The Automation Data Bargain under Worker Constraints *

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Abstract

In contrast to the traditional automation process, workers provide a key input in AI-driven automation: data. This paper documents that workers often do not make a connection of data collection with automation use and that asymmetric information, firm power and liquidity constraints can substantially distort workers' decision. In a randomized field experiment with factory workers in India, we elicit the minimum additional daily payment required by workers to make first-person recordings of their work tasks. We randomize the disclosure about the downstream use of the data for automation and who makes the offer (employer firm or an outside organization), and follow-up on belief changes, liquidity, skill specificity and pivotality. We find that, relative to a fully disclosed offer from a non-employer, withholding information lowers the workers' reservation price by 36 percent of the daily wage, and the same offer from the worker's own employer lowers it further by 13 percent of daily wage. Follow-up survey shows that, under status quo, workers treat data recording as additional standardized work within the contract. This makes the reservation payments sensitive to liquidity constraints and flattens the skill price relationship observed when workers can bargain with a non-employer under full information. These findings reveal that information asymmetry lowers workers' reservation prices for training data, giving firms scope to capture a larger share of the gains from automation. Workers' replaceability as data suppliers and weak bargaining positions compound this advantage.

Keywords: automation, artificial intelligence, information asymmetry, bargaining power
JEL codes: C93, D82, J31, J42, J63, O14, O33

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1 Introduction

Today's workers hold one of the key inputs that may determine the progress of artificial intelligence driven automation in the factories of the future: data. Recent advances in large language models have relied on the availability of vast, internet-scale training datasets. These models exhibit a strong regularity known as a scaling law, under which model performance follows an approximate power-law relationship with the amount of training data (Kaplan et al., 2020). Sustaining this pace of progress as AI expands to a wider range of tasks, particularly physical tasks within firms' production processes, will require new sources of data. Much of the knowledge needed to generate these data has not yet been codified and resides with workers. For example, handling different types of fabric while sewing is relatively straightforward for humans and forms part of jobs performed by millions of workers, yet large, systematic datasets demonstrating these tasks remain scarce for training robots. Many production tasks also rely on tacit knowledge that workers use every day but cannot fully articulate, making it difficult for firms to reproduce their expertise through written instructions (Polanyi, 1966; Autor, 2014). Perhaps unsurprisingly, numerous firms and new ventures have rushed to create these datasets by incentivizing workers to record their work tasks and tacit knowledge — often receiving critical media coverage as "workers training their own displacement"[1].

To the extent that workers face a choice in providing the data, their individual decisions determine the cumulative flow of expertise as data from labor to AI-driven machines. These individual decisions, however, may be far from socially optimal. Workers, especially in low income settings, face numerous information, contractual and liquidity frictions which coupled with coordination failures can substantially distort their decision or the compensation that they are able to demand for this data. A compensation which might not even cover the displacement risk generated by the AI automation process let alone provide a share in the surplus generated by the productivity improvements. The existing economics literature on automation mostly abstracts from any role of the workers in providing an input in the automation process and therefore provides little theoretical or empirical guidance on the relative importance of the different sources of distortions and implied policy recommendations.[2]

In this paper, we use a randomized field experiment to measure workers' reservation compensation for a data sharing decision under frictions and study its implications for the speed and distribution of gains from a data-led AI transition. We offer hypothetical contracts to record first person videos of work tasks to factory workers in India and find that worker decisions suffer from large asymmetries in information and contractual power. Despite media coverage and high automation salience of the data collection method, most workers do not make a connection of data recording with use in AI training and automation when the information is not disclosed. Work-

[1] See, https://www.ft.com/content/e5fd2655-f95f-4183-9dd9-b3c1ebe67a6b?syn-25a6b1a6=1, and https://www.theguardian.com/global-development/2026/jun/24/indian-factory-workers-told-film-themselves-for-ai-robots

[2] In Champernowne (1961), Zeira (1998), Acemoglu and Autor (2011), Acemoglu and Restrepo (2018a) firm simply decides to either use machine or labor at a given task depending on whichever has a lower marginal cost, and worker decisions play no role.

ers mostly instead trade off the payments from recording with immediate costs such as increased surveillance and disutility of wearing the cameras or assume this additional work to be a part of their employer relationship — thus significantly reducing the demanded compensation when the offer comes from within the firm and without full disclosure. Moreover, we find that asymmetric information also makes worker decisions to be more sensitive to temporary shocks such as liquidity constraints and flattens the skill price relationship observed under disclosure. While workers do respond that they can get higher compensation under collective bargaining, race to the bottom dynamics are also dampened as, in the baseline, workers do not price the displacement risk and therefore also don't strategically lower price anticipating an earlier displacement due to actions of other workers.

Our study is conducted with workers in advanced electronics and garment factories in industrial areas around Delhi. The tasks that workers in these firms perform are done by millions of workers globally but have resisted traditional automation as the tasks often require high level of dexterity and judgment. Pre-AI industrial robots excel at repetitive tasks on rigid objects, but they struggle with variability such as adjusting to clothes or mobile phones of different shapes and specifications, and with tasks that require delicate control such as handling flexible garment materials for sewing and fitting small parts in electronics. Rapid rise in AI model capabilities combined with dexterous robots have a potential to excel at these tasks, but they face a data constraint as unlike the tasks which are done digitally, manual work often leaves a low amount of trailing data that can be used to train the models. Thus, there has been a sharp rise in the demand for data to train AI in these sectors and significant amount of data collection is done in developing countries where workers face large labor market frictions.

We recruit workers for the study in areas close to the factories and offer them hypothetical contracts to record their work tasks by wearing a first-person head mounted camera— with an increasing ladder of offer prices. Our main outcome variable is the offer price at which the decision of the workers turns from a no to yes for participation in the recording process, and we refer to it as the reservation price or the reservation compensation. To isolate the information and contractual asymmetries, we randomly disclose the information about the downstream use of the data to train AI-driven automation and also vary, within worker, the data recording offer to be either coming from their employer firm or an outside organization. After eliciting the reservation price, we follow up with workers about the reasons for their decision, the beliefs about automation, the role of the data in facilitating the automation, and also collect information on their skills, liquidity constraints, views on collective bargaining and pivotality.

We find that withholding the information that the recordings will be used for automation training decreases the reservation compensation demanded by workers. When the offer comes from the employer, disclosure arm workers demand Rs 434 to agree for a recording of their tasks while under non-disclosure the payments fall to Rs 229. Workers in the disclosure arm thus demand about 92 percent more than the non-disclosure mean. In units of their own daily wage, workers in the disclosure arm demand an additional 0.35 of daily wage from their employer, against

non-disclosure mean of 0.35. Workers' stated reasons indicate that disclosure changes the considerations underlying their responses. In the non-disclosure arm, only two of the 149 workers who explain their response to the employer offer mentions the possibility that a machine could learn their task and threaten their job. Under disclosure, 33 of 150 workers cite this concern ($p<0.001$). In both arms, however, the most common explanations concern the immediate costs of recording, particularly the burden of wearing a camera for eight hours and the need to work more carefully while being recorded. These considerations are cited by 61 percent of workers in the non-disclosure arm and 53 percent in the disclosure arm.

Workers require 89 rupees more per day when the recording request comes from the outside research organization rather than from their own employer ($p<0.001$). Workers' responses suggest that the employment relationship contributes to this gap: 78 percent expect their employer to dismiss them if they refuse to participate.

Non-disclosure also increases the sensitivity of the workers' reservation payments to their current liquidity constraints and flattens the skill price relationship. Under non-disclosure workers who face liquidity constraints demand 107 rupees less than workers who do not face such constraints. This relationship gets flipped under the disclosure arm. Similarly, under non-disclosure workers who report having unique skills at their workplace do not demand a different premium. Whereas under disclosure, the gap opens up to 100 rupees.

Overall, our results point towards large asymmetries in information and contractual power over data use in our setting. These asymmetries also substantially distort worker decision and may lead to fast erosion of the worker expertise and lower the worker share in the eventual transition. Collective bargaining and mandatory information policies or better defined contracts over the worker data might be useful ways to tackle these distortions.

Literature and contributions Our paper is related to two main strands of literature. The first strand provides theory and evidence on decisions that determine the adoption of automation technologies and their economic consequences. Early papers in this literature mostly focus on the decisions of the firm and imply a frictionless adoption of automation technologies at the task level if it provides a cost reduction over labor (Champernowne, 1961; Zeira, 1998; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018b, 2019, 2022). The resulting equilibrium under these models can also generate excessive automation, either because technologies substitute for labor without commensurate productivity gains (Acemoglu and Restrepo, 2020), the tax system favors capital over labor (Acemoglu et al., 2020), or firms dissipate rents in the race to automate (Acemoglu and Restrepo, 2026), and studies policies that can correct these incentives (Guerreiro et al., 2022; Costinot and Werning, 2023). Relatively few papers focus on the role of the worker in this literature with a few exceptions such as Beraja and Zorzi (2025). However, the role of the worker is still limited as they focus on frictions which might lead to inefficient reallocations but do not document or theorize how workers decisions can impact automation itself. Our paper therefore adds into this literature by documenting how the frictions faced by workers can distort the provision of

an input into automation and hence change the pace and gains from automation itself.

Second, our paper adds to the literature on economics of data and its role for automation. Jones and Tonetti (2020), Farboodi et al. (2019) and Farboodi and Veldkamp (2021) show how the non-rival, by-product and feedback nature of data can generate increasing returns to scale and draw implications for market structure, firm dynamics and property rights. This data is also important for automation and Farboodi et al. (2026) draw out the implications in a dynamic model and show that, along the transition path, data can simultaneously augment the productivity of already-automated tasks and expand the automation frontier. The role of the worker has also been limited in this literature. While an empirical strand documents the labor involved in producing training data and the contracting and outsourcing arrangements through which firms acquire it (Gray and Suri, 2019; Miceli and Posada, 2022; Kapania et al., 2026), our setting differs from standard consumer-data markets because the data encode the worker's own expertise and can be used to enhance the productivity of capital that substitutes labor.

One recent exception is Cullen et al. (2026), who study workers' supply of expertise to AI, provide experimental evidence on its responsiveness to career incentives, and analyze the implications for data ownership. Relative to them, we examine two different empirical margins that affect data sharing: incomplete information about the intended use of data and bargaining constraints within the employment relationship due to monopsony power or incomplete contracts. We show that in the low income settings, these frictions can substantially distort worker decisions and make the data sharing decisions more sensitive to liquidity constraints and unlink them from the worker expertise. Our setting of manufacturing which requires low digital trace and requires an additional effort to generate and bargain for data that captures tasks and tacit knowledge also separates us from previous work.

Lastly, the questions we address are particularly consequential for developing economies, where manufacturing has historically provided employment and a path to higher productivity and structural transformation. Automation adopted in high-income economies can already reduce demand for labor in developing countries through trade (Faber, 2020; Artuc et al., 2019, 2023). Worker-generated training data introduce an additional channel: workers in developing economies may help create technologies that substitute for the very forms of labor on which their economies still rely. When firms in other countries own these technologies, the gains from automation may accrue to those firms while workers bear the costs of displacement. The terms on which workers supply their data can therefore shape how these gains are divided between workers and firms and across countries.

2 Research Design

We use an experiment to identify how asymmetric information and worker bargaining power affect the compensation that workers demand for providing data that may lead to their displacement. We also elicit workers' beliefs about the timing of automation, their anticipated earnings

losses following displacement, and their prior awareness of requests to record their work.

2.1 Context: Worker Video Data for Physical AI Training in Skilled Manufacturing

Our sample consists of adult factory workers in the National Capital Region of Delhi. We recruit from three industry groups: textiles and garments; electronics; and other manufacturing, including metal and vehicle-component assembly and paper packaging.

Industry, Firms and Existing Automation We focus on these three industries because they employ a large share of middle-skill workers and face an automation threat accelerated by the rapid recent advances in artificial intelligence and robotics. The six broad industry divisions corresponding to our sample together accounted for approximately 6.1 million workers in 2023–24, or 31.2% of total employment covered by the Annual Survey of Industries (Ministry of Statistics and Programme Implementation, 2025). The wages of all the workers in our sample lie above the median daily wages of Indian workers (Table 1) and they also report a relatively stable number of days worked in a month. Automation in these occupations could therefore erode an important source of jobs for millions of workers in a developing country like India.

The jobs in our setting have survived automation threats by advances in non-AI industrial robotics since the early 2000s as the tasks that they perform often require a high degree of judgment and manual dexterity. Pre-AI industrial robots excel at repetitive tasks on rigid objects, but they struggle with high variability such as adjusting to clothes or mobile phones of different shapes and specifications, and with tasks that require delicate control such as handling flexible garment materials for sewing and fitting small parts in electronics (Vashisht and Rani, 2020; Bárcia de Mattos et al., 2020; Zhu and Hu, 2018). Garment sewing, electronic component assembly, and manual packing – all the tasks that we focus on in this paper[3] – require such kind of work and thus helps us to avoid the confounding effects of traditional automation from AI driven automation in a low-and-middle income country setting.[4]

To further isolate AI driven rather than traditional automation, we recruit workers from advanced factories that either serve as local manufacturers for international firms or are large, capital-intensive firms producing for the local consumption and exports. Appendix Table A10 provides the summary statistics for our respondents' employers which we were able to match with the Prowess database and compares them with the average Indian manufacturing firm in the same sectors in the Indian Annual Survey of Industries. Prowess covers mainly large firms, but we match 13 firms which cover about 20% of the employment in our sample. These firms have sev-

[3] Appendix Table A8 notes the tasks the workers in our sample perform in their occupation.

[4] Anecdotally, large firms like Apple and Nike still rely heavily on human labor in these tasks, despite repeated automation attempts, as their product designs change often which incurs a large fixed cost for re-calibrating traditional robots (https://appleinsider.com/articles/20/06/04/how-apple-learned-automation-cant-match-human-skill) or traditional robots haven't had success in simple tasks such as picking and placing small screws in electronics or working with seams on fabrics which bunch and stretch when they are worked with in a production setting (https://fashionlawjournal.com/why-robots-still-cant-sew-your-clothes/)

eral orders of magnitude larger sales than a typical Indian manufacturing firm, are six times more likely to be an exporter and about 30% of the firms report R&D spending. Our sample therefore helps ensure that the firms are operating closer to the current automation technological frontier.

Physical AI and the role of Worker Training Data Recent progress in artificial intelligence opens the door to tackling the challenges of high variability and dexterity that have limited traditional automation, but faces a key bottleneck – data. In a short span of time, large language models (LLMs) have gone from struggling with basic arithmetic to having advanced capabilities which can perform a large fraction of the tasks done by knowledge workers across the economy. The bedrock for this improvement has been the internet scale datasets used to train these models. In fact, LLMs exhibit a strong regularity called scaling laws wherein their error rates can be expressed as a declining log-linear relationship with the size of the training data. There is a relative abundance of such data for the digital knowledge work but physical work, on the other hand, faces a large data scarcity to train models that can learn from the largely tacit know-how of performing dexterous manual work.

The data that physical-AI models need is embodied in the actions of workers as they perform their tasks. Firms around the world have rushed to collect this data, primarily by incentivizing workers to record egocentric videos of their hands and annotate them with speech as they perform their job. Experts in the development of AI robotics posit that the use of worker training might not just limit to video data but also expand teleoperation or real life feedbacks for reinforcement learning or fine-tuning once these robots are deployed in various production settings (Lin, 2022; Ma et al., 2026; He et al., 2025).

Worker Characteristics and Market Frictions While the training data is an important bottleneck for physical AI training, sharing their data exposes the workers to a potential automation of their own jobs — and the frictions that the workers face might significantly distort their decisions. The workers in our setting are at a high risk of facing these frictions. Table 1 documents the summary statistics of the workers that are a part of our study. The mean years of schooling is only 10.5 years and only about 30 percent of the workers hold a copy of the written contract with their employers. This makes the workers more likely to be prone to information barriers and ambiguity over the nature of the contract and the residual rights over additional work such as on the job data collection. About forty percent of the workers are also unable to raise Rs. 2000 within a week and report a marginal propensity to consume of about 0.74 from an unexpected windfall of Rs. 1000

2.2 Experimental design

The key insight that we want to examine in the experiment is that while making the decision to provide their data the workers might not, by default, make a causal connection between recording their work activities and its subsequent use for training of AI models for automation. Thus withholding information about the AI training use of the data might lower their reservation price

or increase the extensive participation margin. Moreover, firm's bargaining power over the workers might further distort their decision as workers fear retaliation or a direct job loss. We design our intervention to directly test these two mechanisms and study their interaction with baseline beliefs, perceived specificity of skills, liquidity constraints and beliefs about other workers.

We construct a design in which we offer workers hypothetical contracts to wear a head-camera to record their work activity and randomly withhold the information about the downstream use of the data while also varying the counterparty of the data recording offer. The workers are then offered take-it-or-leave-it contracts over an increasing ladder of compensation payments. Simultaneously, we elicit workers beliefs and their mental causal models of the consequences of doing the video recording to isolate the mechanisms. Lastly, we follow up with a survey to gather information about liquidity, skills and expected losses in case of a job loss.

Treatment Our design manipulates the contract features of a hypothetical data recording offer. We randomize the following three aspects of the offer in the experiment:

1. *Disclosure of data use for automation.* We vary whether workers are informed about the downstream use of the recording.

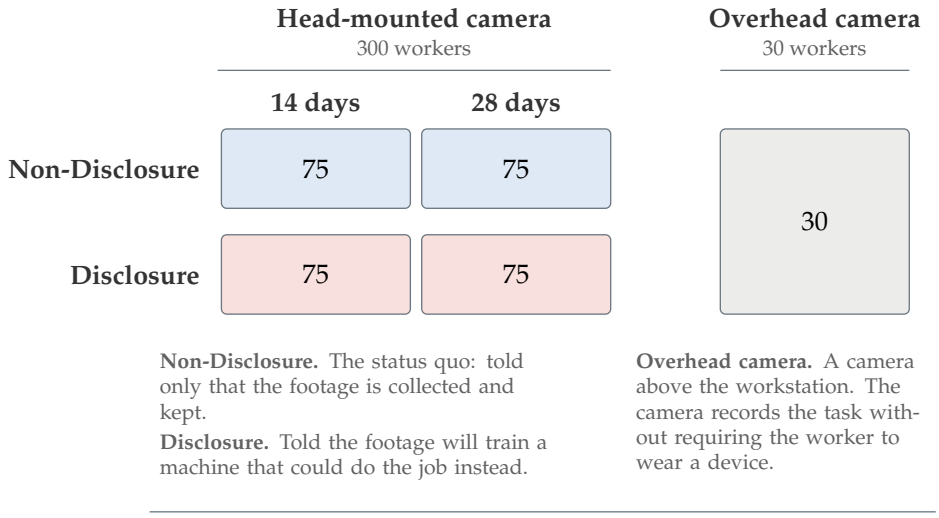
    - Disclosure: Workers are told about the downstream use of the data. In particular, they are told that the recordings will be used to teach a machine to perform their work, and if the machine learns the task, it could replace them.
    - Non-disclosure: This arm captures the status-quo where workers are not told anything about how the recording will be used. The workers are informed that the recording will be kept by the company making the offer.

2. *Recording duration.* We vary whether the worker will have to record themselves for 2 weeks or 4 weeks. The number of hours per day is kept constant at eight.

3. *Counterparty to the offer.* This variation tests whether workers require different compensation depending on whether the request comes from their employer or an outside organization.

    - Current employer: The worker's employer requests the recordings and provides the additional compensation.
    - Outside organization: An outside research or technology organization requests the recordings and pays the worker separately. The worker continues working at their employer's factory and receiving their regular wage. The employer has no role in the additional payment.

Disclosure and recording duration are randomized across workers. Crossing these two dimensions produces four treatment cells: non-disclosure for 14 days, disclosure for 14 days, non-disclosure for 28 days, and disclosure for 28 days. Each cell has 75 workers.



Each worker in the four cells on the left states the compensation they would demand for the same recording twice, in randomized order: once from their own employer and once from an outside research organization.

Figure 1: Treatment cells and assigned sample.

Counterparty varies within workers. Every worker in these four cells evaluates both the employer offer and the outside-organization offer, with the information provided and recording duration held fixed. We randomize which offer comes first and balance this order within each treatment cell and industry group. This allows us to compare the compensation the same worker requires from the two organizations for the same recording task.

A separate group of 30 workers evaluates an employer offer involving a camera installed directly above the workstation. Recording lasts 14 days, and the script does not disclose the automation use. Workers are told that they would be doing their usual work without wearing a device. This group provides a benchmark for compensation for being recorded without wearing a camera. Together, the four main cells and this additional group give a sample of 330 workers. Figure 1 summarizes the design.

Outcome: Reservation Payment for Recording Work Tasks Video Data Workers are told that all offers are explicitly hypothetical. No recording is implemented and no compensation is paid for accepting an offer. Before the first head-camera offer, workers watch a short video showing a worker wearing the device while working. This is done to ensure that they have a good understanding of the task that they are being asked to price. Each worker considers two offers to make the recording: one from their employer and one from an outside organization. We randomly assign which offer they consider first. For each offer, the enumerator first asks whether the worker would participate without additional compensation, participate only with additional compensation, or refuse at any amount. All compensation discussed is in addition to the worker's regular

wage.

For workers who require extra compensation for the first offer, the enumerator starts by asking whether they would agree to record for Rs 50 more per day. If they say no, the enumerator asks about Rs 100, then Rs 200, and continues through a list of eleven amounts up to Rs 1,200. The questions stop when the worker first agrees. At each step, the enumerator states both the daily amount and the total for the recording period. For example, Rs 50 per day for 14 days means Rs 700 in total. Workers who reject every amount are asked to state the lowest daily compensation they would accept.

The worker then considers the offer from the other organization. Again, they first indicate whether they would record without extra compensation, require compensation, or refuse altogether. If they require compensation, they state the minimum daily amount directly; the enumerator does not read the list again.

Workers assigned to the separate overhead-camera group consider only an offer from their employer to record their work using a camera above the workstation. They answer the same participation question and, if they require compensation, the same sequence of amounts. Workers in the main non-disclosure cells also consider an overhead-camera offer, but only after evaluating both head-camera offers. Those who require compensation state an amount directly. The separate group therefore measures responses to the overhead camera without first asking workers to consider wearing a camera.

Discussion: What the comparisons measure The disclosure comparison tests whether explaining the link between recording and possible displacement changes workers' decisions. At a given recording duration, the physical task and compensation procedure are the same across information arms. An increase in required compensation is consistent with workers taking greater account of future earnings losses once the intended use is explained. Disclosure may provide new information or draw attention to a risk workers already recognize; the comparison does not distinguish these channels. We examine both compensation and the shares willing to participate without payment or unwilling to participate at any amount.

The comparison between the employer and the outside organization tests whether the employment relationship affects required compensation. Each worker evaluates the same recording task under both offers. Lower compensation for the employer is consistent with a relationship wedge: workers may accept less because they believe refusal could threaten their current employment. Differences in trust or perceived obligations could also contribute to this gap. Questions about the consequences of refusal help assess these explanations.

The duration comparison asks how compensation changes when the recording period doubles. If workers require compensation only for a constant daily burden, required compensation per day should remain unchanged. Comparing the disclosure effect across durations also tests whether workers respond differently to the automation use when more footage is collected.

The overhead-camera cell provides a benchmark for compensation when workers are recorded

but do not wear a device. Its closest comparison is the employer offer in Cell 1, which also lasts 14 days and does not disclose automation use. The difference helps assess the additional burden associated with the head-camera arrangement.

Survey Measures: Automation Beliefs, Liquidity, Skills and Pivotality The remaining survey modules help us interpret how workers evaluate the recording offers and connect their stated compensation requirements to the mechanisms in the conceptual framework.

We first measure workers' beliefs about automation and about the role of their own recordings in facilitating it. We ask each worker to report the probability that a machine could perform their entire job within two years and within five years. We then ask about the five-year probability of automation under two counterfactual scenarios: one in which the worker supplies the assigned recordings, and another in which the worker refuses and no other worker records in their place. The difference between these two responses measures the worker's perceived contribution of the assigned recordings to the probability of automation. This measure is conceptually distinct from the worker's general belief about whether automation will eventually become technologically feasible.

We next measure workers' beliefs about how easily firms could obtain similar recordings from other workers. We ask how many coworkers perform the same tasks, whether the respondent possesses skills that few other workers have, and how easily the firm could find another worker willing to record. Workers assigned to the disclosure arm also report whether they believe a replacement worker would be more willing to participate if the automation-related use of the recordings were not disclosed. In addition, we ask workers to evaluate compensation under a collective-bargaining scenario. These questions allow us to examine whether workers view their individual refusal as consequential and whether they believe coordination among workers could affect the terms on which training data are supplied.

We measure the expected cost of displacement by asking workers to consider a scenario in which machines displace them from their current job. Workers report how they would earn a living after displacement, how long they expect it would take to resume regular earnings, the monthly earnings they expect to receive once they do so, and how long they expect it would take to return to their current earnings level. These responses allow us to characterize both the magnitude and the expected duration of the income loss associated with displacement.

We also measure liquidity and the value workers place on immediate compensation. Workers report whether they could meet an unexpected Rs 2,000 expense within one week without borrowing, selling an asset, or postponing another necessary payment. We separately ask what share of an unexpected Rs 1,000 payment they would spend within two weeks, treating repayment of outstanding loans as saving rather than consumption.

Finally, we measure workers' prior exposure to automation and to workplace recording. We ask whether workers had previously encountered automation technologies or requests to record their work, which allows us to characterize their familiarity with the practices described in the

experiment. We administer these questions only after the compensation elicitations so that they do not reveal the automation-related use of the recordings before workers in the non-disclosure arm evaluate the offer. Because we measure both automation beliefs and prior awareness after treatment, disclosure itself may influence these responses. We therefore interpret their relationship with stated compensation with appropriate caution.

2.3 Implementation and Protocols

Stratification To ensure the representativeness of our sample we stratify our recruitment across three sectors: textiles and garments; electronics; and other manufacturing, including metal and vehicle-component assembly and paper packaging. The total sample size was 330 workers.

Worker Recruitment for the Experiment The field work was conducted during the months of August, September and October of 2026. The first story of workers being asked to wear cameras in the factories around Delhi was reported in May 2026. The field team recruited workers in residential neighborhoods and public parks near factory clusters in the National Capital Region. Enumerators approached workers in these locations and screened them for eligibility based on their industry and job tasks. We excluded workers employed in lifting jobs, which are common across factories, because our study focuses on tasks requiring fine manual dexterity. Enumerators received a separate list of unique IDs for each industry group. Each ID was linked to a preassigned treatment condition. Enumerators were not informed of these assignments in advance and learned the worker's treatment status only after entering the ID and beginning the interview. Recruitment and eligibility screening therefore preceded the enumerator's knowledge of the worker's assignment.

3 Data and Empirical Strategy

3.1 Summary Statistics and Balance

Table 1 describes the characteristics of workers. The sample is mostly male. Workers are 29 years old on average and have completed about 10.5 years of schooling. Their average monthly earnings are approximately Rs 17,100. Households at their permanent homes have 5.6 members on average. Among workers with recorded caste information, 21% are classified as Scheduled Castes or Scheduled Tribes.

The employment profile helps explain what workers may put at risk when they supply recordings of their work. Skilled craftsmen account for 37% of the sample, and machine operators account for another 30%. Workers have spent an average of 6 years doing their kind of work, compared with 1.7 years at their current employer. Their experience thus extends well beyond their current employment relationship. If automation reduces demand for the tasks they perform across firms, finding another employer may not be enough to preserve the value of that experience.

Formal documentation of employment is uncommon. Only 30% of workers have a written contract, and 35% receive no wage slip. A further 32% are paid by a subcontractor rather than directly by the company where they work. These features motivate examining whether workers feel able to refuse an employer's request for recordings or negotiate additional compensation. Many workers also have limited access to cash: 38% report that they could not raise Rs 2,000 within a week for an essential expense without borrowing or selling an asset. After receiving an unexpected Rs 1,000, workers expect to have only Rs 260 left, on average, two weeks later. These financial constraints may make an immediate payment attractive even when workers are concerned about the recording's consequences for their future earnings.

The randomization produced arms that are balanced on observable characteristics. Table A4 in Appendix B.1 compares workers in the non-disclosure and disclosure arms on 19 characteristics: demographics, household income and liquidity, the terms of employment, and whether the worker had heard of camera recording before the interview. Of these, two differ between the arms at the 10 percent level and one at the 5 percent level. Taken together, the characteristics do not predict assignment ($F = 0.96$, $p = 0.51$, $N = 300$).

3.2 Empirical specification

We estimate the effect of disclosure with

$$Y_i = \alpha + \beta D_i + X_i'\gamma + \lambda_{\ell(i)} + \omega_{o(i)} + \varepsilon_i, \tag{3.1}$$

where Y_i is the additional daily compensation, in rupees, that worker i demands from a given counterparty (employer firm or outside organization), and D_i equals one if the worker is in the disclosure arm. We control for the worker's daily wage, whether they had heard of camera recording before the survey, and years of education (X_i). The terms $\lambda_{\ell(i)}$ and $\omega_{o(i)}$ are fixed effects for the recording length and for the order of the two offers.

A worker who would record without additional payment enters with $Y_i = 0$, and a worker who refuses at any payment enters at Rs 1,200, the top rung of the ladder. Because a refuser may demand more than Rs 1,200, we also treat refusals as right-censored at Rs 1,200 and estimate equation (3.1) by interval regression. We further express Y_i in units of the worker's daily wage, and we estimate linear probability models for the two extensive-margin outcomes: recording without additional payment and refusing at any payment.

We estimate the effect of the counterparty in two ways: First, we estimate equation (3.1) separately for the employer offer and the outside-organization offer. Second, we estimate a pooled version that stacks each worker's two offers, adds an indicator for the outside organization, and clusters standard errors by worker. This is estimated using the following specification

$$Y_{ic} = \mu_i + \theta\, O_c + \varepsilon_{ic}, \tag{3.2}$$

where Y_{ic} is the compensation worker i demands from counterparty c, O_c equals one for the out-

Table 1: Sample characteristics

	Mean	SD	N
Panel A. Demographics			
Age (years)	28.6	8.7	330
Female	0.02	0.12	330
Education (years)	10.5	3.1	330
Household size (members)	5.6	2.4	330
Caste			
General or OBC	0.79	0.41	313
SC/ST	0.21	0.41	313
Household monthly income (INR)	41,913	24,480	313
Could not raise INR 2,000 in a week	0.38	0.49	330
MPC out of an unexpected INR 1,000	0.74	0.30	311
Panel B. Employment			
Monthly pay (INR)	17,108	3,201	330
Years in this industry	6.3	7.1	330
Years at this company	1.7	2.5	330
Sector			
Garments or textiles	0.50	0.50	330
Electronics	0.33	0.47	330
Metal or vehicle parts	0.15	0.35	330
Job type			
Skilled craftsman	0.37	0.48	330
Machine operator	0.30	0.46	330
Helper	0.15	0.35	330
Other	0.18	0.39	330
Wages paid by			
The company	0.68	0.47	330
A subcontractor	0.32	0.47	330
Has a written contract	0.30	0.46	330
Receives a wage slip	0.65	0.48	330
Factory has CCTV over the work area	0.95	0.23	330

Notes: SD is the standard deviation across workers. Household income, household size, and monthly pay are winsorized at the 5th and 95th percentiles. General or OBC combines general castes and other backward classes; SC/ST is scheduled castes and tribes. Household size counts the people living at the worker's permanent home. Years in this industry is time spent in this kind of work, at any employer. Monthly pay is the worker's own earnings from this job. "Could not raise INR 2,000" is the share who could not arrange that sum within a week for an essential expense without borrowing or selling an asset. The marginal propensity to consume is one minus the share of an unexpected INR 1,000 the worker expects to still hold after two weeks. CCTV records whether the worker reports that cameras are installed in the factory covering the work area.

side organization, and μ_i is a worker fixed effect. We cluster standard errors by worker. Each worker evaluates the same recording from both counterparties, so we interpret θ as the additional compensation the worker demands from the outside organization, holding the worker and the task fixed. We absorb the information arm, the recording length, and the offer order in the worker fixed effect, since none of them varies within a worker. The experiment randomizes which counterparty the worker faces first, and the first offer always uses the ladder, so we estimate θ as an average over the two elicitation formats.

In this context, the coefficient β measures the impact of the information on the downstream use of worker data for automation on the worker's reservation payment to share the data. Workers could potentially already have full information about the egocentric video data collection and its use for training AI models, under this scenario β should be close to zero and statistically insignificant. Conversely, if under non-disclosure workers do not establish by themselves the link between a video recording and heightened probability of automation risk we should expect a positive and significant value for β. Similarly, under the null hypothesis that worker decision problem is the same regardless of the data sharing offer coming from their employer versus an external organization, we should expect the coefficient θ to be close to zero and insignificant. An estimated value of $\theta \neq 0$ would rather suggest that the workers face a different problem depending on the counterparty – with the sign providing information on whether the firm enjoys a relationship subsidy or whether workers penalize the firm offer more.

4 Experimental Results

Our experiment results show that, in our setting, workers often do not connect data collection with potential use for automation — even for a highly salient automation-data collection method such as first-person egocentric recordings of work tasks. We also document that, withholding information about the data use therefore substantially reduces the reservation payments required by workers, and that it is further exacerbated by the firm power in the employer-employee relationship. Not trading-off the pecuniary benefits of data sharing with potential job loss also makes the workers' reservation payments more sensitive to current liquidity constraints.

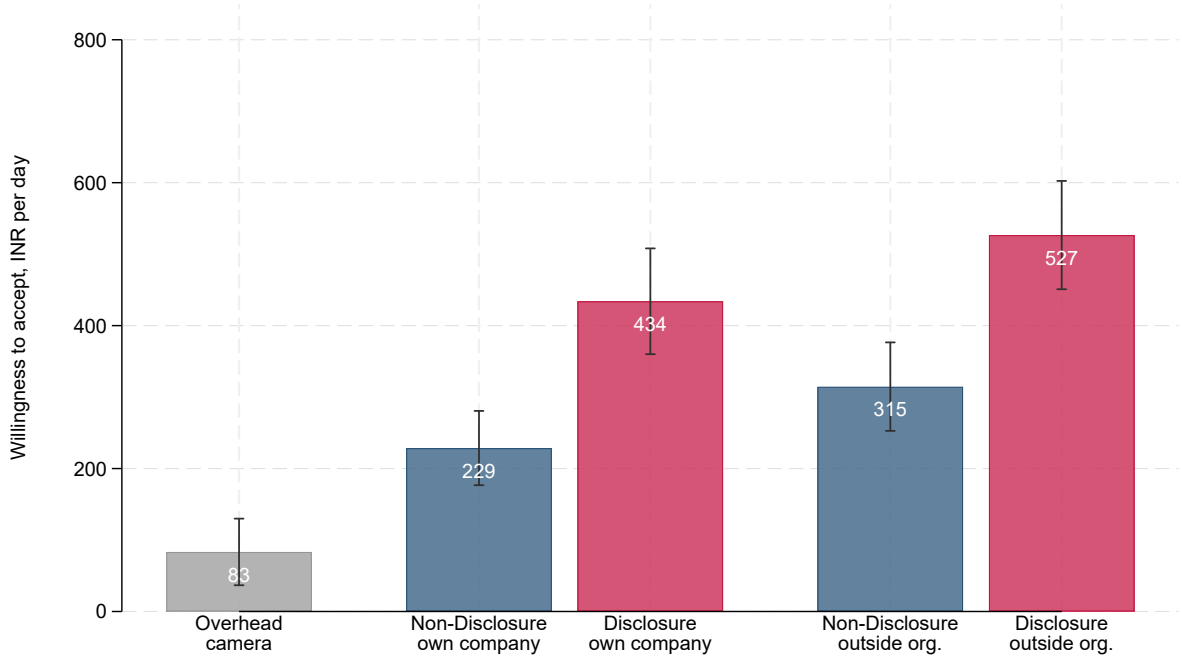
We first provide the experiment results about the effects of non-disclosure and then show that they are primarily driven by workers not linking data collection with automation use in the status quo. We then describe the results based on randomizing offer-counterparty and the relationship of reservation payments with liquidity constraints, skills, pivotality and collective bargaining.

4.1 The Effect of Non-disclosure on the Reservation Payment

Figure 2 shows that the mean reservation payment is substantially lower under non-disclosure as compared to the disclosure arm. When the offer comes from the employer, disclosure arm workers demand Rs 434 to agree for a recording of their tasks while under non-disclosure the payments fall to Rs 229. To compare the difference between the two arms, we report estimates of specification

equation 3.1 in Table 2. Panel A reports that workers in the disclosure arm demand 209 rupees a day more from their employer than workers in the non-disclosure arm (p<0.001; column 2). Workers in the disclosure arm thus demand about 92 percent more than the non-disclosure mean. From the outside organization, workers in the disclosure arm demand 216 rupees more (p<0.001; column 3), against a non-disclosure mean of 315 rupees. When we pool the two offers, we estimate an increase of 213 rupees (p<0.001; column 1). In units of their own daily wage, workers in the disclosure arm demand an additional 0.35 of a day's wage from their employer and 0.36 from the outside organization (columns 4 and 5), against non-disclosure means of 0.35 and 0.49.

Figure 2: Compensation demanded under each treatment



Notes: Bars are means for each treatment cell (pooled for both lengths) with 95 per cent confidence intervals. Workers who would be recorded without additional compensation are assigned a zero and workers who refuse at any price are allotted a price at the top rung of the ladder. .

Workers also respond to disclosure at both extensive margins – always participating without any compensation or never participating (Panel B). In the non-disclosure arm, workers are willing to record without additional payment in 6 percent of offers. Workers in the disclosure arm, on the other hand, are 4 percentage points less likely to accept on these terms, so almost no informed worker would record without additional compensation. In terms of refusing at any payment, workers in the disclosure arm are 18 percentage points more likely to never participate, from a non-disclosure share of 5 percent (column 1). Informed workers thus move out of the group that would record at no cost and into the group that would not record at any payment.

Because we assign refusers the top rung of the ladder in Panel A, workers who refuse contribute part of the increase in mean compensation. In Panel C, we treat refusals as right-censored

above Rs 1,200. Workers in the disclosure arm demand 244 rupees more from their employer (p<0.001) and 262 rupees more from the outside organization (p<0.001), and we estimate 253 rupees when we pool the two offers. We obtain larger estimates than in Panel A. In Appendix Table A9, we provide robustness of the results with varying thresholds.

Robustness Checks and Heterogeneity Our results are similar when we add enumerator fixed effects to equation 3.1 as shown in Appendix Table A5. When we drop the worker controls and keep the length and order fixed effects (Appendix Table A6), workers in the disclosure arm demand 205 rupees more from their employer (p<0.001) and 212 rupees more from the outside organization (p<0.001). With interval regression, we estimate 240 rupees for the employer offer (p<0.001).

We also estimate equation 3.1 separately by sector and by recording length in Appendix Table A2. Workers offered a 28-day recording demand 242 rupees more under disclosure (p<0.001), and workers offered a 14-day recording demand 177 rupees more (p=0.009). We cannot distinguish the two effects (p=0.459). For sectoral heterogeneity, we find that garment workers in the disclosure arm demand 157 rupees more from their employer (p=0.016; $N = 149$) while electronics workers have a difference of 201 rupees (p=0.029; $N = 97$). We cannot reject that the two effects are equal (p=0.509).

4.2 Baseline Beliefs about Data-Use and What Changes Under Disclosure?

We interpret the disclosure effect as the additional compensation workers require once they price in the displacement risk of the video recordings — a mechanism which is not priced in when the information about the data use is withheld. We support this interpretation in four steps. First, we show that workers in the non-disclosure arm primarily price non-automation related costs of recording, such as the burden of wearing the camera and the need to work more carefully due to surveillance. The disclosure effect therefore arises relative to a baseline with a clear economic interpretation. Second, we show that disclosure leaves these costs unaffected; instead, it changes workers' beliefs about the role their recordings play in enabling automation. Third, we provide evidence that workers that already understand the automation-related use of the recordings demand a higher price even without the disclosure. Lastly, using the follow-up survey we provide evidence against the concern that disclosed workers merely speculate about consequences they do not genuinely believe by eliciting their beliefs about how other workers would respond in the absence of the information and comparing it to the actual responses.

Stated costs for the reservation price under disclosure and non-disclosure After asking the workers about their willingness to participate and eliciting the reservation payment, the experiment follows up with a survey questionnaire in which we ask about their reasons for their decision and the demanded price. Figure 3 shows a distribution of the workers stated reasons. Among those who state a finite amount for the employer offer, the two most common explanations are

Table 2: The effect of disclosure on compensation demanded

	Both offers (1)	Own company (2)	Outside org. (3)	Own per wage (4)	Outside per wage (5)
Panel A. Compensation					
Disclosure	212.76***	209.28***	216.25***	0.35***	0.36***
	(45.32)	(45.27)	(48.40)	(0.07)	(0.08)
Non-Disclosure mean	271.64	228.67	314.61	0.35	0.49
Length and order FE	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes
Workers	300	300	300	300	300
Observations	600	300	300	300	300
Panel B. Extensive margin					
Would record for free	-0.038*	-0.045*	-0.031		
	(0.021)	(0.027)	(0.020)		
Refuses at any price	0.180***	0.174***	0.185***		
	(0.038)	(0.038)	(0.040)		
Non-Disclosure mean, records for free	0.063	0.080	0.047		
Non-Disclosure mean, refuses	0.050	0.047	0.053		
Length and order FE	Yes	Yes	Yes		
Worker controls	Yes	Yes	Yes		
Workers	300	300	300		
Observations	600	300	300		
Panel C. Interval regression					
Disclosure	252.56***	243.64***	261.62***	0.41***	0.44***
	(53.48)	(52.86)	(56.66)	(0.09)	(0.09)
Non-Disclosure mean	271.64	228.67	314.61	0.35	0.49
Refusals, right-censored	84	40	44	40	44
Length and order FE	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes
Workers	300	300	300	300	300
Observations	600	300	300	300	300

Notes: The sample is workers in the four main cells. Column 1 stacks each worker's two offers and includes an indicator for the outside organisation, with standard errors clustered on the worker; columns 2 to 5 are one observation per worker. Columns 4 and 5 divide the reservation payment by the worker's daily wage. Worker controls include whether the worker had heard of camera recording before the survey, years of education for all columns and daily wage for columns 1-3. Panel A assigns zero to a worker who would be recorded without additional compensation and INR 1,200, the top rung of the ladder, to a worker who refuses at any price. Panel B reports linear probability models for those two outcomes. Panel C estimates an interval regression that treats each named amount as exact and each refusal as right-censored above INR 1,200. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

that recording would require them to work more carefully and with greater responsibility, and that wearing the camera for eight hours would be burdensome. The first response captures the cost of intensified surveillance, while the second captures the physical burden of wearing the device. We therefore interpret the compensation demanded in the non-disclosure arm as payment for these immediate non-automation related recording costs. The additional compensation induced by disclosure is measured relative to this baseline.

We next examine whether disclosure changes the considerations workers attach to participation. If the treatment simply made workers more concerned about monitoring or about the burden of wearing the device, informed workers who remain willing to participate should cite these costs more frequently. By contrast, if disclosure causes workers to incorporate displacement risk into their decision, the immediate costs of recording should remain similar among participants, while concerns about job loss should become more prominent among workers who refuse.

The responses support the latter interpretation. Among workers who state a finite amount, the two leading reasons appear at similar rates across the two arms: 27 and 29 percent cite the need to work more carefully, while 35 and 38 percent cite the burden of wearing the camera. Informed workers are also less likely to cite the cost of living, at 10 percent compared with 24 percent in the non-disclosure arm. The sharpest difference appears among workers who refuse to participate at any payment. Of the 33 informed refusers, 88 percent report that a machine could learn their work and cost them their job, compared with 29 percent of the 7 refusers in the non-disclosure arm. Uninformed refusers instead more often object to being watched or recorded. These patterns suggest that disclosure does not primarily increase the perceived burden of recording; rather, it introduces displacement risk as an additional consideration, which affects participation chiefly through refusal.

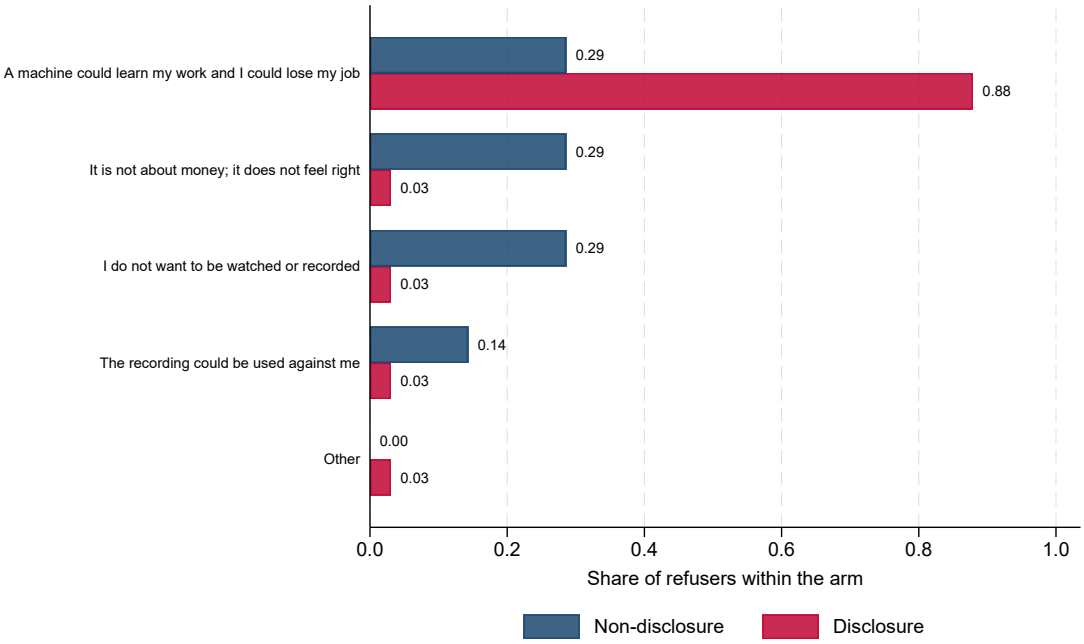
Price sensitivity to removing one of the baseline costs As the offers are hypothetical, stated compensation may not reflect willingness to accept an implemented recording arrangement. If workers instead demand this amount as payment for real costs of recording, they should demand less when we remove one of those costs. As shown above, a worker under non-disclosure primarily states two such costs: being monitored while they work[5], and disutility of wearing a camera for eight hours a day.

We remove the cost of wearing the device, while keeping the recording, with an option to provide the recording with a workstation camera (Panel B of Table 4). Workers in the audit cell evaluate only a camera mounted above their workstation, which records the same work without requiring workers to wear a camera. They demand 83 rupees a day ($N = 30$), 142 rupees less than non-disclosure workers demand for the head camera (p<0.001). Non-disclosure workers in the main cells also state an amount for the workstation camera after the head camera, and they demand 116 rupees less for it (p<0.001), against a head-camera mean of 210 rupees. Workers thus demand about 62 percent less between workers, and about 55 percent less within worker,

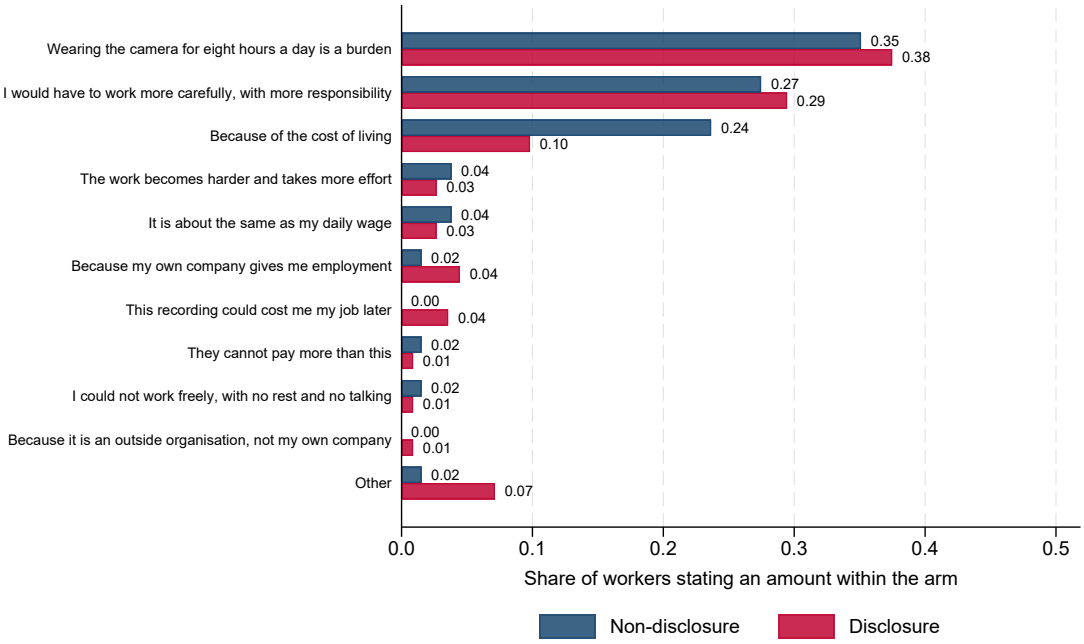
[5]Factory workers may bear a cost when others can observe them, because they change how they work; in a large mobile-phone factory, workers concealed productive deviations from prescribed methods while supervisors could observe them (Bernstein, 2012)

Figure 3: Reasons workers give for their answer to the employer offer, by information arm

Panel A. Workers who would not record at any payment



Panel B. Workers who state an amount



Notes: Panel A reports why workers would not record for their employer at any payment: 7 workers in the non-disclosure arm and 33 in the disclosure arm. Panel B reports the main reason for the amount among workers who state one: 131 and 112 workers. Bars are shares within each arm. The enumerator does not read the options aloud and records each answer against the list.

when they do not have to wear the camera. The lower compensation requested for workstation recording is consistent with workers assigning a cost to wearing the device.[6]

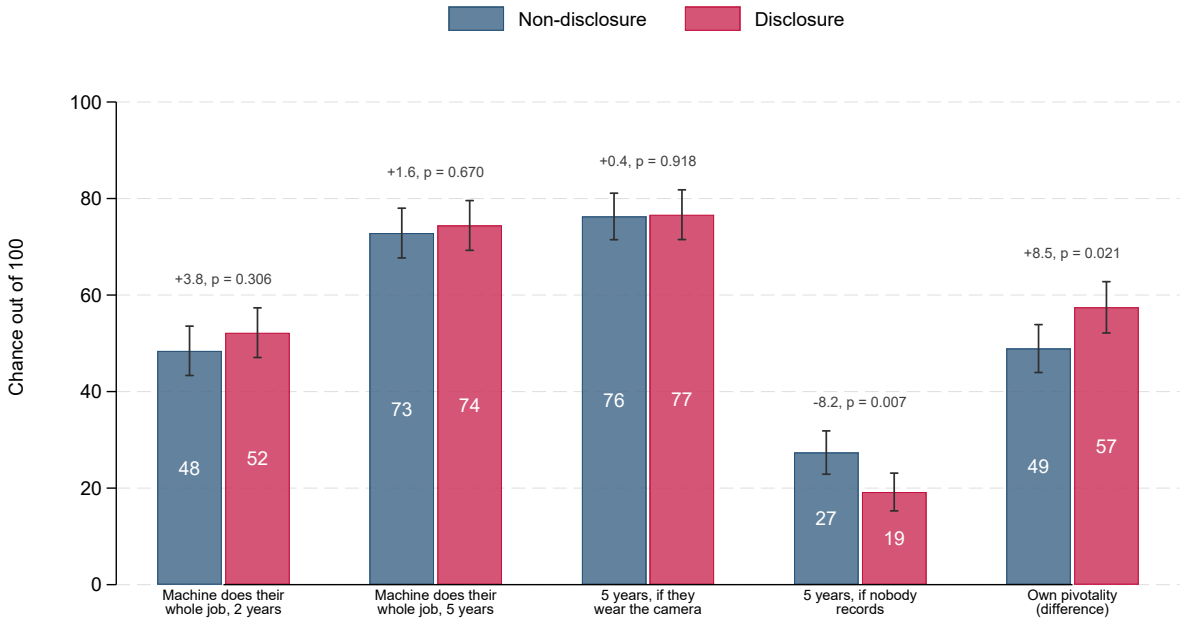
What beliefs does the disclosure impact? We next examine what workers learn from disclosure. A potential concern is that the treatment affects responses simply by making automation and job loss more salient. Mentioning displacement may lead workers to place greater weight on automation risk in general, analogous to the way consumers respond more strongly to taxes when they are made more salient (Chetty et al., 2009). If this mechanism drives the treatment effect, disclosure should increase workers' overall beliefs about the likelihood that their jobs will be automated. By contrast, if disclosure primarily informs workers about the role of their recordings in facilitating automation, it should change beliefs that depend on whether recording occurs while leaving broader automation beliefs unchanged.

We measure these beliefs after treatment and compare them across arms in Figure 4 (Haaland et al., 2023). The results support the second interpretation. In the first set of questions we ask workers about their general beliefs about automation of their jobs within the next two years and five years. Workers in the disclosure and non-disclosure arms (first four bars in Fig. 4) report similar probabilities that a machine could perform their entire job within two years (48% and 52%; p=0.306) and within five years (73% and 74%; p=0.670). Next we ask the workers about their beliefs about automation conditional on them sharing the data and conditional on no worker sharing the data. Across arms, workers report similar probabilities of automation within five years if they themselves provide the recordings — the treatment instead changes beliefs about the counterfactual in which no worker records. Informed workers assign a lower probability to automation in that case, 19 compared with 27 (p=0.007), and therefore attribute 8.5 additional percentage points of automation risk to the provision of recordings (p=0.021). Disclosure thus changes workers' beliefs about the contribution of recording to automation without changing their general expectations about technological progress. This pattern is consistent with the treatment conveying information about the downstream use of the data rather than merely increasing the salience of automation risk.

Heterogeneity based on worker's pre-treatment information set We now turn to two alternative readings of the disclosure effect. The first is that workers already know how firms use such recordings, and that uninformed workers demand less because they weigh this use against benefits that we do not observe. If so, many workers in the non-disclosure arm would already hold the information, and some would cite such benefits. However, only 24 percent of workers in the main

[6] A potential concern is that workers may already be accustomed to workplace surveillance: 95 percent report that closed-circuit television cameras are installed above their work area. If these cameras captured detailed information on how workers perform their tasks, the marginal cost of an additional overhead camera should be small. In practice, however, workers describe existing factory cameras as serving primarily security and general monitoring functions rather than recording the task-level actions of individual workers. The overhead-camera offer therefore introduces a distinct form of observation: it records how the worker performs the task itself. Workers demand compensation for this additional monitoring.

Figure 4: Automation beliefs by information arm



Notes: Bars are means with 95 percent confidence intervals for workers in the four main cells. The first two groups report the chance out of 100 that a machine or robot could do the worker's whole job within two and within five years. The next two report that chance within five years if the worker wears the camera, and if the worker refuses and no other worker records in their place. Own pivotality is the difference between these two. The label above each group gives the disclosure-minus-non-disclosure difference and its p-value from a regression on an arm indicator with heteroskedasticity-robust standard errors.

cells had heard of workers wearing a head camera whose recordings teach a machine (Appendix Figure A3), and no worker, in any free-text answer, mentions a benefit that the machine or the recording would bring them. In the non-disclosure arm, workers who had heard of the practice demand 333 rupees from their employer, against 189 rupees for workers who had not (p=0.037). Most uninformed workers therefore lack the information about the use of the data recording for automation training and having the information brings their reservation payments closer to providing the information directly through an information disclosure.

Worker's understanding of the mechanism after disclosure Another alternative explanation is that disclosure simply induces workers to infer the consequences of recording from the information we provide, without reflecting a more general understanding of how this information affects workers' decisions. To examine this possibility, we ask workers in the disclosure arm to predict how workers who are not told the purpose of the recording would respond (Appendix Figure A2). They expect 73 of 100 uninformed workers to agree to wear the camera, compared with 42 of 100 informed workers (p<0.001). They also expect uninformed workers to require 308 rupees per day, compared with 457 rupees for informed workers (p<0.001). Thus, informed workers predict that withholding information increases participation and lowers required compensation. Their

prediction for uninformed workers, 308 rupees, matches the 301 rupees that workers in the non-disclosure arm expect other workers to demand. These responses suggest that informed workers understand how knowledge of the recordings' downstream use affects workers' willingness to participate and the compensation they require.

Taken together, the evidence supports the following interpretation of the disclosure effect. Workers in the non-disclosure arm primarily demand compensation for the immediate costs of recording, including monitoring and the burden of wearing the camera. Disclosure adds a second consideration: the possibility that the recordings may help train a machine that substitutes for their labor. Workers respond to this information by demanding greater compensation and, in some cases, by refusing to participate altogether. The disclosure effect measures the change in stated compensation and participation induced by explaining the recordings' potentially labor-substituting use. The supplementary evidence is consistent with displacement concerns contributing to this response, but does not isolate their contribution from other responses to the disclosure script.

4.3 The effect of external (non-employer) counterparty on compensation demanded

To isolate the effect of employer-employee relationship wedge on the reservation payment, each respondent in the experiment design is asked to state the compensation they would demand for the same recording twice: once from their employer and once from an outside research organization, in a randomized order. We report estimates of equation 3.2 in Table 3.

Workers demand 89 rupees a day more from the outside organization than from their employer (p<0.001; column 1), against an average of 331 rupees from the employer. In proportional terms, workers demand about 21 percent less from their employer than from the outside organization. Workers in both arms demand a premium of similar size: 86 rupees in the non-disclosure arm and 93 rupees in the disclosure arm (columns 2 and 3). Workers therefore accept less from their employer regardless of knowing that the recordings will train a machine.

Table 3: The counterparty premium, within worker

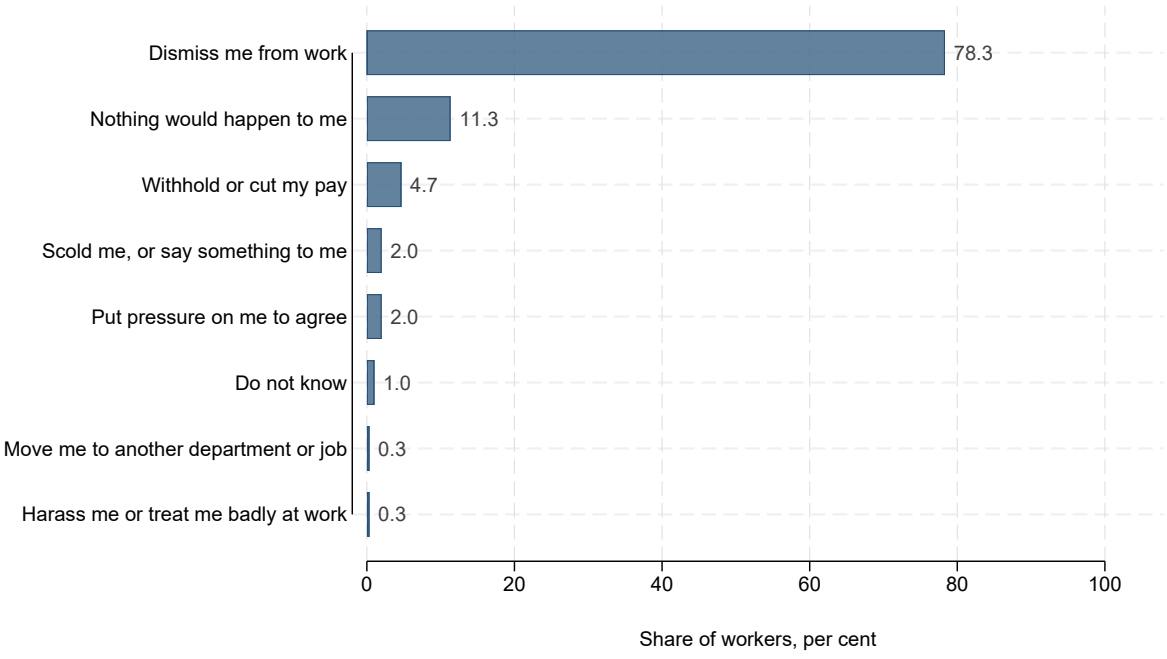
	(1)	(2)	(3)
Outside organisation	89.31***	85.95***	92.67***
	(11.42)	(15.48)	(16.87)
Own-company mean	331.33	228.67	434.00
Sample	All	Non-Disclosure	Disclosure
Workers	300	150	150
Observations	600	300	300

Notes: Each worker's two offers are stacked, giving two observations per worker, and the dependent variable is the compensation demanded in INR per day. All columns include a worker fixed effect, and standard errors are clustered at the worker level. Columns 2 and 3 restrict the sample to one information arm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Stated reasons for the rise in demanded compensation The follow-up survey asks workers about the consequences of refusal and workers' responses suggest the dynamic employer-employee relationship terms as the main driver of the change in reservation price. When asked how their employer would respond if they refused to wear the camera, 78 percent expect to be dismissed, whereas 11 percent expect no consequence (Figure 5). Few workers anticipate intermediate responses such as a pay cut, transfer, or reprimand, and dismissal expectations are similar across the two information arms. These responses indicate that many workers view refusal to an employer request as carrying a meaningful risk to their current employment. This perceived cost of refusal provides a natural explanation for why workers require less compensation from their employer than from the outside organization.

Workers' stated explanations for the counterparty gap are consistent with this interpretation, but also point to additional factors. Among the 118 workers who require different payments from the two organizations, 65 say that they are willing to accept less from their employer because it provides them with employment. Others report that the outside organization can afford to pay more (18) or that they trust it less (22). We therefore do not interpret the full counterparty difference as arising from employer power alone.

Figure 5: What workers expect the company to do if they refuse to wear the camera



Notes: Bars are the share of the 300 workers in the four main cells choosing each answer. The arms are pooled.

4.4 Role of Liquidity Constraints, Skills and Collective Bargaining

The preceding two subsections use the experimental variation to identify the role of information and the employer-employee relationship wedge in determining the reservation payments demanded by workers to share their data for use in automation. Here we document the cross-sectional and across experiment arms relationship of the reservation amounts with workers' liquidity constraints, their skills, perceived pivotality and their beliefs about the impact of collective bargaining.

Liquidity Constraints The liquidity constraints faced by workers can potentially impact the reservation payments they demand depending on how much they weigh the displacement risk in their decisions. Under no future considerations, the worker just trades off the disutility and surveillance cost of the recording against the marginal benefit of the additional payment. Liquidity constraints increase the marginal utility of current consumption thus the worker might agree to share the data at a significantly lower reservation price. However, liquidity constraints also imply that the worker has a smaller buffer stock of saving in case of potential displacement and therefore if they consider the future losses they might demand more.

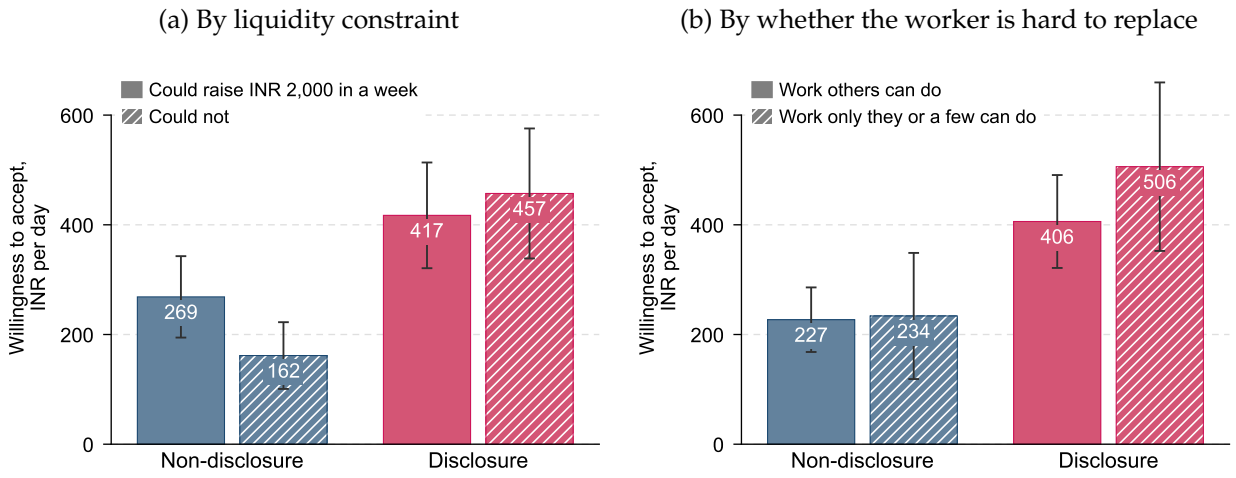
In the follow-up survey we ask the workers whether they would be able to raise Rs 2,000 within a week without borrowing or selling an asset. Using this question we split the workers as liquidity constrained and non-liquidity constrained (Figure 6a). In the non-disclosure arm, workers who could not raise the sum demand 107 rupees less from their employer than workers who could, which is consistent with liquidity needs making an immediate payment more attractive. Under disclosure, workers who could raise the sum demand 149 rupees more than their non-disclosure counterparts, and workers who could not demand 296 rupees more. The disclosure thus adds another consideration in the workers decision set apart from maximizing current utility and the overall impact is therefore determined jointly by balancing the high current marginal utility with a future job loss potential.

Worker Skills The degree of substitutability of the workers skills determines their bargaining power over the data sharing contract. A worker whose workplace tasks are easily substitutable should demand a lower price considering the fact that it would be easy for the firm or the outside organization to find a substitute worker.

In the follow-up survey, we ask workers about their perceived substitutability of their skills and examine its relationship with their demanded reservation price (Figure 6b). We classify workers according to whether they report performing tasks that only they, or very few other workers, can perform. In the non-disclosure arm, these workers require 234 rupees per day from their employer, compared with 227 rupees among workers who are less pivotal. Under disclosure, the corresponding amounts are 506 and 406 rupees. The more pronounced difference appears on the extensive margin. Once informed about the automation use of the recordings, 29 percent of workers with relatively unique skills refuse to participate at any payment, compared with 19 percent of

other workers. One interpretation is that these workers perceive both greater value in the knowledge embodied in their work and a greater ability to withhold it, making refusal a more relevant response to the prospect that their recordings could facilitate automation.

Figure 6: The own-company reservation payment by liquidity constraint and by whether the worker is hard to replace



Notes: Bars are means of the own-company reservation payment with 95 per cent confidence intervals. Panel (a): the survey asks whether the worker could arrange INR 2,000 within a week for an essential household expense without borrowing or selling an asset. In the non-disclosure arm 94 workers answer yes and 56 answer no; in the disclosure arm 87 answer yes and 63 answer no. Panel (b): the survey asks whether the worker does work that only they, or very few workers, can do. In the non-disclosure arm 37 of 150 workers answer yes, and in the disclosure arm 42 of 150. Workers who would be recorded without additional compensation enter at zero and workers who refuse at any price enter at the top rung of the ladder, INR 1,200. The two recording lengths are pooled.

Collective Bargaining and Pivotality We report two additional comparisons, about collective bargaining in Panel A of Table 4 and about pivotality in Panel C of Appendix Table A1. First, we ask workers what amount they and their co-workers would agree on if they bargained together (Panel A). We stack each worker's individual demand from the employer with this collective demand, and we include recording-length fixed effects and the worker controls. Workers demand 99 rupees a day more when they bargain together ($p<0.001$), against an individual mean of 331 rupees. Workers in the non-disclosure arm raise their demand by 110 rupees ($p<0.001$), and workers in the disclosure arm by 92 rupees ($p=0.012$). Workers state higher minimum acceptable payments under the collective-bargaining scenario. This pattern is consistent with coordination affecting compensation demands, but does not establish that collective bargaining would produce higher realized payments.

Whether an individual worker can prevent the firm from obtaining similar recordings is less clear. If they refuse to participate, 54 percent expect the company to find it difficult to replace them, while workers expect 51 out of 100 other workers to agree to wear the camera. As discussed in Section 4.2, workers in the disclosure arm also expect replacement to be easier when potential substitutes are not informed about the purpose of the recording: only 12 percent expect the

company to have difficulty finding a replacement in that case, and they expect 73 out of 100 uninformed workers to participate. These responses suggest that workers recognize an important limit to their individual bargaining position: even when they view their own recordings as valuable for automation, firms may be able to obtain similar data from other workers, especially when those workers are not informed about its downstream use.

Table 4: Compensation demanded for secondary offers

Panel A. Compensation under collective bargaining			
	All workers	Non-Disclosure arm	Disclosure arm
Collective demand	99.31***	110.18***	92.47**
	(22.09)	(25.02)	(36.31)
Individual demand, mean	331.33	228.67	434.00
Recording-length FE	Yes	Yes	Yes
Worker FE	No	No	No
Worker controls	Yes	Yes	Yes
Workers	300	150	150
Observations	585	294	291
Panel B. Compensation for overhead versus head-mounted recording			
	Between worker	Within worker	
Overhead camera	-141.87***	-116.06***	
	(35.20)	(17.91)	
Sample	Audit + non-disclosure	Non-Disclosure arm	
Head-camera price, mean	228.67	209.93	
Recording-length FE	No	Absorbed	
Worker FE	No	Yes	
Worker controls	Yes	Absorbed	
Workers	180	146	
Observations	180	292	
Panel C. What other workers would demand			
	All workers		
Disclosure	157.91***		
	(35.07)		
Non-Disclosure mean	301.10		
Recording-length FE	Yes		
Worker FE	No		
Worker controls	Yes		
Workers	289		
Observations	289		

Notes: The dependent variable is a reservation payment in INR per day throughout. Worker controls are the daily wage, whether the worker had heard of camera recording before the survey, and years of education. Panel A stacks each worker's individual reservation price for the employer offer with the collective price they state when the whole line bargains together; workers who give no collective price contribute only their individual price. Panel B prices the overhead camera two ways: between worker, where the audit cell prices a camera above the workstation and the non-disclosure arm prices a head camera, and within worker, where a non-disclosure-arm worker prices both. Panel C compares the arms on what the worker expects other workers to demand. Standard errors are in parentheses, clustered at the worker level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Reservation Payments as a Fraction of Expected Losses from Job Automation

Workers nevertheless expect displacement to impose substantial short-run earnings losses. If machines eliminated their current type of work, 55 percent report that they would start a business or enter self-employment, 21 percent would seek a different type of paid work, 10 percent would turn to farming, and 8 percent would search for similar work with another employer. On average, workers expect it to take 4 months to resume regular earnings and 15 months for their earnings to return to their current level.

In this subsection, we compare the premium each worker in the disclosure arm asks with the loss that worker expects if they record.

$$E_i = p_i \left[w_i \, s_i + (w_i - w_i')^+ \, (r_i - s_i)^+ \right], \qquad P_i = \left(b_i - \bar{b}^N \right) T_i, \tag{4.1}$$

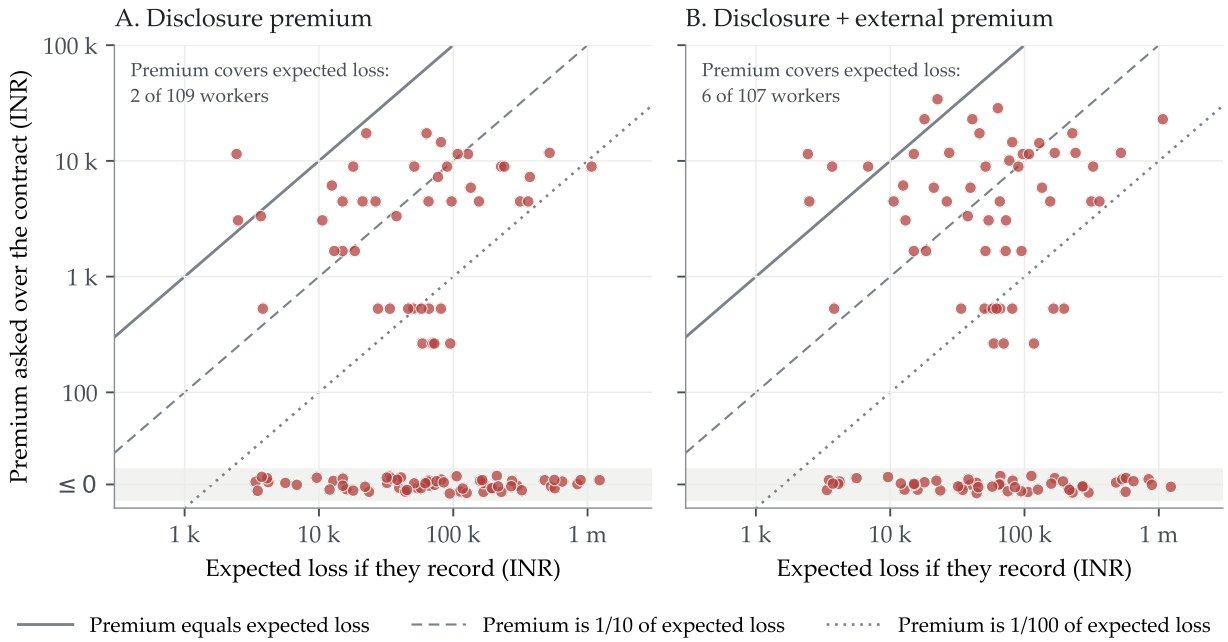
where p_i is the worker's stated chance of being replaced by a machine within five years if they record, w_i is their current monthly pay, s_i is the number of months they expect to wait before earning regularly again if displacement happens, w_i' is what they expect to earn each month once they start earning again after displacement, and r_i is the number of months until their earnings return to w_i.

The bracket captures the pay lost while the worker has no regular work, plus the shortfall in pay until earnings recover. In the premium, b_i is the daily amount the worker asks, $\bar{b}^N$ is the average daily amount that non-disclosure workers who state an amount ask of their employer, and T_i is the number of days recorded. We restrict the comparison to workers who state an amount, on both sides of the premium. A worker who refuses at any payment declines every amount we could offer, so we cannot compare their demand with their expected loss, and we report these workers separately. We plot P_i against E_i in Figure 7.

Among informed workers willing to record, almost none request a premium large enough to cover their expected loss. Only 2 of the 109 workers who state an amount for the employer offer request a premium at least as large as that loss; the corresponding figure for the outside organization is 6 of 107. For the employer offer, most of these workers (65 of 109) request no more than 181 rupees per day, the mean among non-disclosure workers who state an amount. Among the 44 who request more, the median ratio of the premium to the expected loss is only 1/13.

These small premiums among willing participants coexist with outright refusal among other informed workers. Of the 135 informed workers who expect a positive loss, 26 refuse the employer offer at any payment, keeping their recordings off the market. Those willing to record, by contrast, generally request premiums that fall far short of their expected losses. Two considerations may help explain this gap. First, E_i is undiscounted, so workers who heavily discount losses that may occur years later could rationally request much smaller premiums. Second, the loss a worker expects from automation need not equal the additional loss caused by supplying their own recordings. A small premium is therefore also consistent with a belief that refusing would do little to prevent displacement because the firm could obtain equivalent footage from someone

Figure 7: The premium workers ask and the loss they expect if they record



Notes: Each dot is one worker in the disclosure arm who states an amount. The axes plot E_i and P_i from equation (4.1) on logarithmic scales. Panel A uses the worker's amount for the employer offer and Panel B their amount for the outside-organization offer. The benchmark $\bar{b}^N$ is the mean employer amount among non-disclosure workers who state one. Workers who refuse at any payment are not shown. Workers with $P_i \leq 0$ appear in the shaded band, and the 5 workers with $E_i = 0$ are omitted.

else.

5 Conclusion

Rapid advances in AI have relied on vast amounts of digital data. Yet data capturing how workers perform manual tasks and apply tacit knowledge remain scarce (Goldberg, 2025). In manufacturing, firms can obtain these data by recording workers as they perform their jobs, creating demonstrations that can be used to train robotic systems. By supplying these recordings, workers help create productive capital that could replace their labor and reduce their future earnings. We study two frictions that shape the terms of this exchange: workers may not know how firms intend to use their recordings, and they may have limited ability to refuse or negotiate compensation when the request comes from their own employer.

Our experiment shows that both frictions materially affect the compensation workers demand. Disclosing that the recordings will be used to train a machine that could perform the worker's task raises the compensation workers demand from their employer by about 92 percent and increases the share who refuse to participate altogether. Workers also demand about 21 percent less from their own employer than from an outside research organization for the same recording. The first result shows that incomplete information about downstream use lowers the price at which

workers are willing to supply automation-relevant data. The second shows that the employment relationship also affects this price: workers accept less from the party that controls their current job, and most expect that refusing an employer's request could result in dismissal.

The accompanying survey evidence clarifies how workers interpret these choices. Disclosure does not materially change workers' general expectations about whether automation will become feasible. Instead, it changes what workers believe their own recordings contribute to that process. Workers in the non-disclosure arm primarily demand compensation for the immediate costs of recording, including monitoring and the burden of wearing the camera, whereas informed workers are more likely to cite displacement when they refuse to participate. Workers also recognize the limits of individual refusal. Informed workers expect the firm to have difficulty replacing them with another informed worker, but not with one who is not told how the recordings will be used. At the same time, they expect substantially higher compensation when bargaining collectively rather than individually. These patterns indicate that the value of workers' productive knowledge does not by itself determine the terms on which firms acquire it; information and bargaining position determine how much of that value workers can claim.

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Appendix

Contents

A Additional Results **35**
A.1 Additional Background and Context . . . 35
A.2 Survey Summary Statistics . . . 35
A.3 Expectations about other workers . . . 37
A.4 Prior awareness of camera recording . . . 37
A.5 The disclosure effect by sector and by recording length . . . 38

B Robustness Checks **38**
B.1 Balance . . . 41
B.2 Enumerators . . . 41
B.3 Without worker controls . . . 42
B.4 Refusals that cite automation . . . 42

C Measurement **45**
C.1 Task content . . . 45
C.2 Winsorization . . . 45
C.3 Refusal as censoring . . . 46
C.4 Employers in Prowess . . . 46

D Details about Survey **48**
D.1 Experiment script . . . 48
D.2 Survey questions used in the analysis . . . 51

A Additional Results

A.1 Additional Background and Context

Figure A1: A garment worker wearing a head-mounted camera at work



A.2 Survey Summary Statistics

Table A1: Automation beliefs, pivotality, and expected displacement

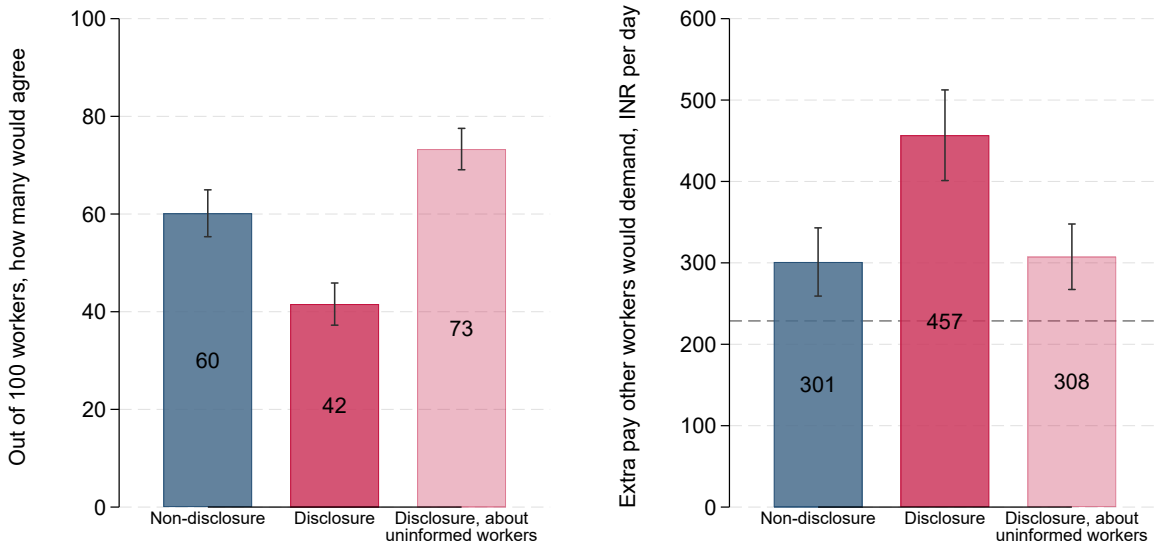
	Mean	SD	*N*
Panel A. Automation			
Stated chance out of 100 that a machine could do their whole job			
Within 2 years	50.8	31.9	330
Within 5 years	74.7	31.8	330
Has already seen such a machine			
A machine that could do all of their work	0.20	0.40	315
A machine that could do some of their work	0.39	0.49	315
Has seen no such machine	0.41	0.49	315
Had heard of camera recording	0.24	0.43	330
Where they heard about camera recording			
Social media	0.55	0.50	80
Television or news	0.05	0.22	80
At a factory or workplace	0.30	0.46	80
From other workers or friends	0.03	0.16	80
Has worn such a camera themselves	0.03	0.16	80
An employer has asked them to wear a camera	0.05	0.22	315
Panel B. Pivotality			
Stated chance out of 100 within 5 years, under two scenarios			
If they wear the camera and their work is recorded	76.5	30.9	300
If they refuse and no other worker records instead	23.3	26.4	300
Difference: how much their own participation adds	53.2	32.1	300
Does work that only they, or very few workers, can do	0.26	0.44	330
Panel C. If the worker refuses			
If the worker refuses and the company looks for someone else			
Says the company would find it hard to replace them	0.54	0.50	300
Out of 100 workers, how many would agree to wear it	50.9	29.7	300
If that someone else is not told the recording trains a machine			
Says the company would find it hard to replace them	0.12	0.33	150
Out of 100 workers, how many would agree to wear it	73.3	26.3	150
Panel D. Job displacement			
What they would do to earn if this kind of work disappeared			
Look for the same work with another employer	0.08	0.27	315
Look for a different kind of paid work	0.21	0.41	315
Start a business or other self-employment	0.55	0.50	315
Start or expand farming	0.10	0.30	315
Something else	0.06	0.23	315
Months before earning regularly again	4.4	5.9	313
Months until earnings return to their current level	14.6	19.9	301

Notes: SD is the standard deviation across workers. Beliefs and awareness are asked of every worker. "Where they heard about camera recording" is asked of the workers who had heard of it. Panel B asks the chance out of 100 that a machine does the worker's whole job within five years, first if the worker records and then if the worker refuses and nobody records in their place. Panel C asks how easy it would be for the company to find another worker willing to wear the camera, on a four-point scale, and the row reports the share answering hard or very hard; the second row asks how many workers out of 100 would agree to wear it. Only the disclosure arm is asked the second pair, which repeats both questions for a worker who is not told the recording will teach a machine. Everything here is elicited after the information script and after both prices, and the arms are pooled.

A.3 Expectations about other workers

We ask all workers to predict how other workers would respond to the recording offer. Specifically, we ask how many of 100 workers they expect would agree to wear the camera and how much additional compensation those workers would require. Workers in the disclosure arm answer the same two questions for a counterfactual group of workers who are not told that the recordings will be used to train a machine. Figure A2 reports these beliefs.

Figure A2: What workers expect of other workers, by information arm

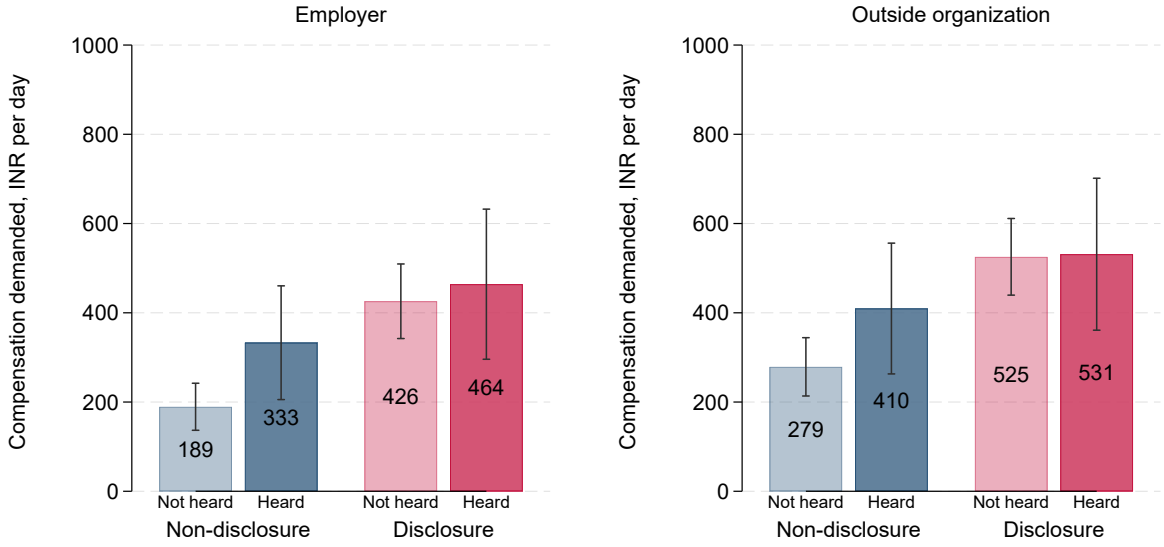


Notes: The left panel reports how many of 100 workers the respondent expects would agree to wear the camera; the right panel reports the extra pay per day the respondent expects other workers would demand. The first two bars in each panel are the answers of the non-disclosure and disclosure arms. The third bar is the disclosure arm's answer to the same question about workers who are not told that the recording will train a machine. The dashed line marks the mean compensation that non-disclosure workers demand from their employer. Bars are means with 95 percent confidence intervals.

A.4 Prior awareness of camera recording

At the end of the interview, we ask workers whether they had previously heard of workers wearing head-mounted cameras to generate recordings used to train a machine. Figure A3 compares the compensation workers demand by prior awareness and information arm.

Figure A3: Compensation demanded by prior awareness of camera recording and information arm



Notes: Workers are split by whether they had heard of workers wearing a head camera whose recordings teach a machine: 41 of 150 workers in the non-disclosure arm and 32 of 150 in the disclosure arm. Bars are means with 95 percent confidence intervals. A worker who would record without additional payment enters at zero and a worker who refuses at any payment enters at Rs 1,200.

A.5 The disclosure effect by sector and by recording length

Table A2 examines heterogeneity in the disclosure effect across worker characteristics, using the same specification as Panel A of Table 2 so that each subgroup estimate can be compared directly with the pooled effect.

Among garment workers, disclosure increases the compensation demanded from the employer by 157 rupees (p=0.016; $N = 149$). Among electronics workers, the corresponding estimate is 201 rupees (p=0.029; $N = 97$). The difference between the two subgroup effects is not statistically significant (p=0.509).

Recording length provides a second source of heterogeneity. Disclosure raises the compensation demanded from the employer by 242 rupees for a 28-day recording (p<0.001), compared with 177 rupees for a 14-day recording (p=0.009). We cannot distinguish the two effects (p=0.459).

B Robustness Checks

Table A2: The disclosure effect by sector and by recording length

	Both offers (1)	Own company (2)	Outside org. (3)	Own per wage (4)	Outside per wage (5)
Panel A. By sector					
Electronics or electrical goods (97)	185.63**	201.47**	169.80*	0.34**	0.29*
	(90.16)	(90.97)	(95.77)	(0.15)	(0.16)
Non-Disclosure mean	328	279	377	0.47	0.63
Disclosure mean	524	489	560	0.81	0.93
Garments, cloth or textiles (149)	165.52**	156.96**	174.07**	0.26***	0.28***
	(64.22)	(64.10)	(70.51)	(0.10)	(0.11)
Non-Disclosure mean	278	228	327	0.34	0.49
Disclosure mean	430	374	485	0.58	0.75
Metal parts, springs or vehicle parts (43)	444.27***	390.99***	497.56***	0.71***	0.80***
	(100.19)	(108.44)	(101.90)	(0.21)	(0.20)
Non-Disclosure mean	139	127	150	0.17	0.19
Disclosure mean	589	540	638	0.92	1.03
Length and order FE	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes
Panel B. By recording length					
14-day recording (150)	181.96***	176.85***	187.08***	0.32***	0.34***
	(66.27)	(66.41)	(69.66)	(0.11)	(0.11)
Non-Disclosure mean	298	263	333	0.40	0.51
Disclosure mean	468	427	509	0.70	0.83
28-day recording (150)	242.23***	242.04***	242.41***	0.39***	0.38***
	(62.42)	(62.34)	(67.99)	(0.10)	(0.11)
Non-Disclosure mean	246	195	297	0.31	0.47
Disclosure mean	493	441	545	0.70	0.85
Offer-order FE	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes

Notes: Each row reports the coefficient on the disclosure indicator estimated within that subgroup. The columns are those of Panel A of Table 2 and carry the same specification: column 1 stacks each worker's two offers and includes an indicator for the outside organisation, with standard errors clustered at worker level, and columns 2 to 5 are one observation per worker with heteroskedasticity-robust standard errors. Columns 4 and 5 divide the reservation payment by the worker's daily wage. Worker controls include whether the worker had heard of camera recording before the survey, years of education for all columns and daily wage for columns 1-3. The number of workers in each subgroup is in parentheses beside its name. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: The disclosure effect by sector and by recording length, with enumerator fixed effects

	All refusals			Machine-reason refusals only		
	Both offers (1)	Own company (2)	Outside org. (3)	Both offers (4)	Own company (5)	Outside org. (6)
Panel A. By sector						
Electronics or electrical goods (97)	183.24**	201.78**	164.69*	247.36***	259.43***	235.88**
	(92.03)	(93.49)	(98.46)	(85.59)	(86.30)	(93.37)
Non-Disclosure mean	328	279	377	260	218	302
Disclosure mean	524	489	560	510	474	547
Garments, cloth or textiles (149)	147.51**	137.63**	157.39**	140.62**	123.36**	157.61**
	(64.19)	(64.67)	(71.65)	(58.74)	(57.62)	(68.10)
Non-Disclosure mean	278	228	327	252	201	303
Disclosure mean	430	374	485	398	340	456
Metal parts, springs or vehicle parts (43)	443.39***	396.46***	490.32***	443.39***	396.46***	490.32***
	(106.77)	(117.79)	(111.28)	(106.77)	(117.79)	(111.28)
Non-Disclosure mean	139	127	150	139	127	150
Disclosure mean	589	540	638	589	540	638
Length and order FE	Yes	Yes	Yes	Yes	Yes	Yes
Enumerator FE	Yes	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. By recording length						
14-day recording (150)	163.20**	157.70**	168.70**	205.36***	196.31***	214.04***
	(65.14)	(65.42)	(69.33)	(60.84)	(60.45)	(66.18)
Non-Disclosure mean	298	263	333	247	210	284
Disclosure mean	468	427	509	463	416	509
28-day recording (150)	254.32***	255.92***	252.72***	235.42***	230.98***	241.17***
	(65.18)	(66.38)	(70.37)	(62.81)	(63.56)	(67.90)
Non-Disclosure mean	246	195	297	226	181	272
Disclosure mean	493	441	545	458	410	508
Offer-order FE	Yes	Yes	Yes	Yes	Yes	Yes
Enumerator FE	Yes	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each row reports the coefficient on the disclosure indicator estimated within that subgroup, with enumerator fixed effects. Columns 1–3 assign INR 1,200 to every worker who refuses at any payment. Columns 4–6 assign INR 1,200 only to workers whose reason for refusing that offer is that a machine could learn their work and cost them their job, and drop workers who refuse for any other reason. Columns 1 and 4 stack each worker's two offers and include an indicator for the outside organisation, with standard errors clustered at the worker level; the other columns are one observation per worker with heteroskedasticity-robust standard errors. Worker controls include the daily wage, whether the worker had heard of camera recording before the survey, and years of education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.1 Balance

Table A4 compares the two arms on the characteristics reported in Table 1, pooling the two recording lengths.

Table A4: Balance on the information arm

	Non-Disclosure	Disclosure	Difference	p	N
Panel A. Demographics					
Age (years)	28.7	28.4	-0.4	0.707	300
Female	0.03	0.01	-0.02	0.177	300
Education (years)	10.5	10.6	0.1	0.812	300
Household size (members)	5.5	5.8	0.4	0.152	300
Caste					
General or OBC	0.76	0.82	0.06	0.259	283
SC/ST	0.24	0.18	-0.06	0.259	283
Household monthly income (INR)	44,537	38,218	-6,320	0.028	283
Could not raise INR 2,000 in a week	0.37	0.42	0.05	0.410	300
MPC out of an unexpected INR 1,000	0.78	0.71	-0.07	0.051	281
Panel B. Employment					
Monthly pay (INR)	17,170	17,108	-62	0.868	300
Years in this industry	6.5	6.3	-0.1	0.879	300
Sector					
Garments or textiles	0.49	0.50	0.01	0.908	300
Electronics	0.33	0.33	0.00	1.000	300
Metal or vehicle parts	0.15	0.14	-0.01	0.745	300
Wages paid by					
The company	0.68	0.70	0.02	0.709	300
A subcontractor	0.32	0.30	-0.02	0.709	300
Has a written contract	0.28	0.33	0.05	0.381	300
Receives a wage slip	0.65	0.64	-0.01	0.810	300
Factory has CCTV over the work area	0.95	0.95	0.01	0.792	300
Had heard of camera recording	0.27	0.21	-0.06	0.227	300
Has seen a machine that could do their work	0.59	0.60	0.00	0.943	285

Notes: The sample is workers in the four main cells, with the 14-day and 28-day recording-length cells pooled. Variable definitions and winsorization are as in Table 1. The difference is the coefficient from a regression of the row variable on an indicator for the disclosure arm, with heteroskedasticity-robust standard errors. In the joint test of all covariates on the information arm reported in the text, missing cells are set to the sample median and an indicator is included for each. The last two rows ask what the worker knew before the survey, but both questions are put after the information script.

B.2 Enumerators

Table A5 adds enumerator fixed effects to the specification in Panel A of Table 2.

Including enumerator fixed effects leaves the disclosure estimates broadly similar. Workers in the disclosure arm demand 206 rupees more from their employer (p<0.001), compared with 209 rupees in the baseline specification, and 210 rupees more from the outside organization (p<0.001),

compared with 216.

Table A5: The disclosure effect with enumerator fixed effects

	Both offers (1)	Own company (2)	Outside org. (3)	Own per wage (4)	Outside per wage (5)
Disclosure	208.28***	206.31***	210.25***	0.34***	0.35***
	(45.62)	(45.84)	(48.80)	(0.07)	(0.08)
Non-Disclosure mean	271.64	228.67	314.61	0.35	0.49
Length and order FE	Yes	Yes	Yes	Yes	Yes
Enumerator FE	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes
Workers	300	300	300	300	300
Observations	600	300	300	300	300

Notes: Each column repeats the matching column of Panel A of Table 2 with enumerator fixed effects added to the recording-length and offer-order fixed effects. Column 1 stacks each worker's two offers and includes an indicator for the outside organisation. Columns 2 to 5 are one observation per worker. Columns 4 and 5 divide the reservation payment by the worker's daily wage. Worker controls include whether the worker had heard of camera recording before the survey, years of education for all columns and daily wage for columns 1-3. Standard errors are clustered at the worker level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Without worker controls

Table A6 therefore re-estimates every specification in Table 2 after removing the three worker controls while retaining the recording-length and offer-order fixed effects.

The estimates are similar without the controls. Disclosure increases the compensation demanded from the employer by 205 rupees (p<0.001), compared with 209 rupees in the baseline specification, and increases the compensation demanded from the outside organization by 212 rupees (p<0.001), compared with 216. In the interval-regression specification, the estimated effect for the employer offer is 240 rupees (p<0.001), compared with 244 rupees with controls. The extensive-margin results are also unchanged: workers in the disclosure arm remain less likely to record without additional compensation and more likely to refuse to participate at any payment. These results confirm that the main estimates do not depend on the inclusion of worker-level covariates.

B.4 Refusals that cite automation

Table A6: The effect of disclosure without worker controls

	Both offers (1)	Own company (2)	Outside org. (3)	Own per wage (4)	Outside per wage (5)
Panel A. Reservation payment, INR per day					
Disclosure	208.69***	205.33***	212.05***	0.34***	0.35***
	(45.95)	(45.75)	(48.91)	(0.08)	(0.08)
Non-Disclosure mean	271.64	228.67	314.61	0.35	0.49
Length and order FE	Yes	Yes	Yes	Yes	Yes
Worker controls	No	No	No	No	No
Workers	300	300	300	300	300
Observations	600	300	300	300	300
Panel B. Extensive margin					
Would record for free	-0.040*	-0.047*	-0.033*		
	(0.021)	(0.027)	(0.020)		
Refuses at any price	0.180***	0.173***	0.187***		
	(0.038)	(0.038)	(0.040)		
Non-Disclosure mean, records for free	0.063	0.080	0.047		
Non-Disclosure mean, refuses	0.050	0.047	0.053		
Length and order FE	Yes	Yes	Yes		
Worker controls	No	No	No		
Workers	300	300	300		
Observations	600	300	300		
Panel C. Interval regression					
Disclosure	248.81***	239.85***	257.95***	0.40***	0.43***
	(54.15)	(53.51)	(57.34)	(0.09)	(0.09)
Non-Disclosure mean	271.64	228.67	314.61	0.35	0.49
Refusals, right-censored	84	40	44	40	44
Length and order FE	Yes	Yes	Yes	Yes	Yes
Worker controls	No	No	No	No	No
Workers	300	300	300	300	300
Observations	600	300	300	300	300

Notes: Every column repeats the matching column of Table 2 with the three worker controls removed. The recording-length and offer-order fixed effects, the samples, the censoring convention and the standard errors are as in that table: column 1 stacks each worker's two offers and includes an indicator for the outside organisation, and columns 2 to 5 are one observation per worker. Columns 4 and 5 divide the reservation payment by the worker's daily wage. Panel A assigns zero to a worker who would be recorded without additional compensation and INR 1,200, the top rung of the ladder, to a worker who refuses at any price. Panel B reports linear probability models for those two outcomes. Panel C estimates an interval regression that treats each named amount as exact and each refusal as right-censored above INR 1,200. Standard errors are clustered at worker level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: The effect of disclosure on compensation demanded, counting only refusals that cite automation

	Both offers (1)	Own company (2)	Outside org. (3)	Own per wage (4)	Outside per wage (5)
Panel A. Compensation					
Disclosure	226.67***	219.26***	234.36***	0.38***	0.40***
	(43.05)	(42.69)	(46.54)	(0.07)	(0.08)
Non-Disclosure mean	236.30	195.17	277.72	0.30	0.43
Refusals dropped, other reason	19	9	10	9	10
Length and order FE	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes
Workers	292	291	290	291	290
Observations	581	291	290	291	290
Panel B. Extensive margin					
Would record for free	-0.039*	-0.046*	-0.032		
	(0.022)	(0.027)	(0.021)		
Refuses at any price	0.193***	0.183***	0.203***		
	(0.035)	(0.034)	(0.036)		
Non-Disclosure mean, records for free	0.066	0.083	0.049		
Non-Disclosure mean, refuses	0.014	0.014	0.014		
Length and order FE	Yes	Yes	Yes		
Worker controls	Yes	Yes	Yes		
Workers	292	291	290		
Observations	581	291	290		
Panel C. Interval regression					
Disclosure	262.23***	248.96***	275.97***	0.43***	0.47***
	(49.63)	(48.78)	(53.04)	(0.08)	(0.09)
Non-Disclosure mean	236.30	195.17	277.72	0.30	0.43
Refusals, right-censored	65	31	34	31	34
Length and order FE	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes
Workers	292	291	290	291	290
Observations	581	291	290	291	290

Notes: The sample is workers in the four main cells. Column 1 stacks each worker's two offers and includes an indicator for the outside organisation, with standard errors clustered on the worker; columns 2 to 5 are one observation per worker. Columns 4 and 5 divide the reservation payment by the worker's daily wage. Worker controls include whether the worker had heard of camera recording before the survey, years of education for all columns and daily wage for columns 1-3. A refusal counts only when the worker's reason for refusing that offer is that a machine could learn their work and cost them their job; a worker who refuses an offer for any other reason is dropped from that offer's columns. Panel A assigns zero to a worker who would be recorded without additional compensation and INR 1,200, the top rung of the ladder, to a worker who refuses for this reason. Panel B reports linear probability models for those two outcomes. Panel C estimates an interval regression that treats each named amount as exact and each refusal as right-censored above INR 1,200. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Measurement

C.1 Task content

The survey asks what the worker does in this work and offers twelve tasks, with an option to write anything else in. Table A8 reports the share naming each.

Table A8: Tasks performed by workers

	Mean	SD	*N*
Offered in the question			
Stitching or sewing	0.28	0.45	330
Fitting parts or assembly	0.30	0.46	330
Checking, testing or quality control	0.17	0.38	330
Collar, cuff or other garment part	0.07	0.26	330
Interlock or overlock	0.05	0.22	330
Pressing or ironing	0.06	0.23	330
Cutting	0.04	0.19	330
Packing	0.02	0.15	330
Folding	0.02	0.12	330
Tagging or labelling	0.03	0.17	330
Thread cutting	0.01	0.08	330
Loading or unloading	0.00	0.00	330
Coded from the free text, not offered			
Soldering or wiring	0.03	0.18	330
Printing, dyeing or colour work	0.02	0.12	330
Machine operation	0.02	0.12	330
Design or sampling	0.01	0.08	330
Measuring or marking	0.00	0.06	330
Finishing	0.01	0.10	330
Material handling	0.01	0.08	330
Instructing other workers	0.01	0.08	330
Embroidery or hand work	0.02	0.12	330
Welding, grinding or other metalwork	0.04	0.19	330
Machine repair	0.01	0.10	330
Number of tasks named	1.2	0.5	330

Notes: Each row is the share of workers naming that task; a worker may name more than one, so the shares do not sum to one. The question asks what the worker does in this work and offers the twelve tasks in the first block, together with "other, specify". We code the free-text answers of 67 workers. An answer that names an offered task goes into the first block, and work the list does not cover goes into the second.

C.2 Winsorization

Household income, own monthly pay, and household size are winsorized at the 5th and 95th percentiles wherever they appear.

C.3 Refusal as censoring

Every elicitation begins with an extensive-margin question, so a worker may state that no payment would induce them to record. We treat that answer as right-censored rather than missing. Dropping these workers would bias the comparison, because disclosure is what moves workers into the refusal category.

We set the censoring threshold by assumption; we do not observe it. The refusal question precedes any mention of an amount, so no refuser saw Rs 1,200 and declined it. In Table A9, we re-estimate Panel C of Table 2 with thresholds from Rs 300 to Rs 5,000. We obtain positive estimates at every threshold, and their magnitude rises with the threshold. Readers should therefore interpret the level of the Panel C estimate together with this table.

Table A9: Interval regression under alternative censoring thresholds

	(1)	(2)	(3)	(4)	(5)	(6)
Disclosure	87.21***	117.04***	168.87***	243.64***	399.08***	993.10***
	(27.51)	(30.54)	(38.56)	(52.86)	(85.93)	(219.44)
Refusal censored at	300	500	800	1,200	2,000	5,000
Estimated σ	243.1	267.8	330.6	444.2	711.7	1,804.5
Observations	300	300	300	300	300	300

Notes: The dependent variable is the reservation payment for the own-company offer. Each column repeats column 2 of Panel C of Table 2, changing only the value above which a refusal is treated as censored. Controls, fixed effects, and standard errors are as in that table. Of the 300 workers, 40 refuse the own-company offer at any price and are right-censored in every column. The refusal question is asked before any amount is named. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Employers in Prowess

Table A10 describes the employers named by workers that we could match to CMIE Prowess, a database of company annual accounts.

Table A10: Characteristics of employers matched to Prowess, and of plants in the same industries

	Matched employers (Prowess)					Same-industry plants (ASI)	
	Mean	Median	p25	p75	*N*	Mean	Median
Panel A. Size							
Sales (Rs crore)	3,544	1,116	401	7,701	13	66	11
Total assets (Rs crore)	1,905	1,038	360	2,487	13	47	8
Net fixed assets (Rs crore)	531	260	69	622	12	14	2
Wage bill (Rs crore)	245	86	44	147	13	5	1
Age (years)	21	19	9	29	13	16	13
Panel B. Cost structure (%)							
Wage bill / total costs	10.0	9.1	1.6	16.4	13	13.7	9.6
Materials / total costs	70.3	66.5	63.3	85.0	13	59.9	65.7
Value added / sales	18.2	22.1	6.6	25.2	13	23.2	17.6
Labour share of value added	47.0	43.9	26.1	61.4	13	56.8	52.7
Panel C. Capital and technology							
Plant and machinery / wage bill	2.0	1.2	0.2	3.3	12	1.9	0.7
Reports R&D spending (% of firms)	31				13	3	
Holds patents or copyrights (% of firms)	8				13		
Pays royalties or technical fees (% of firms)	23				13		
Panel D. Trade and ownership (% of firms)							
Exporter	54				13	9	
Business group or foreign owned	31				13		
Listed on a stock exchange	15				13		

Notes: Employers named by workers in the survey, matched to CMIE Prowess by company name and registered address. 13 employers are matched, employing 69 of the surveyed workers; 6 are matched on name and a Noida address and the rest on name and main product. Where an employer matched several Prowess entities, the operating entity is used. Standalone annual accounts for each firm's latest 12-month financial year (2024 or 2025). Rs 1 crore is Rs 10 million. Value added is the wage bill plus profit before depreciation, interest, tax and amortisation. Total costs are total expenses; materials are raw materials and purchased finished goods. Indicators equal one if the item is positive in any of the firm's latest three years; Prowess does not distinguish an unreported item from zero. Exporters are firms receiving export incentives such as duty drawback. Patents and copyrights count only when held as an asset on the balance sheet. Plant and machinery is the net value. Prowess does not report employment for these firms, so per-worker measures are not shown. The ASI columns are the 8,755 operating plants in the 2022–23 Annual Survey of Industries in the same ten 4-digit NIC industries as the matched employers, across India, weighted by the sampling multipliers to represent 23,993 plants. ASI figures are per plant, not per firm, and age counts years since initial production. In ASI, value added is gross value added as the survey defines it; R&D is R&D spending or an R&D unit; an exporter exports some of its products directly. ASI ratios are winsorized at the 1st and 99th percentiles. Blank ASI cells have no counterpart in the survey.

D Details about Survey

Enumerators conducted the interviews in Hindi. The text produced here is the translated version. Italic brackets mark enumerator instructions and values filled in for each worker.

D.1 Experiment script

This section reproduces the script used in the experiment.

Script 1: Own company, non-disclosure

> Please listen carefully. First I will describe a situation involving your own company.
>
> This first situation is hypothetical, which means it is only an example for the survey and not a real offer.
>
> Suppose the company you currently work for gives you a proposal. You will continue doing your normal factory work, and you will continue to receive your regular daily wage as before. In addition, your company will pay you extra money, because you will wear a small camera on your head while working.
>
> *[Now show the respondent the video. Play the entire video. Do not explain anything other than the script.]*
>
> Did the video clearly explain what it means to wear a small camera on your head while working? *[Yes / No]*
>
> As you saw in the video, the worker wears a small camera on their head while doing normal work. The work shown in the video may be different from your work, but the idea is the same. You will wear a small camera on your head while doing your normal work.
>
> This camera will record how you do your work. For example, it will record how you move your hands, how you pick up items, how you place items, and how you perform different parts of the task.
>
> You will wear the camera for 8 hours every day while working. This recording will continue for *[2 or 4]* weeks, that is, a total of *[14 or 28]* days.
>
> The company will keep these recordings with itself.
>
> Now please think about this hypothetical situation and answer.
>
> Now think about this offer from your company. Would you be willing to do this recording? *[Read out all three options.]*
>
> 1. Yes, even without any extra payment
> 2. Yes, but only if I get extra payment
> 3. No, I would not do it at any payment

Script 2: Own company, disclosure

Please listen carefully. First I will describe a situation involving your own company.

This first situation is hypothetical, which means it is only an example for the survey and not a real offer.

Suppose the company you currently work for gives you a proposal. You will continue doing your normal factory work, and you will continue to receive your regular daily wage as before. In addition, your company will pay you extra money, because you will wear a small camera on your head while working.

[Now show the respondent the video. Play the entire video. Do not explain anything other than the script.]

Did the video clearly explain what it means to wear a small camera on your head while working? *[Yes / No]*

As you saw in the video, the worker wears a small camera on their head while doing normal work. The work shown in the video may be different from your work, but the idea is the same. You will wear a small camera on your head while doing your normal work.

This camera will record how you do your work. For example, it will record how you move your hands, how you pick up items, how you place items, and how you perform different parts of the task.

You will wear the camera for 8 hours every day while working. This recording will continue for *[2 or 4]* weeks, that is, a total of *[14 or 28]* days.

The company would use these recordings to teach a machine to do your kind of work. If the machine learns to do it well, the company could use the machine instead of you, and you could lose this job.

Now please think about this hypothetical situation and answer.

Now think about this offer from your company. Would you be willing to do this recording? *[Read out all three options.]*

1. Yes, even without any extra payment
2. Yes, but only if I get extra payment
3. No, I would not do it at any payment

Script 3: Outside organization, non-disclosure

Please listen carefully. First I will describe a situation involving an outside research or technology organisation.

[Now show the respondent the video. Play the entire video. Do not explain anything other than the script.]

Did the video clearly explain what it means to wear a small camera on your head while working? *[Yes / No]*

Suppose an outside research or technology organisation asks you to make a recording.

You will not need to go anywhere else for the recording. You will carry on in your own factory, at your usual place, doing your normal work as before.

While working you will wear on your head the same small camera you saw in the video. This camera will record how you do your work: how you move your hands, how you pick things up and put them down, and how you do the different parts of your job.

You will wear this camera for eight hours every day. The recording will run for *[2 or 4]* weeks, that is *[14 or 28]* days in total.

Your regular daily wage will keep coming from your company as before. For the recording, the outside organisation will pay you separately, on top of that. How much that payment is will be settled between you and that organisation. Your company will have no role in this payment.

The outside organisation will keep these recordings with itself.

Now think about this offer from the outside organisation. Would you be willing to do this recording? *[Read out all three options.]*

1. Yes, even without any extra payment
2. Yes, but only if I get extra payment
3. No, I would not do it at any payment

Script 4: Outside organization, disclosure

Please listen carefully. First I will describe a situation involving an outside research or technology organisation.

[Now show the respondent the video. Play the entire video. Do not explain anything other than the script.]

Did the video clearly explain what it means to wear a small camera on your head while working? *[Yes / No]*

Suppose an outside research or technology organisation asks you to make a recording.

You will not need to go anywhere else for the recording. You will carry on in your own factory, at your usual place, doing your normal work as before.

While working you will wear on your head the same small camera you saw in the video. This camera will record how you do your work: how you move your hands, how you pick things up and put them down, and how you do the different parts of your job.

You will wear this camera for eight hours every day. The recording will run for *[2 or 4]* weeks, that is *[14 or 28]* days in total.

Your regular daily wage will keep coming from your company as before. For the recording, the outside organisation will pay you separately, on top of that. How much that payment is will be settled between you and that organisation. Your company will have no role in this payment.

The outside organisation will keep these recordings with itself and will use them to teach a machine or robot to do your work. If the machine learns to do it well, the company could use the machine instead of you, and you could lose this job.

Now think about this offer from the outside organisation. Would you be willing to do this recording? *[Read out all three options.]*

1. Yes, even without any extra payment
2. Yes, but only if I get extra payment
3. No, I would not do it at any payment

D.2 Survey questions used in the analysis

This section reproduces the questions behind the belief, bargaining, earnings-loss and overhead-camera results.

Conditional automation beliefs

Out of 100, what is the chance that within the next 2 years a machine or robot will be able to do your whole current job on its own?

In your opinion, what is the chance that within the next 5 years a machine or robot will be able to do your whole current job on its own? Please give a number out of 100.

Now I will ask the same question about two different situations. In each one, tell me out of 100 what the chance is that within the next 5 years a machine or robot will be able to do your whole current job on its own.

First, suppose you wear the camera and your work is recorded for these *[14 or 28]* days. Out of 100, what is the chance?

Now suppose you refuse, and no other worker records in your place either, so this recording does not happen at all. Out of 100, what is the chance?

Refusal consequences

If you refuse to wear the camera and record your work, what would the company do to you? *[Do not read the options aloud. Record the answer against the list.]*

1. Dismiss me from work
2. Withhold or cut my pay
3. Move me to another department or another job
4. Scold me, or say something to me
5. Put pressure on me to agree
6. Harass me or treat me badly at work
7. Nothing would happen to me
8. Other, specify
9. Do not know

Collective bargaining

Workers in the four main cells answer both questions.

> Now suppose that you and all the workers in your factory who do the same kind of work as you are collectively bargaining with the company over how much you should be paid for the recording.
>
> You all agree that no worker will accept the recording for less than the amount you negotiate together.
>
> When deciding on your own, *[restates the worker's answer to the employer's offer, for example "you said Rs 300 extra per day"]*.
>
> If you were now bargaining together as a group, what is the lowest extra amount per day you would agree to accept from the company for the recording?

Earnings losses and recovery

All workers answer these questions.

> Now suppose that in many factories and workplaces, machines or robots start doing the main work that you currently do. Employers start using these machines or robots, so this kind of work stops being available to you. Many other people with skills and experience similar to yours also stop getting this work, and they start looking for other work at the same time.
>
> In addition, since so many people will be looking for new work at the same time, it may be somewhat harder for you to find new work as well.
>
> For the next questions, assume that this is certain to happen. State future earnings in today's rupees, and assume that prices of things will not change.
>
> In this situation, what would you most likely do to earn money? *[Read all options before recording the answer.]*
>
> 1. Look for the same type of work somewhere else
> 2. Look for a different type of paid work
> 3. Start my own business or another form of self-employment
> 4. Start farming or do more farming
> 5. Do more of another work or business that I already do
> 6. Move to another place to look for work
> 7. Stop working for some time
> 8. Stop working permanently
> 9. Do something else
> 10. Do not know
>
> After losing this work, about how many months would it take before you began earning regularly again from any work or income-earning activity? *[Enter 0 if regular earnings would begin immediately. If it would take less than one month, enter a fraction: 0.25 for about one week and 0.5 for about two weeks.]*

Once you began earning regularly again, approximately how much would you personally earn in a typical month from the main work or activity you would then be doing? *[Include only earnings from that work or activity. Do not include earnings from other work, farming, or business. If it is farming, a business, or self-employment, report the amount remaining after the expenses required to do that activity.]*

About how many months after losing your current work would it take for your monthly earnings from the new work or activity to reach Rs *[current monthly pay]* or more? *[Count from the time your current work is lost, not from the time the new work begins. Enter 0 if the new earnings would immediately be equal to or higher than current earnings.]*

Overhead-camera offer: audit cell

Workers in the audit cell hear only this offer.

Please listen carefully. Now I will describe a hypothetical situation, which means it is only an example for the survey and not a real offer. Suppose the company you work in puts a camera above the place where you work. This camera records everything you do while you are working: how you move your hands, how you pick things up, how you place them, and how you do the different parts of your job. This is different from a CCTV camera, because this camera is installed directly above your workstation. You carry on with your normal work, eight hours a day, for *[14 or 28]* days, and your regular daily wage continues as before. The company keeps these recordings with itself.

Now think about this situation. Would you be willing to let the company record your work with this camera? *[Read out all three options.]*

1. Yes, even without any extra payment
2. Yes, but only if I get extra payment
3. No, I would not do it at any payment

[If the worker answers 2:] Now suppose the company pays you some extra money each day for this recording, on top of your regular daily wage. I will now read out different amounts. For each amount, tell me whether you would agree to this recording for that much extra per day.

Would you let the company record your work with this camera for Rs 50 extra per day, that is Rs *[50 times the number of days]* in total for the *[14 or 28]* days? *[The question is repeated at Rs 100, 200, 300, 400, 500, 600, 700, 800, 1,000 and 1,200 until the worker first says yes.]*

[If the worker says no at every amount:] You have said no to every amount up to Rs 1,200. What is the smallest extra amount per day at which you would let the company record your work with this camera?

Overhead-camera offer: main non-disclosure cells

Workers in the non-disclosure arm of the main cells hear this offer after both head-camera offers.

Now suppose the company does not ask you to wear anything. Instead, the company puts a camera above the place where you work. This camera records everything you do while you

are working. The company keeps these recordings with itself. Everything else stays the same: your normal work, eight hours a day, for *[14 or 28]* days, and your regular daily wage continues as before. This is a hypothetical situation.

For the camera worn on the head, when your own company asked, *[restates the worker's answer to the employer's offer]*.

Now think about this camera above your workstation instead. What is the smallest extra amount per day at which you would agree to it? You may say any amount.

Would you be willing to let the company record your work with this camera above your workstation? *[Read out all three options.]*

1. Yes, even without any extra payment
2. Yes, but only if I get extra payment
3. No, I would not do it at any payment

[If the worker answers 2, record the amount in rupees per day.]