policies may affect workers' perception of how much effort is required to complete a monitored job, which may be a potential confounder. In Study 2, we seek to 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: 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 has been

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

recommended by many scholars (e.g., Palan and Schitter 2018, Peer et al. 2017). 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, as shown in Figure 3, 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. 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 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).

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).

Figure 3. An Example of Job Preference Question in Study 2

We 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 to $5, after learning from the AMT experiment that a rather small share of respondents 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, since 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 US 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, since 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 7-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 a monitored job and an unmonitored job with different wage premiums and different monitoring policies (i.e., whether they choose the monitored jobs over the unmonitored ones). Equation (1) provides the estimation model on how the wage premium and monitoring policy affect workers' decisions to accept monitoring (or not).

$$choice_i = \beta_0 + \beta_1 wage\_premium_i + \beta_2 monitoring\_policy_i + \alpha X_i + \varepsilon_i \tag{1}$$

Here, we use *i* to index workers. The dependent variable $choice_i$ equals 1 if worker i chooses the monitored job, and 0 otherwise. The variable $monitoring\_policy_i$ denotes the monitoring policy for worker *i* and will be represented by a set of dummies. X_i represents the demographic attributes of worker *i*, including gender, race, education, working experience, prior experience of working under monitoring, 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 subsection, 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

$$WTA_i = \gamma X_i + v_i \tag{2}$$

where the random variable v_i represents the baseline WTA of worker *i* and 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*. Following the convention in measuring WTA/WTP (Mas and Pallais 2017), we do not restrict WTA_i to be positive and assume that v_i follows a normal distribution with mean μ and variance σ. In the case when WTA_i needs to be nonnegative, we can use the following specification instead:

$$WTA_i = \exp(\gamma X_i + v_i) \tag{3}$$

A worker chooses the monitored job when the wage premium for the monitored job exceeds his/her WTA for monitoring. Given that the WTA is a random variable, the probability that worker *i* chooses the monitored job is given by:

$$P(choice_i = 1) = \Pr\left(wage\_premium_i - WTA_i > 0\right) \tag{4}$$

where WTA_i is given by Equation (2), or Equation (3) when nonnegativity of WTA is desired. Following the distributional assumption on v_i (i.e., $v_i \sim N(\mu, \sigma^2)$),

$$\begin{aligned} P(choice_i = 1) &= \Pr(wage\_premium_i - \gamma X_i - v_i > 0) \\ &= \Phi\left(\frac{wage\_premium_i - \gamma X_i - \mu}{\sigma}\right) \end{aligned} \tag{5}$$

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

Let $\beta_1 = \frac{1}{\sigma},\ \beta_2 = -\gamma\beta_1,\ \beta_0 = -\mu\beta_1$, we have:

$$P(choice_i = 1) = \Phi(\beta_0 + \beta_1 wage\_premium_i + \beta_2 X_i) \tag{6}$$

The set of parameters $\{\beta_0, \beta_1, \beta_2\}$ in Equation (6) can be estimated using a probit model, from which we can infer $\{\mu, \sigma, \gamma\}$. The latter set of parameters characterize workers' WTA for monitoring. Therefore, the above 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 some data cleaning.[14] Table 4 summarizes the descriptive statistics of workers' job choices, the treatment variables (i.e., monitoring policy dummies), the wage premium, the privacy concerns of workers, the perceived payment protection from monitoring, and several key demographic attributes of workers.

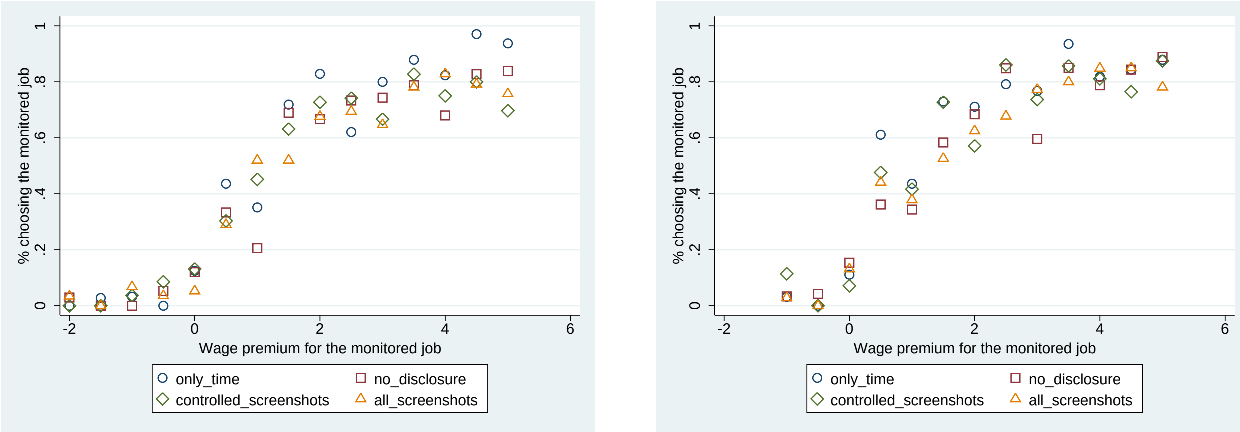
Table 4. Definition and Summary Statistics of Variables

Variable	Definition	AMT				Prolific			
		Mean	SD	Min	Max	Mean	SD	Min	Max
choice	Dummy variable, =1 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, =1 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, =1 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, =1 if the monitoring system tracks time and selective screenshots that workers are comfortable of sharing	0.25	0.43	0.00	1.00	0.25	0.43	0.00	1.00
all_screenshtos	Dummy variable, =1 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, =1 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
monitor_experience	Dummy variable, =1 if the worker has some experience of being monitored in his/her job	0.16	0.37	0.00	1.00	0.16	0.37	0.00	1.00
gig_hourlywage	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 7-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 7-point Likert scale)	5.50	0.50	1.00	7.00	5.25	0.50	1.00	7.00

Note: As shown in Appendix C, the demographic distribution of AMT workers recruited by us closely resembles that of the AMT worker population in the US. Randomization checks and the number of observations in each experiment group are provided in Appendix D.

[14] We removed incomplete responses, duplicated responses from the same IP addresses, responses from non-English speakers, responses from workers whose self-reported hourly wages were less than \$0.5/hr (unlikely for US workers), and responses with zero image-labeling time.

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.



(a) AMT (b) Prolific

Figure 4. Model-free Evidence on the Impact of Monitoring Policy on Job Choices

As shown in Figures 4a and 4b, 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 wage premium for the monitored job is zero, roughly 10% of workers chose the monitored job on both AMT and Prolific. These workers have below average privacy concerns but perceive above average payment protection from monitoring, suggesting that they value payment protection more than privacy. 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/hr.

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. We do not consider the *controlled_screenshots* group in this comparison because this group also involves control. 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 monitoring policy at low and high intensities, namely, the *only_time* and *all_screenshots* groups. Lastly, 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 users control over the monitored information. Table 5 summarizes our strategy to estimate the effects of different dimensions of monitoring policies.

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

Dimension of Monitoring	Groups Used for Comparison
Intensity	*only_time* vs. *all_screenshots*
Transparency	*no_disclosure* vs. *only_time* (low intensity) *no_disclosure* vs. *all_screenshots* (high intensity)
Control	*all_screenshots* vs. *controlled_screenshots*

Next, we estimate the impact of each dimension of monitoring policy on workers' job choices using the LPM model given by Equation (1). When estimating the effect of each dimension, we remove the group(s) that are not used for comparison and set the left-hand side group in the second column of Table 5 as the baseline group for the regression analysis, that is, *only_time*, *no_disclosure*, *and all_screenshots* are the baseline groups for the intensity, transparency, and control dimensions, respectively.

5.2.1. Intensity

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

As shown in Column 1 of Table 6, as expected, 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 to choose the monitored job by 6.3%, which is equivalent to the effect of a \$0.42/hr decrease in the wage premium for the monitored job (−0.063 / 0.150 = −0.42, where −0.063 and 0.150 are the coefficients of *all_screenshots* and *wage_premium* in Column 1 of Table 6). Similarly, in the Prolific sample, the effect of taking computer screenshots translates to a \$0.47/hr decrease in the wage premium for the monitored job (−0.070 / 0.148 = −0.47).

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

	AMT				Prolific			
	Choice	Privacy	Protection	Choice	Choice	Privacy	Protection	Choice
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
all_screenshots	-0.063**	0.187**	0.119	-0.053**	-0.070***	0.197**	0.065	-0.052**
	(0.025)	(0.093)	(0.089)	(0.023)	(0.027)	(0.091)	(0.087)	(0.024)
male	-0.071***	0.268***	-0.110	-0.044*	-0.072***	0.116	-0.174**	-0.050**
	(0.025)	(0.094)	(0.090)	(0.023)	(0.027)	(0.092)	(0.087)	(0.024)
wage_premium	0.150***	-0.081***	0.023	0.142***	0.148***	-0.028	0.024	0.144***
	(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				0.042***				0.053***
				(0.009)				(0.009)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	966	966	966	966	941	941	941	941
R^2	0.445	0.080	0.052	0.527	0.342	0.041	0.041	0.469

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The reference group is *only_time*. The control variables include workers' education, race, working experience, average hourly wage on the platform, prior experience with monitoring, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we do not include any worker-level control variables or when we use probit instead of LPM models for workers' job choices.

To delve into the mechanisms behind the treatment effect of intensity, we examine how intensity influences workers' privacy concerns and perceived payment protection. To that end, we estimate two LPM models similar to Equation (1), except that we replace the dependent variable with workers' privacy concerns and perceived payment protection, respectively. The results of these two models are reported in Columns 2-3 of Table 6 for the AMT sample and Columns 6-7 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 does 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 a 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 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 estimate their mediation effects using a bias-corrected bootstrapping approach (Hayes and Scharkow 2013). The mediation effects of these two variables are reported in Table 7. The results suggest that only privacy concerns play a statistically significant mediation role. The mediation effect of payment protection is not significant likely because the effect of intensity on payment protection is not significant in Columns 3 and 7 of Table 6.

Table 7. Mediation Analysis on Intensity

	AMT			Prolific		
	Estimate	Bootstrap SE	*p*-value	Estimate	Bootstrap SE	*p*-value
mediation effect through privacy	-0.015	0.008	0.050	-0.022	0.010	0.032
mediation effect through protection	0.005	0.004	0.249	0.003	0.005	0.468

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 the *no_disclosure* as the reference group, as the other two groups both presume transparent disclosure of monitoring policy. The regression results on the transparency dimension are summarized in Table 8, which 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 is not helpful in increasing the propensity of choosing monitored jobs when the monitoring intensity is high. These findings confirm our arguments in Section 2 that transparency increases the acceptance of monitoring only when the monitoring intensity is low. Our study 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 (Acquisti et al. 2015, Foxman and Kilcoyne 1993).

Table 8. Effects of Transparency on Job Preferences

	AMT				Prolific			
	Choice (1)	Privacy (2)	Protection (3)	Choice (4)	Choice (5)	Privacy (6)	Protection (7)	Choice (8)
only_time	0.071***	-0.280***	0.060	0.042*	0.070***	-0.239***	0.203**	0.035
	(0.025)	(0.093)	(0.088)	(0.023)	(0.027)	(0.089)	(0.087)	(0.024)
all_screenshots	0.010	-0.097	0.184**	-0.007	0.002	-0.050	0.268***	-0.017
	(0.025)	(0.093)	(0.088)	(0.023)	(0.027)	(0.090)	(0.088)	(0.024)
male	-0.056***	0.193**	-0.175**	-0.030	-0.095***	0.084	-0.151**	-0.079***
	(0.021)	(0.076)	(0.073)	(0.019)	(0.022)	(0.074)	(0.072)	(0.020)
wage_premium	0.148***	-0.077***	0.035**	0.140***	0.151***	-0.052***	0.022	0.144***
	(0.005)	(0.017)	(0.016)	(0.004)	(0.006)	(0.020)	(0.020)	(0.005)
privacy				-0.093***				-0.107***
				(0.007)				(0.007)
protection				0.043***				0.049***
				(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	0.434	0.070	0.056	0.528	0.350	0.038	0.033	0.463

Note: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01. The reference group is *no_disclosure*. The control variables include workers' education, race, working experience, average hourly wage on the platform, prior experience with monitoring, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we do not include any worker-level control variables or when we use probit instead of LPM models for workers' job choices.

The coefficients of *only_time* and *all_screenshots* in Columns 2 and 6 show that transparent disclosure significantly lowers privacy concerns when the monitoring intensity 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 on AMT (insignificant) and Prolific (significant). 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 payment protection with bootstrapped standard errors. When the monitoring intensity is low, transparency significantly increases workers' propensity to choose monitored jobs by lowering their privacy concerns. Meanwhile, when the monitoring intensity is high, transparency (marginally) significantly increases workers' propensity to choose monitored jobs by 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.

Table 9. Mediation Analysis on Transparency

		AMT			Prolific		
		Estimate	Bootstrap SE	*p*-value	Estimate	Bootstrap SE	*p*-value
Low intensity	mediation effect through privacy	-0.022	0.008	0.008	-0.025	0.009	0.007
	mediation effect through protection	-0.003	0.004	0.467	-0.011	0.005	0.032
High intensity	mediation effect through privacy	-0.012	0.010	0.232	-0.007	0.010	0.491
	mediation effect through protection	-0.006	0.003	0.079	-0.011	0.004	0.009

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. As shown in Table 4, the variation in privacy concerns is also much larger than that in payment protection. Together, these findings suggest that that privacy concerns may play a more pronounced mediation role than payment protection in influencing workers' job choices. In other words, workers' job choice decisions are primarily driven by privacy concerns, rather than perceived payment protection. This explains why transparency does not affect workers' job choices when the monitoring intensity is high, even though it significantly increases workers' perceived payment protection.

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 that does not offer control as the reference group. Table 10 summarizes the effects of control on workers' perception and acceptance of monitoring. Surprisingly, while 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 perceived procedural fairness), the estimated effect is not significant on either platform. One likely reason for this null finding is that the option to remove sensitive screenshots also reminds workers that the monitoring system may collect sensitive information, which is also known as the cueing effect (Acquisti et al. 2017, John et al. 2010). The cueing effect may have canceled out the negative effect of control on privacy concerns.

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 not difficult to understand why the effect of control on workers' job choices is also not significant.

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

	AMT			Prolific		
	Choice	Privacy	Protection	Choice	Privacy	Protection
	(1)	(2)	(3)	(4)	(5)	(6)
controlled_screenshots	0.005	0.088	-0.123	0.033	-0.086	-0.101
	(0.026)	(0.091)	(0.088)	(0.027)	(0.091)	(0.087)
male	-0.054**	0.125	-0.123	-0.076***	0.264***	-0.245***
	(0.026)	(0.091)	(0.088)	(0.027)	(0.092)	(0.088)
price_monitoring	0.136***	-0.022	0.017	0.152***	-0.065***	-0.016
	(0.006)	(0.021)	(0.020)	(0.007)	(0.025)	(0.024)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	948	948	948	941	941	941
R^2	0.377	0.074	0.055	0.334	0.058	0.036

Note: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01. The reference group is *all_screenshots*. The control variables include workers' education, race, working experience, average hourly wage on the platform, prior experience with monitoring, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we do not include any worker-level control variables or when we use probit instead of LPM models for workers' job choices.

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 an average wage premium under different monitoring policies. Since we use a linear model, the difference in the predicted probabilities for any two groups is the same as the difference in average treatment effects (ATEs) of the two groups. A higher predicted probability to choose the monitored job indicates a higher level of acceptance over a particular monitoring policy. Figure 5 shows that workers' relative acceptance levels of different monitoring policies are consistent across the two gig platforms AMT and Prolific. In addition to estimating the effect of monitoring policy dimension-by-dimension as summarized in Table 5, we have also estimated 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 Appendix E.

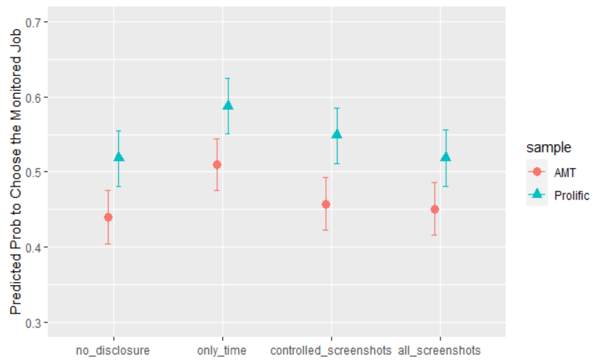


Figure 5. Predicted Probability to Choose the Monitored Job by Monitoring Policy

Note: Error bars represent 95% confidence intervals.

5.3. Gender Differences

To examine the gender differences in workers' perception and acceptance of monitoring, we conducted several additional analyses as reported in Table 11. On average, males are less likely to accept monitoring than females 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 (Hollenbaugh and Everett 2013, Sheehan 1999, Denniston et al. 2010). 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 more risk-averse than males (Croson and Gneezy 2009, Fellner and Maciejovsky 2007). The lower privacy concerns and higher payment protection reported by females well explain why females are more willing to choose monitored jobs than males.

Table 11. Gender Difference in Perception and Acceptance of Monitoring

	AMT			Prolific		
	Choice	Privacy	Protection	Choice	Privacy	Protection
	(1)	(2)	(3)	(4)	(5)	(6)
male	-0.036*	0.113*	-0.124**	-0.084***	0.132**	-0.176***
	(0.018)	(0.066)	(0.063)	(0.019)	(0.063)	(0.062)
no_disclosure	-0.068***	0.275***	-0.076	-0.069***	0.244***	-0.200**
	(0.025)	(0.092)	(0.088)	(0.027)	(0.089)	(0.087)
controlled_screenshots	-0.050**	0.265***	-0.016	-0.039	0.091	-0.046
	(0.025)	(0.091)	(0.087)	(0.027)	(0.089)	(0.087)
all_screenshots	-0.060**	0.196**	0.111	-0.069***	0.188**	0.061
	(0.025)	(0.091)	(0.086)	(0.027)	(0.089)	(0.087)
wage_premium	0.144***	-0.054***	0.024*	0.153***	-0.061***	0.006
	(0.004)	(0.015)	(0.014)	(0.005)	(0.017)	(0.017)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,895	1,895	1,895	1,882	1,882	1,882
R^2	0.408	0.053	0.048	0.337	0.037	0.025

Note: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01. The reference group is *only_time*. The control variables include workers' education, race, working experience, average hourly wage on the platform, prior experience with monitoring, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we do not include any worker-level control variables or when we use probit instead of LPM models for workers' job choices.

5.4. WTA for Monitoring

To help employers make more informed decisions regarding whether they should adopt monitoring and which monitoring policy to use, 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 type of monitoring policy, as well as its bootstrap confidence interval, in Table 12.

On average, the WTA for monitoring for the four monitoring policies is \$1.8/hr for AMT workers and \$1.6/hr for Prolific workers, which respectively amount to 37.3% and 28.5% of their average hourly wages (\$4.8 for AMT workers and \$5.6 for Prolific workers). Consistent with the earlier findings that lowering intensity and increasing transparency (when the intensity is low) can 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.

Table 12. WTA for Monitoring

Sample: AMT	Average WTA	WTA due to privacy concerns	WTA due to payment protection
only_time	1.47 (1.20, 1.73)	3.91 (3.43, 4.39)	-2.17 (-2.80, -1.57)
no_disclosure	1.99 (1.70, 2.29)	4.08 (3.58, 4.59)	-2.15 (-2.78, -1.55)
controlled_screenshots	1.91 (1.62, 2.20)	4.10 (3.60, 4.61)	-2.15 (-2.78, -1.55)
all_screenshots	2.01 (1.75, 2.28)	4.05 (3.55, 4.55)	-2.20 (-2.85, -1.59)
Sample: Prolific	Average WTA	WTA due to privacy concerns	WTA due to payment protection
only_time	1.29 (1.00, 1.58)	4.01 (3.45, 4.61)	-2.47 (-3.03, -1.94)
no_disclosure	1.78 (1.49, 2.06)	4.21 (3.62, 4.84)	-2.38 (-2.92, -1.87)
controlled_screenshots	1.57 (1.29, 1.84)	4.10 (3.52, 4.71)	-2.45 (-3.00, -1.92)
all_screenshots	1.82 (1.56, 2.12)	4.19 (3.60, 4.81)	-2.50 (-3.07, -1.96)

Note: 95% confidence intervals based on 1,000 bootstraps are reported in parentheses. Workers' WTA due to 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 payment protection.

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, though 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 workers in the *no_disclosure* group how they think they would be monitored if they chose the monitored job. Over 50% (80%) of them expected their screenshots (working hours) to be recorded, which suggests that the majority of workers assumed the monitoring to be intense 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 due to privacy concerns and perceived payment protection, by adding the privacy concerns and payment protection as two extra regressors in Equation (2). For workers in each group, we examine how much their average perceived privacy concern (payment protection) differs from a benchmark, i.e., the lowest possible privacy concern (payment protection),[15] and then calculate the change in WTA due to the difference in privacy concerns (payment protection). The WTAs due to privacy concerns (payment protection) for different groups are reported in the second (third) column of Table 12, with 95% confidence intervals obtained using 1,000 bootstrap estimates. Workers' WTA due to privacy concerns is the lowest in the *only_time* group, in line with the lowest privacy concern of workers in this group. On the other hand, we find that AMT (Prolific) workers are willing to be paid 2.1~2.2 (2.3~2.5) dollars less per hour in exchange for the payment protection from monitoring. The WTA due to payment protection is the highest for workers in the *all_screenshots* group, which is not surprising given that 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 for monitoring are \$1.74/hr (\$1.42/hr) for females and \$1.97/hr (\$1.86/hr) for males.

5.5. Robustness Checks

We conduct a series of robustness checks for our analyses. Due to page limits, we report the results of these analyses in the 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 (Appendix F). 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 (Appendix G). Third, we show that results are consistent when we use Principal Component Analysis (PCA) to construct the measure for privacy concerns (Appendix H).

6. Discussion and Conclusion

Due to 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

[15] The benchmark can be interpreted as the perceived privacy concern (payment protection) in the absence of monitoring. For simplicity, we assume that the perceived privacy concern (payment protection) without monitoring is the lowest possible value, which is 1 on a seven-point Likert scale. Note that the choice of the benchmark value does not affect the difference in WTA due to privacy concern (payment protection) across groups.

productivity. To help employers make more informed decisions about whether to adopt monitoring and what monitoring policy to use, we make a first attempt to comprehensively investigate how different monitoring policies affect 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, which represent three common aspects in industry practices that are respectively aligned with the three common practices to alleviate workers' privacy concerns and lower their resistance against monitoring. We find that, as the monitoring intensity increases, workers become less likely to accept monitored jobs due to elevated privacy concerns. Furthermore, we find that transparent disclosure of monitoring policy can increase workers' willingness to accept monitored jobs, but only when the monitoring intensity is low. When the monitoring intensity is high, while transparency can increase workers' perceived level of payment protection, it does not significantly reduce workers' privacy concerns or increase workers' propensity to choose monitored jobs. Interestingly, providing control over monitored information, a policy designed to address workers' concerns over the sharing of sensitive information, is not effective in reducing workers' privacy concerns over high-intensity monitoring. As a result, providing control has no significant effect on workers' propensity to choose monitored jobs. Finally, we observe a nuanced gender difference in the perception and acceptance of monitoring. Specifically, compared with male workers, females sense stronger payment protection from monitoring and yet have lower privacy concerns over monitoring, rendering them more willing to choose monitored jobs than males.

Our findings have important managerial implications. First, implementing monitoring can add a nonnegligible cost for labor recruitment. On average, the hourly wage compensation required for gig workers to accept monitoring is 1.6~1.8 dollars, which amounts to roughly 28.5%~37.3% 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 monitoring policy (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) while 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 to 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 up opportunities for ample future research. 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 put up with 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. Moreover, our online experiment is conducted in the image-labeling context, wherein it is relatively easy to monitor workers. Future research can investigate the effect of monitoring policy on other types of more sophisticated jobs such as software development and jobs that involves creative processes such as graphics design and writing. In addition, the mediators measured in our experiments can be endogenous due to unobserved confounders, meaning that our estimated mediation effects may not be causal. However, it should be noted that the estimated effects of monitoring policies on workers' perception and acceptance of monitoring still have causal interpretations. 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.

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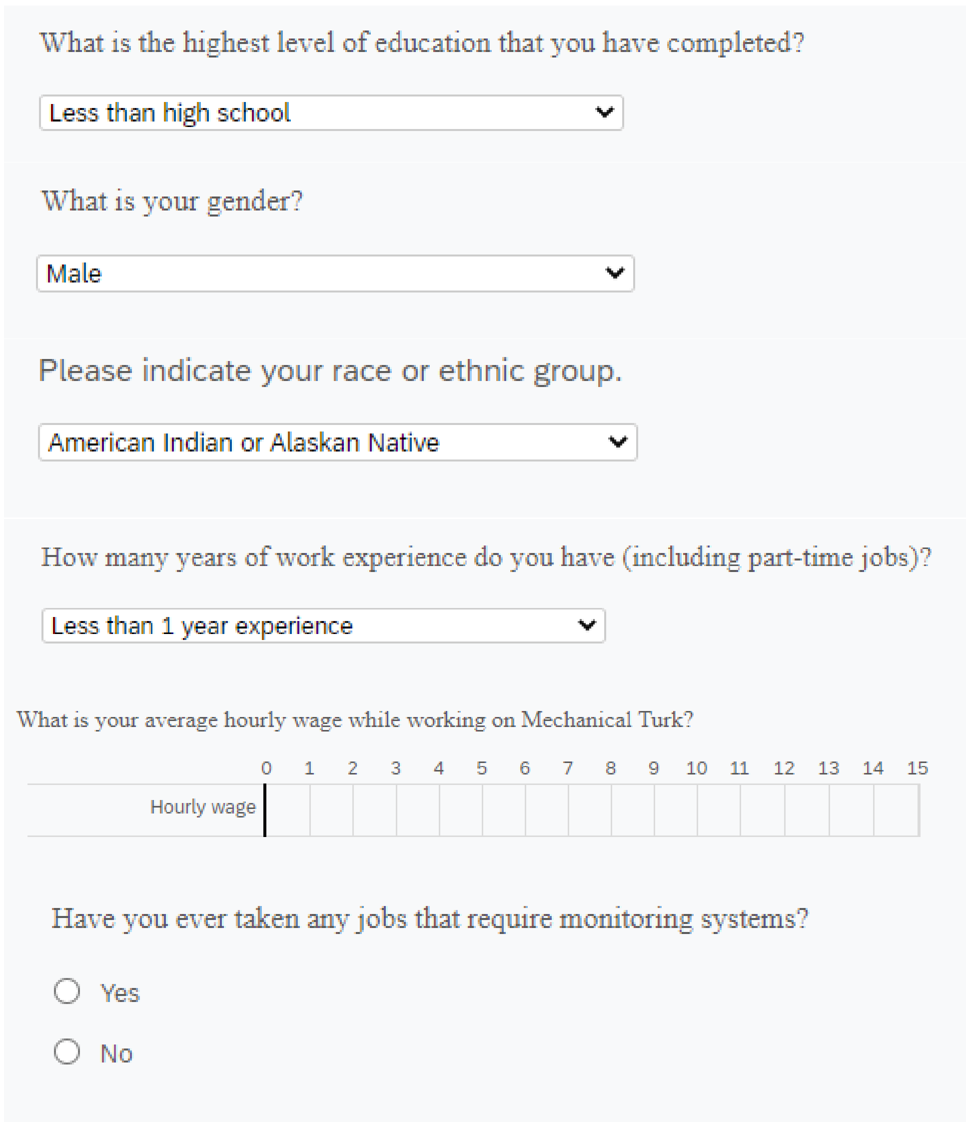
Supplementary Online Appendices

Appendix A. Screenshots of the Flow of the Experiment

Step 1: Demographics


What is the highest level of education that you have completed?

Less than high school

What is your gender?

Male

Please indicate your race or ethnic group.

American Indian or Alaskan Native

How many years of work experience do you have (including part-time jobs)?

Less than 1 year experience

What is your average hourly wage while working on Mechanical Turk?

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15

Hourly wage

Have you ever taken any jobs that require monitoring systems?

Yes

No

Figure A1. Demographic Questions

Step 2: Image-labeling Test

This page aims at assessing your capability in labeling images.

Below are 20 images shown in 4 groups. Please identify the gender of the person in each image. If a picture does not include any human being or you are uncertain about the gender, please choose "Other or not applicable".

	Male	Female	Other or not applicable
Picture1	○	○	○
Picture2	○	○	○
Picture3	○	○	○
Picture4	○	○	○
Picture5	○	○	○

	Male	Female	Other or not applicable
Picture1	○	○	○
Picture2	○	○	○
Picture3	○	○	○
Picture4	○	○	○
Picture5	○	○	○

Figure A2. Pre-treatment Image-Labeling Test

Step 3: Monitoring Policy

Figures A3-A6 show the descriptions of the monitoring system for workers assigned to different monitoring policy groups.

Introduction to Monitoring System

In online labor marketplaces, employees often work for employers remotely. For the purpose of quality control and progress management, some employers use monitoring tools to track the activities of their remote employees.

Figure A3. Tutorial for the *no_disclosure* group

Introduction to Monitoring System

In online labor marketplaces, employees often work for employers remotely. For the purpose of quality control and progress management, some employers use monitoring tools to track the activities of their remote employees.

The monitoring system will **only track how long** the employee works for the project. But it will **not take screenshots** of the employee's computer.

Figure A4. Tutorial for the *only_time* group

Introduction to Monitoring System

In online labor marketplaces, employees often work for employers remotely. For quality control and progress management, some employers use monitoring tools to track the activities of their remote employees.

The monitoring system will **track how long** the employee works for the project. Meanwhile, it will **take screenshots** of the employee's computer at regular or irregular time intervals while s/he is working. To protect the privacy of the employee, the employee **may delete a few screenshots** s/he does not feel comfortable to upload.

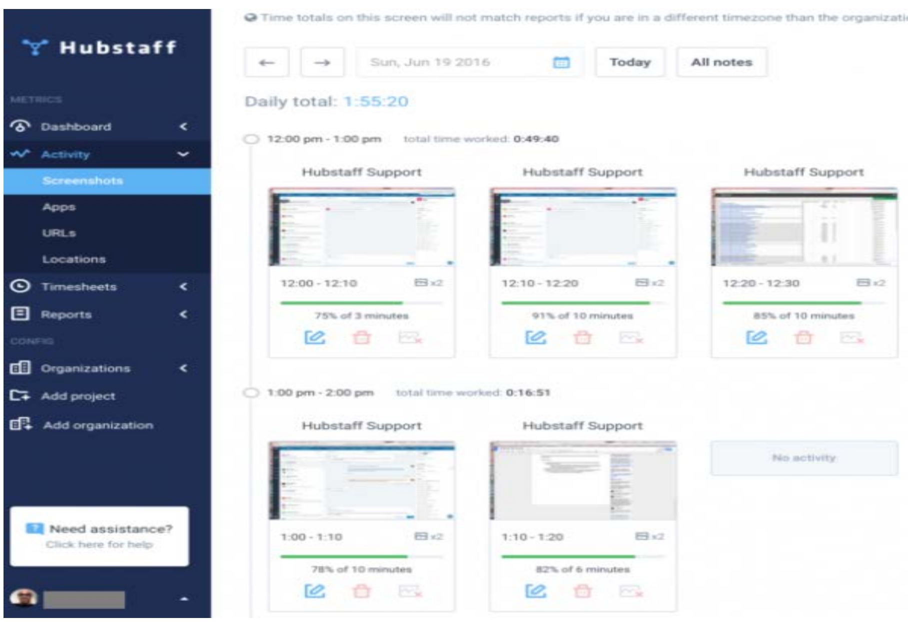


Figure A5. Tutorial for the *controlled_screenshots* group

Introduction to Monitoring System

In online labor marketplaces, employees often work for employers remotely. For the purpose of quality control and progress management, some employers use monitoring tools to track the activities of their remote employees.

The monitoring system will **track how long** the employee works for the project. Meanwhile, it will **take screenshots** of the employee's computer at regular or irregular time intervals while s/he is working. Once those screenshots are taken, the employee **cannot delete any screenshot**.

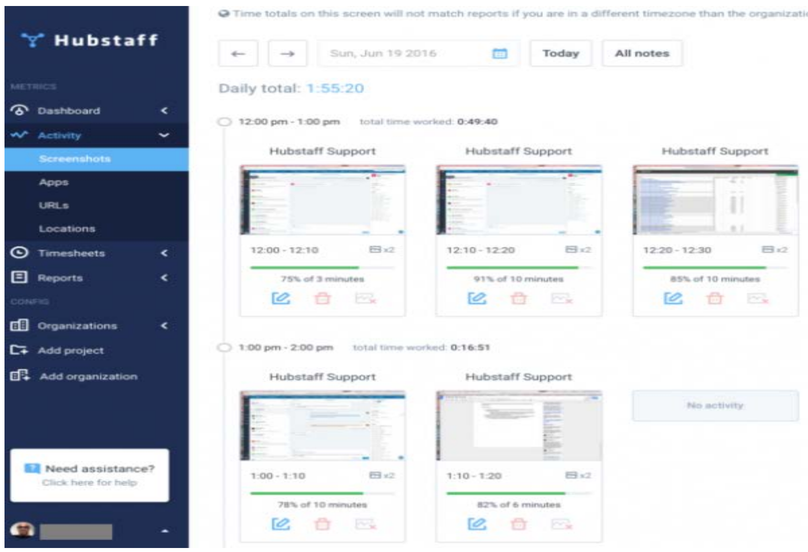


Figure A6. Tutorial for the *all_screenshots* group

Step 4: Job Choice

Figures A7 and A8 are two screenshots of the job preference questions presented to prospective workers in Study 2 (i.e., the Prolific experiment), with a $1 and $-1 wage premium for the monitored job, respectively.

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 9 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.

Figure A7. A Job Preference Question with a $1 Wage Premium for the Monitored Job

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 1,800 correctly labeled images (it usually takes about one hour to correctly label 1,800 images).

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).

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

Figure A8. A Job Preference Question with a $-1 Wage Premium for the Monitored Job

Step 5: Perception of Monitoring

Figure A9 shows the scale used to measure privacy concerns in both Study 1 and Study 2. Please refer to Appendix B for more details on the design and reliability of this scale.

Suppose you are monitored while working, to what degree you agree or disagree with the following statements regarding your privacy concerns.

All things considered, the monitoring system would cause serious privacy problems.

Disagree a little

- Disagree strongly
- Disagree moderately
- Disagree a little
- Neither agree nor disagree
- Agree a little
- Agree moderately
- Agree strongly

Compared to others, I am more sensitive about the way the monitoring system handles my personal information.

To me, it is the most important thing to keep my privacy intact from the monitoring system.

I believe other people are too much concerned with online privacy issues in the usage of the monitoring system.

Compared with other subjects on my mind, personal privacy is very important.

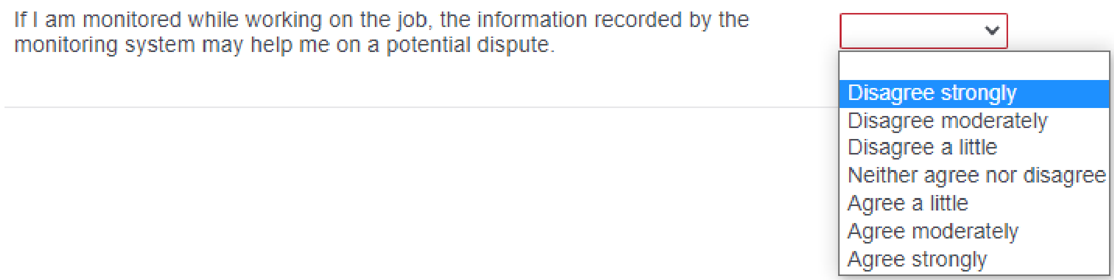
I am concerned about threats to my personal privacy while being monitored.

Figure A9. Privacy Concern Questions

Figures A10 and A11 represent the questions used to measure workers' perceived payment protection from monitoring in Study 1 and Study 2, respectively. We changed the wording of the question in Study 2 as workers are paid by the number of correctly labeled images, rather than working hours or other proxies of efforts.

	Disagree strongly	Disagree moderately	Disagree a little	Neither agree nor disagree	Agree a little	Agree moderately	Agree strongly
Monitoring system can provide evidence of my effort.	○	○	○	○	○	○	○

Figure A10. Payment Protection Question in Study 1 (AMT)



If I am monitored while working on the job, the information recorded by the monitoring system may help me on a potential dispute.

Disagree strongly
Disagree moderately
Disagree a little
Neither agree nor disagree
Agree a little
Agree moderately
Agree strongly

Figure A11. Payment Protection Question in Study 2 (Prolific)

Step 6: ACT Test

A customer gives a cashier a $20 bill to pay for a cup of coffee that costs $3.84, including tax. How much change should the cashier give back to the customer?

- $15.26
- $16.16
- $16.26
- $16.84
- $17.16

Over the last five days, you made the following numbers of calls: 8, 7, 9, 5, and 7. On average, how many calls did you make each day?

- 5.8
- 7.0
- 7.2
- 9.0
- 36.0

Figure A12. ACT Test Questions

Request for Information (RFI) Log

RFI #	Request date	Title	Status	Response date
RFI-0393	02/06	Mechanical Room Duct Sleeve	Canceled	
RFI-0392	02/05	Bathroom Ceilings	In Review	02/06
RFI-0391	02/04	AHU Alarm Monitoring Clarification	New Item	
RFI-0890	02/03	Union Station Ceiling Conflict	Closed	02/03
RFI-0389	02/02	AHU Smoke Damper Control	Canceled	
RFI-0388	02/02	URGENT: Terminal Unit Accessories	Canceled	
RFI-0387	01/30	Base in Vestibule	Closed	01/30
RFI-0386	01/29	Hardware for Existing Door	Pending	01/30
RFI-0385	01/28	Door	Pending	01/29
RFI-0384	01/28	Union Station Hood Fire Protection	Closed	01/29

A construction manager is reviewing the Request for Information (RFI) Log shown above.

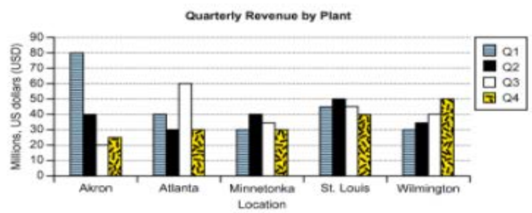
When was RFI-0386 requested?

01/28

01/29

01/30

02/02



A company would like to reallocate budgets to locations that had the most quarters under 40 million dollars in revenue. Based on the quarterly review shown in the above graph, which location should be chosen?

Akron

Atlanta

Minnetonka

St. Louis

Figure A12. ACT Test Questions (Continued)

Step 7: Attention Check

In the previous question on job preference, which type of job did you choose?

- a job being monitored
- a job without being monitored

Figure A13. Attention Check Question

Appendix B. Measurement of Privacy Concerns

We use the following six questions adapted from the "Global Information Privacy Concern Scale" (Malhotra et al. 2004) to measure the privacy concerns of workers:

1) All things considered, the monitoring system would cause serious privacy problems.

2) Compared to others, I am more sensitive about the way the monitoring system handles my personal information.

3) To me, the most important thing is to keep my privacy intact from the monitoring system.

4) I believe other people are too much concerned with online privacy issues with the usage of the monitoring system.

5) Compared with other issues in my mind, personal privacy is very important.

6) I am concerned about threats to my personal privacy while being monitored.

We use the Stata command *alpha* to analyze the reliability of our privacy concern scale. The reliability analysis results on the AMT and Prolific samples are highly consistent and are summarized in Tables B1 and B2, respectively. The item-rest correlation, i.e., the correlation between a given item (i.e., question) and the scale formed by all the other items (Nunnally and Bernstein 1994), is the lowest for item 4. Additionally, Cronbach's alpha is the highest after removing item 4. Therefore, we exclude item 4 and use the average of the rest five items as the measured level of privacy concerns. Note that our results are consistent if we keep item 4 while computing the average.

Table B1. Reliability of the Privacy Concern Scale on AMT

Item	Obs	Sign	Item-rest correlation	Alpha without the row item
privacy_1	1895	+	0.689	0.858
privacy_2	1895	+	0.770	0.844
privacy_3	1895	+	0.783	0.842
privacy_4 (reverse)	1895	+	0.412	0.902
privacy_5	1895	+	0.670	0.861
privacy_6	1895	+	0.817	0.836

Note: If we retain all six items, Cronbach's alpha is 0.879.

Table B2. Reliability of the Privacy Concern Scale on Prolific

Item	Obs	Sign	Item-rest correlation	Alpha without the row item
privacy_1	1882	+	0.669	0.856
privacy_2	1882	+	0.764	0.840
privacy_3	1882	+	0.732	0.845
privacy_4 (reverse)	1882	+	0.485	0.886
privacy_5	1882	+	0.646	0.860
privacy_6	1882	+	0.793	0.835

Note: If we retain all six items, Cronbach's alpha is 0.876.

Appendix C. Representativeness of Workers

In order to examine whether the AMT workers recruited by us are representative of the overall AMT worker population, we use the API provided by Difallah et al. (2018) to collect the overall demographic information of AMT workers from Jan 1st, 2018 to April 1st, 2018. Table C1 compares the demographics of AMT workers in our experiment with those in the US. The demographics of AMT workers in our experiment are similar to those of the AMT workers in the US. The comparison is not feasible for the recruited Prolific workers, since we are not aware of a similar API to collect the overall demographic information of Prolific workers.

Table C1. Comparison of Recruited AMT Workers with AMT Population

		AMT Workers in this Experiment	AMT Workers in the US
		(1)	(2)
Gender	Female	55.94%	53.35%
Education	Less than high school	0.37%	0.75%
	High school diploma or equivalent	9.02%	10.57%
	Some college, no degree	22.33%	27.50%
	Associate’s degree	11.61%	12.12%
	Bachelor’s degree	42.32%	36.13%
	Master’s degree	12.35%	10.61%
	Doctoral or professional degree	2.01%	2.31%
Race	Asian or Asian American	7.34%	--
	Black or African American	8.50%	--
	Hispanic or Latino	6.86%	--
	White	74.56%	--
	other	2.75%	--
Observations		1,895	2,120

Note: The race information is not available from the API provided by Difallah et al. (2018).

Appendix D. Randomization Check

Table D1 reports the average of worker-level variables grouped by monitoring policy for both the AMT and Prolific samples. The means of these variables are highly similar across different monitoring policies. ANOVA tests suggest that the differences in worker-level variables are not statistically significant across different monitoring policy groups, except for a few exceptions that are likely to occur by chance, demonstrating proper randomization.

Table D1. Randomization Check

Panel A: AMT		only_time	no_disclosure	controlled_ screenshots	all_screenshots	*p*-value
Gender	Female	0.554	0.592	0.537	0.556	0.388
Education	Less than high school	0.004	0.002	0.008	0.000	0.174
	High school diploma or equivalent	0.104	0.083	0.104	0.069	0.180
	Some college, no degree	0.169	0.268	0.22	0.213	0.003
	Postsecondary nondegree award	0.006	0.009	0.004	0.008	0.817
	Associate's degree	0.132	0.11	0.097	0.124	0.335
	Bachelor's degree	0.452	0.406	0.376	0.457	0.033
	Master's degree	0.122	0.099	0.161	0.112	0.026
	Doctoral or professional degree	0.010	0.024	0.03	0.017	0.154
Race	Asian or Asian American	0.094	0.064	0.061	0.074	0.201
	Black or African American	0.069	0.088	0.082	0.101	0.359
	Hispanic or Latino	0.055	0.066	0.072	0.082	0.405
	White	0.747	0.759	0.759	0.718	0.425
	other	0.035	0.024	0.025	0.025	0.730
Panel B: Prolific		**only_time**	**no_disclosure**	**controlled_ screenshots**	**all_screenshots**	***p*-value**
Gender	Female	0.514	0.532	0.501	0.549	0.470
Education	Less than high school	0.004	0.004	0.019	0.006	0.038
	High school diploma or equivalent	0.120	0.124	0.141	0.120	0.735
	Some college, no degree	0.219	0.242	0.240	0.238	0.821
	Postsecondary nondegree award	0.008	0.002	0.006	0.002	0.405
	Associate's degree	0.105	0.067	0.08	0.099	0.139
	Bachelor's degree	0.368	0.367	0.352	0.373	0.910
	Master's degree	0.135	0.155	0.135	0.127	0.646
	Doctoral or professional degree	0.040	0.039	0.027	0.034	0.717
Race	Asian or Asian American	0.133	0.118	0.107	0.144	0.348
	Black or African American	0.095	0.082	0.072	0.088	0.616
	Hispanic or Latino	0.065	0.064	0.084	0.082	0.518
	White	0.661	0.697	0.695	0.637	0.153
	other	0.046	0.039	0.042	0.049	0.865

Note: The *p*-values of the ANOVA tests are reported in the last column.

Tables D2 and D3 summarize the treatment assignments by gender and by wage premium, respectively.

Table D2. Treatment Assignments by Gender

	AMT			Prolific		
	Female	Male	Total	Female	Male	Total
only_time	272	219	491	244	231	475
no_disclosure	270	186	456	248	218	466
controlled_screenshots	254	219	473	238	237	475
all_screenshots	264	211	475	256	210	466
Total	1,060	835	1,895	986	896	1,882

Table D3. Treatment Assignments by Wage Premium

Panel A: AMT

wage premium	wage of the monitored job	wage of the unmonitored job	only_time (#obs)	no_disclosure (#obs)	controlled _screenshots (#obs)	all _screenshots (#obs)
-2	7	9	35	34	28	29
-1.5	7.5	9	36	33	30	27
-1	8	9	31	25	27	44
-0.5	8.5	9	30	38	35	28
0	9	9	24	25	38	38
0.5	9	8.5	39	24	33	31
1	9	8	37	34	31	25
1.5	9	7.5	32	29	38	25
2	9	7	35	27	33	34
2.5	9	6.5	29	30	31	36
3	9	6	30	39	24	34
3.5	9	5.5	33	33	29	32
4	9	5	34	25	28	35
4.5	9	4.5	34	29	35	24
5	9	4	32	31	33	33
Total			491	456	473	475

Panel B: Prolific

wage premium	wage of the monitored job	wage of the unmonitored job	only_time (#obs)	no_disclosure (#obs)	controlled _screenshots (#obs)	all _screenshots (#obs)
-1	9	10	31	30	35	35
-0.5	9.5	10	29	47	50	34
0	10	10	27	39	28	38
0.5	10	9.5	36	47	42	34
1	10	9	39	32	48	37
1.5	10	8.5	37	36	33	38
2	10	8	45	38	35	40
2.5	10	7.5	48	33	43	31
3	10	7	43	52	38	44
3.5	10	6.5	31	20	28	30
4	10	6	44	33	37	33
4.5	10	5.5	32	32	34	40
5	10	5	33	27	24	32
Total			475	466	475	466

Appendix E. Full Sample Analysis on All Monitoring Policies

In our main analysis, we run a series of subsample analyses that only consider the relevant groups summarized in Table 5 to estimate the effect of each monitoring dimension directly. Below we estimate the effects of the three dimensions of monitoring (i.e., intensity, transparency, and control) based on a full sample analysis on workers in all four monitoring groups. The effects of the different monitoring policies on job choices, using the *only_time* policy as the reference group, are summarized in Table E1. The significant and negative coefficients of *no_disclosure* in Columns 1 and 5 suggest that being transparent on low intensity monitoring can increase workers' acceptance of monitoring. The significant and negative coefficients of *all_screenshots* in Columns 1 and 5 demonstrate that workers are less likely to choose monitored jobs as the intensity increases. The coefficients of *controlled_screenshots* and *all_screenshots* are not significantly different in either Column 1 or 5, suggesting again that providing workers with control over the collected information has no effect on workers' propensity to accept monitoring.

The positive and significant coefficients of *all_screenshots* in Columns 2 and 6 show that workers' privacy concerns increase with the intensity of monitoring. The coefficients of *no_disclosure* are also positive in these two columns, suggesting that a lack of transparency on a low intensity monitoring policy can also significantly increase workers' privacy concerns. In Columns 3 and 7, the coefficients of *no_disclosure* and *all_screenshots* are significantly different ($p<0.05$ and $p<0.01$ on the AMT and Prolific samples, respectively). [16] All the above findings are consistent with those discussed in Section 5.2.

[16] We use the "lincom" command in Stata to test whether the difference of the coefficients on *no_disclosure* and *all_screenshots* are significantly different from zero.

Table E1. Effects of Monitoring Policies on Perception and Acceptance of Monitoring

	AMT				Prolific			
	Choice	Privacy	Protection	Choice	Choice	Privacy	Protection	Choice
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
no_disclosure	-0.070***	0.283***	-0.076	-0.040*	-0.069***	0.244***	-0.200**	-0.032
	(0.025)	(0.092)	(0.088)	(0.023)	(0.027)	(0.089)	(0.087)	(0.024)
controlled_screenshots	-0.052**	0.274***	-0.016	-0.025	-0.039	0.091	-0.046	-0.027
	(0.025)	(0.091)	(0.087)	(0.023)	(0.027)	(0.089)	(0.087)	(0.024)
all_screenshots	-0.058**	0.188**	0.111	-0.046**	-0.069***	0.188**	0.061	-0.052**
	(0.025)	(0.090)	(0.087)	(0.023)	(0.027)	(0.089)	(0.087)	(0.024)
male	-0.038**	0.123*	-0.124**	-0.020	-0.084***	0.132**	-0.176***	-0.061***
	(0.018)	(0.065)	(0.063)	(0.017)	(0.019)	(0.063)	(0.062)	(0.017)
wage_premium	0.145***	-0.056***	0.024*	0.138***	0.153***	-0.061***	0.006	0.146***
	(0.004)	(0.015)	(0.014)	(0.004)	(0.005)	(0.017)	(0.017)	(0.005)
privacy				-0.093***				-0.107***
				(0.006)				(0.006)
protection				0.048***				0.053***
				(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	0.412	0.062	0.048	0.511	0.337	0.037	0.025	0.455

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The reference group is *only_time*. The control variables include workers' education, race, working experience, average hourly wage on the platform, prior experience with monitoring, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we do not include any worker-level control variables or when we use probit instead of LPM models for workers' job choices.

Appendix F. Modeling Inattentive Responses

To alleviate the concern that our findings are driven by inattentive responses from workers, we re-estimate the effect of monitoring policy on job choice using a finite mixture model that explicitly models workers' inattention (Mas and Pallais 2017). Specifically, assuming that there is a probability of η that a worker is inattentive and chooses randomly between the monitored and unmonitored jobs, Equation (6) can be adapted to the following:

$$P(choice_i = 1) = \Phi(\beta_0 + \beta_1 wage\_premium_i + \beta_2 X_i)(1 - \eta) + \eta/2 \tag{F1}$$

The parameters in the above model can be estimated using the maximum likelihood method. Table F1 summarizes the results from the finite mixture model. The results in Table F1 are highly consistent with those results shown in Section 5.2, which demonstrate that our findings are unlikely to be driven by inattentive responses.

Table F1. Effects of Monitoring Policies on Job Choices Using a Finite Mixture Model

	AMT			Prolific		
	Choice	Choice	Choice	Choice	Choice	Choice
Baseline	only_time	no_disclosure	all_screenshots	only_time	no_disclosure	all_screenshots
Dimension	Intensity	Transparency	Control	Intensity	Transparency	Control
	(1)	(2)	(3)	(4)	(5)	(6)
only_time		0.343***			0.364***	
		(0.114)			(0.141)	
controlled_screenshots			0.021			0.223
			(0.098)			(0.187)
all_screenshots	-0.326***	0.058		-0.296*	0.069	
	(0.120)	(0.108)		(0.161)	(0.143)	
male	-0.357***	-0.244***	-0.196**	-0.279*	-0.444***	-0.381**
	(0.125)	(0.090)	(0.099)	(0.163)	(0.126)	(0.187)
wage_premium	0.609***	0.544***	0.454***	0.793***	0.703***	0.914***
	(0.068)	(0.056)	(0.027)	(0.111)	(0.093)	(0.137)
η	0.049	0.017	0.000	0.188	0.150	0.233
	(0.038)	(0.038)	(0.000)	(0.041)	(0.044)	(0.040)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	966	1,422	948	941	1,407	941
Log-likelihood	-405.87	-609.39	-441.17	-452.30	-679.41	-467.30

Note: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01. The control variables include workers' education, race, working experience, average hourly wage on the platform, prior experience with monitoring, and whether the job choice was made before measuring privacy concerns (AMT only).

Appendix G. Robustness Check on Reverse Causality

As we explained in Section 3.3, to address the potential reverse causality, we proactively randomize the order of the questions on job choice and privacy concerns in the AMT experiment. In our main analysis, we account for the potential order effect by controlling for whether workers' privacy concerns are measured before or after the job choice. As an alternative way to rule out the concern that a worker's privacy concerns might be affected by his/her job choice, we rerun the analysis in Table E1 by focusing on the subsample of AMT workers whose privacy concerns are measured before their job choices. The results of this analysis are summarized in Table G1. The findings are consistent with those in Table E1, suggesting that our findings are unlikely to be an artifact of reverse causality.

Table G1. Subsample Analysis on AMT Workers Whose Privacy Concerns Are Measured before Job Choices

	Choice (1)	Privacy (2)	Protection (3)	Choice (4)
no_disclosure	-0.102***	0.334***	-0.105	-0.072**
	(0.037)	(0.128)	(0.126)	(0.035)
controlled_screenshots	-0.080**	0.246*	-0.021	-0.061*
	(0.036)	(0.126)	(0.124)	(0.034)
all_screenshots	-0.060*	0.178	0.054	-0.050
	(0.035)	(0.122)	(0.120)	(0.033)
male	-0.053**	0.200**	-0.076	-0.035
	(0.026)	(0.090)	(0.089)	(0.025)
wage_premium	0.140***		0.009	0.140***
	(0.006)		(0.020)	(0.006)
privacy				-0.073***
				(0.009)
protection				0.047***
				(0.009)
Control variables	Yes	Yes	Yes	Yes
Observations	950	950	950	950
R^2	0.410	0.065	0.055	0.473

Note: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01. The baseline monitoring policy group is *only_time*. The result is calculated based on the AMT sample because we only randomize the present order in the AMT experiment. The control variables include workers' education, race, working experience, average hourly wage on the platform, and prior experience with monitoring. The results are similar when we do not include any worker-level control variables.

Appendix H. Results Using a PCA-based Privacy Concern Measure

As explained in Appendix B, we use the average score of privacy-related questions to measure workers' privacy concerns. In addition to the average score, we also consider using PCA to extract an integrated measure from the privacy concern scale. We remove the least relevant question (i.e., item 4) while conducting PCA, though the results are similar if we keep it. Following the convention of using one as the cutoff for eigenvalues (Kaiser 1960, Osborne et al. 2011), we retain only the first principal component that explains 72.0% and 68.9% of the variances in the AMT and Prolific samples, respectively. We re-estimate the models in Table E1 using this alternative privacy concern score obtained from PCA (denoted as *PCA_privacy*) and the results are summarized in Table H1. The results are highly similar to those in Table E1.

Table H1. Results Using a PCA-based Privacy Concern Measure

	AMT			Prolific		
	Choice	PCA_privacy	Choice	Choice	PCA_Privacy	Choice
	(1)	(2)	(3)	(4)	(5)	(6)
no_disclosure	-0.070***	0.370***	-0.041*	-0.069***	0.320***	-0.042*
	(0.025)	(0.122)	(0.024)	(0.027)	(0.120)	(0.025)
controlled_screenshots	-0.052**	0.359***	-0.024	-0.039	0.114	-0.029
	(0.025)	(0.120)	(0.023)	(0.027)	(0.120)	(0.025)
all_screenshots	-0.058**	0.245**	-0.039*	-0.069***	0.249**	-0.048*
	(0.025)	(0.120)	(0.023)	(0.027)	(0.120)	(0.025)
male	-0.038**	0.158*	-0.026	-0.084***	0.174**	-0.069***
	(0.018)	(0.087)	(0.017)	(0.019)	(0.086)	(0.018)
wage_premium	0.145***	-0.074***	0.139***	0.153***	-0.081***	0.146***
	(0.004)	(0.020)	(0.004)	(0.005)	(0.024)	(0.005)
pca_privacy			-0.078***			-0.085***
			(0.004)			(0.005)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,895	1,895	1,895	1,882	1,882	1,882
R^2	0.062	0.412	0.494	0.036	0.337	0.434

Note: $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01. The reference group is *only_time*. The control variables include workers' education, race, working experience, average hourly wage on the platform, prior experience with monitoring, and whether the job choice was made before measuring privacy concerns (AMT only). The results are similar when we do not include any worker-level control variables or when we use probit instead of LPM models for workers' job choices.

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