Asymmetric Information and Selection in the Gig Economy: Evidence from an Online Experiment

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Abstract

For gig workers facing uncertain output, hourly wage contracts provide implicit insurance compared to self-employment or piece-rate pay. But like any insurance product, these contracts are prone to market distortions through moral hazard and adverse selection. I investigate these distortions through a field experiment in which online workers are offered a choice between a randomized hourly wage and a standardized piece rate in exchange for performing a simple data-entry task. A standard treatment-on-the-treated estimation isolates incentive effects of hourly wages (moral hazard). At the same time, comparing realized output across workers who decline different hourly wage offers isolates a selection effect—both groups work under the same form of compensation but faced different ex-ante menus of contracts. Results from a small-scale pilot experiment find statistically significant selection effects. A one-dollar increase in hourly wage offer corresponds to a \$0.25 (SE=0.101) increase in hourly output value among those declining the hourly offer in favor of the piece rate. I develop a theoretical framework showing how this adverse selection can lead to inefficiently low provision of hourly wage contracts.

1 Introduction

The proliferation of "gig work" has transformed how millions of workers are paid (Garin et al., 2023; Collins et al., 2019; Katz and Krueger, 2019; Abraham et al., 2017; Jackson et al., 2017). Rather than clocking their hours, workers are increasingly compensated by the number of miles driven, pages written, or tasks completed. Compared to traditional time-based wages, this type of compensation can be risky and unpredictable—an hourly worker knows what they'll earn from a day's work, whereas a gig worker's earnings often depend on uncertain factors like weather or traffic. But if workers value the insurance provided by hourly wages, why are so many short-term labor markets dominated by risky, piece-rate compensation and self-employment?

In this paper, I investigate how two distortionary forces—moral hazard and adverse selection—can lead to inefficiently low provision of hourly work. On the one hand, hourly wages might reduce effort through moral hazard (Lazear, 2000), leading employers to amplify the performance-based component of wage contracts. On the other hand, if ex-ante less productive workers adversely select into hourly wage contracts, firms might post exclusively piece-rate positions to avoid attracting the wrong type of worker. Distinguishing the relative magnitudes of these two effects has important policy implications. Because employers internalize the costs of reduced work effort, the government has no comparative advantage in mitigating the effects of moral hazard—no policy intervention could avoid the inherent tradeoff between monitoring costs and insurance benefits (Einav et al., 2010b). By contrast, the welfare consequences of adverse selection, can often be ameliorated with government policies. In this case, mandates or subsidies that promote hourly wages among "high types" might facilitate Pareto-improving exchanges.

Measuring the impact of information asymmetries in labor markets poses several empirical challenges. First, both moral hazard and adverse selection predict a negative correlation between hourly compensation and observed productivity. Testing for this correlation can establish the existence of one or both phenomena (Chiappori and Salanie, 2000), but separately identifying the two typically requires estimating how workers' effort and contract decisions respond to exogenous variation in wages (Einav et al., 2010a). Finding such variation can be difficult, as observed wage changes are often driven by endogenous shifts in labor supply or worker composition. Second, even if one isolates exogenous variation in wages, such variation is only observed over existing wage contracts. This type of "under-the-lamppost" analysis can understate the consequences of adverse selection, as the largest welfare losses likely come from contracts that do not exist due to unraveling (Einav et al., 2010b). Attempts to quantify information asymmetries in these "missing markets" often rely on constructing hypothetical contract preferences from survey data on subjective beliefs (Hendren, 2013, 2017; Herbst and Hendren, 2021), but predicting demand for a contract that does not exist typically requires strong parametric assumptions.

To overcome these empirical challenges, I design a field experiment that randomly varies hourly wage offers for a short-term data-entry task. This experimental approach gives me discretion over offers, allowing me to observe choices over a wide range of contracts, including those that may not otherwise exist due to unraveling. And by randomizing the menu of wage offers relative to a standardized piece rate, my design allows me to separately identify moral hazard and adverse selection into these contracts. Standard treatment-effects estimation isolates moral hazard, while comparing realized output across workers who decline different hourly wage offers isolates selection—both groups work under the same form of compensation but faced different ex-ante menus of contracts. Results from a small-scale pilot experiment find statistically significant selection effects. A one-dollar increase in hourly wage offer corresponds to a \$0.25 (SE=0.101) increase in output value among those declining the offer in favor of the piece rate.

I place these experimental estimates into a theoretical framework that builds upon Einav et al. (2010a) and Herbst and Hendren (2021). Using this framework, I show how the provision of hourly employment contracts is determined by two curves: a worker's reservation wage—the minimum compensation they will accept in exchange for an hour of labor—and the average value of output among workers with comparatively lower reservation wages. These objects can be straightforwardly identified for workers in my experimental sample—first by comparing the shares of workers opting into hourly wages across offer treatments, then by comparing the average output among hourly workers in each group. I then show how to use these model estimates to quantify the welfare loss associated with inefficiently low provision of hourly positions.

This study relates to several streams of existing research. Building upon the seminal work of Akerlof (1970), several studies have applied the theory of adverse selection to labor markets, showing how the self-sorting of workers by unobserved productivity can lead to inefficient hiring, compensation, or other labor contract provisions (Weiss, 1980; Jovanovic, 1982; Greenwald, 1986; Lazear, 1986; Gibbons and Katz, 1991; Levine, 1991; Kugler and Saint-Paul, 2004; Moen and Rosen, 2005; Emanuel and Harrington, 2023). While empirical analyses of these selection phenomena are less common, several document differential sorting across compensation schemes (Shearer, 1996; Lazear, 2000; Angrist et al., 2021; Shearer, 2004; Kantarevic and Kralj, 2016). These and other studies use observational data to estimate selection and incentive effects in both labor markets and elsewhere (Einav et al., 2010a; Chiappori and Salanie, 2000; Hendren, 2017), but few have used experimental methods to form these estimates. Karlan and Zinman (2009), which randomizes contract offerings on microfinance loans in South Africa, is a notable exception. Their experiment isolates selection on unobservables by comparing borrowers who faced different menus of options but ultimately chose the same contract terms. They find strong evidence of moral hazard and weaker evidence of adverse selection.

My study design also builds upon existing experimental work using online freelancer platforms. In particular, Pallais (2014) and Pallais and Sands (2016) demonstrate the signaling benefit of entry-level hiring and employer references using online experiments, as well as DellaVigna and Pope (2018) and DellaVigna and Pope (2022), which estimate the effects of both monetary and non-monetary incentives in an online typing task. My paper would complement such findings, as the unraveling phenomenon I investigate could help explain why Spence (1973)-style information treatments provide a net social benefit.

Relative to existing work on adverse selection in labor markets, my proposed experiment offers several distinct advantages. First, my experiment would reveal workers' decisions over contracts that are unavailable to them in the real world, allowing me to quantify welfare losses in unraveled markets where efficient wage contracts cannot be observed. Second, the ability to randomize wage offers allows me to reliably estimate selection into these contracts, ensuring that such patterns are not driven by unobserved characteristics of firms, contracts, or the populations of workers to which their offered. Finally, my experimental design, in which workers can choose between a randomized set of wage offers, allows me to separately identify selection-on-unobservables from the treatment effects of different compensation schemes.

The rest of this proposal proceeds as follows: In Section 2, I describe my experiment and underlying empirical strategy. In Section 3, I describe the experimental setting and discuss external validity. In Section 4, I discuss results from a small-scale pilot experiment. In Section 5, I provide a model of adverse selection in wage contracts. In Section 5.2, I map this model to experimental estimands and show how it can be used to quantify welfare losses from adverse selection.

2 Experimental Design

In this section, I describe my experimental design and empirical strategy. The goal of my experiment is to two-fold: First, I aim to identify the incentive effects of hourly wage contracts on worker performance (moral hazard). Second, I want to identify how workers with different unobserved productive potentials self-select into these contracts (adverse selection). Separately identifying these forces poses an empirical challenge—differences in realized output between workers who opted into a given wage offer reflect both the ex-ante productivity differences between those self-selected groups and the causal effect of the different wage offers they chose.

To overcome this challenge, my experimental design offers workers a choice between a randomized hourly wage and a standardized piece rate. Comparing realized output between individuals who faced different hourly wage offers but ultimately chose the common piece rate identifies adverse selection—both groups ultimately face the same compensation scheme but made decisions under different alternative options. So, if workers choose contracts based on their privately known productivities, those who decline more generous hourly payments should perform better than those foregoing more modest wages. At the same time, because I observe worker output under both contract choices in each treatment group, a standard two-stage-least-squares estimation allows me to separately identify treatment effects of hourly wages among those who accept the offer.

To formalize this intuition, consider a potential outcomes framework in which some worker i chooses between two mutually exclusive contracts—a piece rate (p) and an hourly wage (w). Let Y_{1i} denote i's output if they work under the hourly wage, and let Y_{0i} denote their output if they decline that wage in favor of the piece rate. Given these potential outcomes, worker i's observed output, Y_i, is given by

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i}, \tag{1}$$

where D_i is a binary indicator for whether i chooses the hourly wage. A comparison of realized outputs between hourly ($D_i = 1$) and piece-rate ($D_i = 0$) workers would yield the following:

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = \underbrace{E[Y_{1i} - Y_{0i}|D_i = 1]}_{\text{Treatment on the Treated } (TOT)} + \underbrace{E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]}_{\text{Selection into Treatment } (\Delta\mu_0)}. \tag{2}$$

This difference is the sum of two components. The first is the treatment-on-the-treated effect, TOT, which equals the average effect of hourly pay among those who accept wage offer w over the piece rate. The second is the selection into treatment, $\Delta\mu_0$, which equals the average difference in potential outcomes under the piece rate between those choosing hourly pay ($D_i = 1$) and those choosing the piece rate ($D_i = 0$). These components are difficult to separate because piece-rate outcomes among hourly workers $(Y_{0i}|D_i = 1)$ are always unobserved.

Now suppose that, rather than face a uniform menu of piece rate and hourly wage offers, workers are randomly assigned to one of two offer conditions, $Z_i \in \{0, 1\}$. Only workers assigned to $Z_i = 1$ are offered the choice between the piece rate and hourly wage, while workers assigned to $Z_i = 0$ are paid the piece rate with no alternative. Comparing worker output across these two treatment-offer groups and scaling by the hourly-wage take-up rate yields the classic TOT estimator from Wald (1940):

$$\begin{aligned} TOT &\equiv E[Y_{1i} - Y_{0i}|D_i = 1] \\ &= \frac{E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]}{\pi}, \end{aligned} \tag{3}$$

where $\pi \equiv Pr(D_i = 1|Z_i = 1)$, the probability an individual accepts the hourly contract conditional on an offer.

In the context of this paper, however, the selection component $\Delta\mu_0$ from Equation (2) is equally as important as treatment effects. I can identify this component by simply comparing output between piece-rate workers in the control group $(Z_i = 0)$ and piece-rate workers in the hourly-offer group $(Z_i = 1)$ who declined the hourly wage offer:

$$\begin{aligned} \Delta\mu_0 &\equiv (E[Y_{0i}|D_i = 1, Z_i = 1] - E[Y_{0i}|D_i = 0, Z_i = 1]) \\ &= \frac{E[Y_i|Z_i = 0] - E[Y_i|D_i = 0, Z_i = 1]}{\pi}, \end{aligned} \tag{4}$$

where equality follows from randomized assignment.[1] Figure 1 provides a graphical illustration of the intuition from Equation (4). The control group, by construction, is subject to the standardized piece rate, while the treatment-offer group is offered an hourly wage as an alternative. Selection is identified by comparing the control group $(D_i = 0, Z_i = 0)$ to those

[1] Randomized assignment implies $E[Y_{0i}|Z_i = 1] = E[Y_{0i}|Z_i = 0] = E[Y_i|Z_i = 0]$, so $E[Y_{0i}|D_i = 1, Z_i = 1] = \frac{E[Y_i|Z_i=0]-(1-\pi)E[Y_i|D_i=0,Z_i=1]}{\pi}$. Equation (4) can also be derived by subtracting the Wald estimator (3) from the difference in hourly versus piece-rate outcomes in the treatment-offer group, $E[Y_i|D_i = 1, Z_i = 1] - E[Y_i|D_i = 0, Z_i = 1]$.

in the treatment group ($D_i = 0, Z_i = 1$) who chose to remain on the piece rate. Since This selection-on-unobservables estimator captures the average difference in potential untreated outcomes for "compliers" versus "never-takers" (Black et al., 2022; Kowalski, 2023; Huber, 2013).

The example above simulates a simplified version of my experimental design with a binary treatment assignment, $Z_i \in \{0, 1\}$. In practice, however, my experiment features several treatment groups facing different hourly wage offers contract terms. Figure 2 illustrates the variety of treatment and selection margins I can investigate in a multiple-treatments framework. The top row of boxes represents individuals in each of the three experimental groups who remain on the piece rate. Because all three groups face the same ex-post payment terms but different ex-ante wage offers, comparisons between them isolates worker selection into each wage offer. As I show in Section 5.2, treating this wage offer as continuous instrument in a marginal-treatment-effects framework identifies (potential) marginal worker output across a range of wage offers. Estimates of these marginal outcomes will directly to my model of asymmetric information, allowing me to estimate welfare losses with minimal parametric assumptions.

3 Setting and Implementation

Participants in my experiment are recruited on Amazon Mechanical Turk (MTurk), an online platform that allows clients to hire online workers for short-term tasks. MTurk is a popular platform for both researchers and private firms seeking survey responses, language translation, data entry, or image classification (DellaVigna and Pope, 2022, 2018; Paolacci and Chandler, 2014; Kuziemko et al., 2015). The job posting for my experiment offers participants a \$1.00 reward for transcribing handwritten text into typed form for ten minutes. Such transcription tasks are common on the MTurk platform. The posting also informs participants they "can earn an additional \$0.03 in bonus compensation for each correctly typed sentence." A screenshot of the job posting is provided in Figure 3A.

Workers could only see my experimental job posting if they met the following screening criteria: (1) located in the United States, (2) successfully completed 100 or more previous tasks, and (3) earned an approval rate above 97 percent on previous tasks. These screening criteria accomplish two things: first, they allow me isolate "professional" MTurk workers who regularly perform tasks to earn income, as opposed to casual users who may take the tasks less seriously. Second, they restrict the sample to workers who are observably equivalent to a hypothetical employer. The goal of my experiment is to identify selection on *private* information, so I want to remove any selection on screenable characteristics.

Workers who accept the job posting are taken to an external link to perform the task.[2] After clicking this link, workers are randomized into one of four experimental groups.[3] Each group is offered a different menu of bonus compensation options for completing the ten-minute data-entry task: In the first treatment group, participants are offered a choice between a flat bonus of $0.50 for completing the task or a piece rate of $0.03 per correctly typed sentence. In the second treatment group, participants are offered a choice between a flat $1.00 bonus or the same $0.03 piece rate. In the third treatment group, participants are offered a $2.00 bonus alongside the $0.03 piece rate. Finally, a control group is offered the $0.03 piece rate for each correctly typed sentence, with no alternative option. Experimental conditions for the pilot are summarized in Table 1.

After receiving detailed instructions on the data-entry task, workers are presented with the bonus options corresponding to their experimental condition, as shown in Figure 3B. Once workers choose their compensation scheme and click "Begin Task," they are brought to a new page displays a handwritten sentence and a text box. The worker types a sentence in the box and clicks the "Next" button, bringing them to a new page with a different sentence. This process continues for ten minutes. Worker output is validated in real time, so workers can see a running tally of their "score" (the number of correctly typed sentences)

[2]The task is hosted on the Qualtrics platform. Readers can view and perform a replication of the task here.

[3]The four experimental groups described here are part of a small-stage pilot launched in March 2024. The full-scale experiment, expected to complete in early summer of 2024, includes several additional treatment arms.

and their bonus earnings in the lower-left corner of each page. Workers also see a countdown timer displaying the number of minutes and seconds remaining in the task.[4] When the timer reaches zero, the screen refreshes to an end-of-task page displaying a performance summary and a unique survey code to validate results on MTurk.

Importantly, requesters on the MTurk platform have the ability to reject or approve a given worker's assignment. Rejected assignments do not earn rewards and lower workers' approval ratings. The reputational damage from rejected assignments is an especially salient concern among MTurk workers. As in most labor markets, this threat of rejection threat creates an incentive for MTurk workers to maintain a minimum standard of performance, even if they are paid a flat hourly wage.

3.1 External Validity

The setting and design for this experiment raise two potential concerns regarding external validity. First, my experimental results may not generalize to other settings or tasks. The pattern of selection on data-entry skills likely differs from how delivery workers would sort on driving ability. Given the division of labor into increasingly specialized roles, such limits to generalizability are nearly ubiquitous in applied research on worker incentives. Whether they come from rideshare drivers (Angrist et al., 2021; Cook et al., 2021), agricultural workers (Brune et al., 2022; Bandiera et al., 2010), cashiers (Mas and Moretti, 2009), or automotive glass repairers (Lazear, 1986), parameter estimates concerning worker productivity are usually difficult generalize beyond narrowly defined labor markets. Indeed, Herbst and Mas (2015) finds that for one particular parameter—peer effects on worker output—estimates vary dramatically from one study to another, regardless of whether estimates are taken from the lab or the field. While my study is not exempt from these limitations, several elements of my experiment are designed to mitigate these concerns. First, workers for my experiment are recruited through MTurk, a widely used and well-established freelancing

[4] Figure 3C provides a screenshot of the task. The display and submission methods for this task designed to prevent workers from cheating through automation software or "bots." While it is possible that some participants may have tried to make use of such software, performance statistics suggest any such attempts were unsuccessful at increasing output.

platform with over 100,000 workers (Difallah et al., 2018). The ubiquity of MTurk and similar platforms (e.g., Upwork, Fiverr) means that even the most conservative interpretation of my estimates holds non-trivial welfare implications. Second, my experimental typing task requires a dimension of effort and skill commonly needed for gig work. "Traditional keyboarding" is a job requirement for 66 percent of American workers (Bureau of Labor Statistics, 2024), suggesting my estimates of selection and incentive effects could plausibly generalize to a variety of labor markets.

The second threat to external validity concerns selection into offered contracts. This concern is especially relevant in research involving information asymmetries, because the presence of those asymmetries can often limit the set of contracts observed in existing markets. As a result, methods using real-world wage contracts are likely to understate the consequences of adverse selection (Einav et al., 2010b). My design holds a distinct advantage over these "under-the-lamppost" methods, as my experiment allows me to create a market for hourly wage contracts that real-world employers might deem unprofitable. While this design allows me to observe outcomes of both accepters and decliners for a broad range of contracts, I can only observe outcomes for those who initially agreed to the task. If my job posting only attracted low-productivity workers, my estimates would exclude selection among high-types because they never received an offer. I mitigate this concern by advertising a generous up-front fee for accepting the task. By posting a guaranteed \$1.00 plus the \$0.03-per-sentence piece rate offered to all treatment groups, I am likely to attract a broad swath of workers who meet my screening criteria.

4 Results

This section describes results from a small-scale pilot ($N = 148$) of the experiment described above. The full-scale experiment ($N \approx 4,000$) is expected to complete in early summer of 2024.

The bar chart in Figure 4 shows the share of borrowers in each treatment group who accepted their hourly wage offer instead of the \$0.03 piece rate. Unsurprisingly, the relative supply of hourly workers increases with the offered wage—acceptance rates for \$3, \$6, and \$12 hourly wage offers were 0.73, 0.75, and 0.82, respectively.

In Figure 5, I examine how output value varies between piece-rate and hourly workers in each experimental group. “Output value” is defined as the number of correctly typed sentences per hour multiplied by \$0.03. Vertical bars measure mean outcomes among those who choose hourly wages (blue) and those who choose piece rates (red). Green circles measure mean outcomes among all individuals in each experimental group.

Comparing piece-rate workers (those declining hourly wage offers) across treatment groups, I find that those declining the \$3/hr offer produce \$0.95 of output value, those declining the \$6/hr offer produce \$1.94 of output value, and those declining the \$12/hr offer produce \$3.19 of output value. While this pattern is consistent with adverse selection on productivity, I cannot reject equality in piece-rate worker output in any two treatment-level means due to the limited power of this small-scale pilot experiment. I can, however, reject null selection effects across continuous wage offers in a linear model. Table 2 reports coefficients from OLS estimates of Equation (19), regressing output value against hourly wage offers interacted with a dummy for whether an individual accepted the hourly offer over the piece rate. The estimated coefficient on “Hourly Wage Offer” implies that a one-dollar increase in hourly wage offer corresponds to a \$0.25 (SE=\$0.1) increase in output value among those declining the offer in favor of the piece rate.

A comparison across any two experimental-group means (green points) in Figure 5 estimates an intent-to-treat effect for one wage offer relative to another. I find no significant change in mean output value between any two experimental groups. I can also estimate the overall treatment effect of hourly wages relative to the piece rate by estimating a two-stage least-squares model where I instrument for hourly wage takeup with treatment-group assignment. This estimate corresponds to the local average treatment effect of hourly wages on output value among “complier” participants who are induced into hourly pay by their treatment group’s wage offer. Table 3 reports estimates of this “treatment-on-the-treated”

(TOT) effect. While point estimates are consistent with labor supply dicincentives under hourly pay, they are small and statisticall indistinguishable from zero.

5 Model of Asymmetric Information in Wage Contracts

In this section, I present a model of asymmetric information in wage contracts. The model borrows from Einav et al. (2010a) and Herbst and Hendren (2021), who develop models of asymmetric information in health insurance markets and college financing markets, respectively. Later, I show how the parameters of this model can be mapped to experimental estimands, which I use to quantify the welfare loss from adverse selection in wage contracts.

Consider a perfectly competitive labor market in which risk-neutral firms face a population of observably equivalent workers.[5] Each worker, i, can produce some level of hourly output, $q_i = f(\zeta_i, e_i, \nu_i)$, which is a function of unobserved worker characteristics (ζ_i), individual effort (e_i), and random noise (ν_i). Firms can buy a worker's labor output at a constant market price of p per unit.[6] Alternatively, they can offer the worker an hourly contract that pays a flat wage w in exchange for a claim on their hourly output, q_i.

For individual i, I define the reservation wage, $\overline{w}_i$, as the minimum w at which they would accept an hourly contract. The relative supply of hourly workers is given by

$$S(w) \equiv \Pr\left(\overline{w}_i < w\right). \tag{5}$$

Assuming strict monotonicity ($S(w) > S(w')$ for all $w > w'$), I index workers by a type parameter, $\theta_i \in [0, 1]$, equal to the share of the worker population willing to accept a lower wage than worker i's reservation wage, $\theta_i \equiv S(\overline{w}_i)$. Assuming $\overline{w}_i$ has continuous support, I

[5]I focus on perfect competition because it serves as a useful benchmark for welfare calculation. It is straightforward to adapt the model to alternative market structures, including those in which employers hold monopsony power.

[6]Directly purchasing a worker's product of labor can be thought of as either piece-rate employment or hiring a self-employed contractor.

can rewrite the reservation wage as a function of worker type:

$$\overline{w}(\theta) \equiv S^{-1}(\theta). \tag{6}$$

Facing this population of observably identical workers with unknown types, employers set wages to maximize profits. I define the *marginal value* of type θ as

$$MV(\theta) \equiv E\left[Y_i|\theta_i = \theta\right], \tag{7}$$

where $Y_i = pq_i$, the incremental value of output q_i produced under an hourly contract relative to a piece rate.[7] Note that $MV(\theta)$ equals type θ's expected earnings under the market piece rate, p. If θ were risk averse, we would expect their reservation wage to fall below this "actuarially fair" wage (i.e., $\overline{w}(\theta) < MV(\theta)$). In other words, they would accept lower expected earnings in exchange for the implicit insurance provided by hourly wages relative to piece rates. In this case, a fully informed employer could profit from offering an hourly wage of $w \equiv \overline{w}(\theta)$ exclusively to type θ.

However, if employers cannot observe types, they cannot prevent borrowers with $\theta_i \neq \theta$ from opting into a contract offered at wage w. In this case, the hourly position would be accepted by all types θ such that $\overline{w}(\theta_i) \leq w$. So instead of obtaining type θ's marginal value, $MV(\theta)$, the employer would obtain their *average value*, defined as

$$AV(\theta) \equiv E\left[Y_i|\theta_i \leq \theta\right]. \tag{8}$$

The average value, $AV(\theta)$, of type θ is given by the average (incremental) value of output produced among all types $\theta_i < \theta$. When we account for this adverse selection into contracts, the employer's profits are given by

$$\Pi(w) = S(w)\left(AV(\theta) - w\right). \tag{9}$$

[7] In other words, Y_i is equal to the amount the firm saves by not paying the piece rate. This measure of incremental value is analogous to the incremental cost of insurance defined in Einav et al. (2010a),

Recalling the identity $\overline{w}(\theta) \equiv S^{-1}(\theta) = w$, the equilibrium condition for the share of workers under hourly contracts, θ^{EQ}, is given by

$$\overline{w}(\theta^{EQ}) = AV(\theta^{EQ}). \tag{10}$$

Figure 6 illustrates the welfare impacts of adverse selection for an example population. An efficient allocation of contracts would lead to hourly employment for all types $\theta \leq \theta^{EF}$, as these workers would accept wages at or below their marginal values ($\overline{w}(\theta) \leq MV(\theta)$). But while type θ^{EF}'s reservation wage (red line) is equal to their marginal value (blue line), an employer offering an hourly wage of $w = \overline{w}(\theta^{EF})$ would only recoup the average value (green line) of labor product among everyone accepting the offer (i.e., all $\theta \leq \theta^{EF}$). The employer could lower their wage offer, but that would drive those with the highest productivity out of the market, further reducing the contract's average value. This process continues across all types for whom $\overline{w}(\theta) > AV(\theta)$, so that the equilibrium share of workers under hourly contracts is θ^{EQ}, where $\overline{w}(\theta^{EQ}) = AV(\theta^{EQ})$.

In this stylized example, roughly one-third of the population—$\theta \in (\theta_{EQ}, \theta_{EF})$—cannot obtain hourly employment despite a willingness to work for less than their expected earnings under the market piece rate. The result is a welfare loss corresponding to the area of the region shaded in pink, which is equal to

$$DWL = \frac{1}{2}(\theta_{EF} - \theta_{EQ})(w_{EQ} - w_{EF}) \tag{11}$$

In summary, because private information creates a gap between the marginal and average values of labor, it has the potential to prevent Pareto-improving exchanges from taking place, reducing welfare below what it would be under a full-information benchmark. In the following section, I demonstrate how my experimental results can be used to estimate this welfare loss.

5.1 Incorporating Moral Hazard

Note that the model above allows for moral hazard effects, even if those effects are not explicitly discussed. Since piece-rate workers sell their output at a constant price per unit, their productivity has no affect on firm profits. So while firms care about a worker's output under the offered hourly wage (Y_{1i}), they don't care how this output compares to the piece-rate counterfactual (Y_{0i}). For this reason, profit conditions and welfare calculations are inclusive of any moral hazard effects—both AV and MV are defined conditional on accepting the hourly contract, and thus depend only on output under hourly wages, Y_{1i}.

Separating the effects of moral hazard can nonetheless be useful, as firms might have ways of ameliorating the moral hazard response to hourly wage contracts. For example, a firm might combine hourly wages with a smaller piece-rate portion to ensure workers have some "skin in the game," similar to restaurant tipping or sales commissions. This type of compensation would likely attenuate disincentive effects, but would do little to prevent adverse selection—low-productivity workers would still prefer the partial insurance of mixed compensation compared to a pure piece rate. This scenario can easily incorporated into my framework—it simply requires reframing the model as a market for supplemental hourly wages on top of a preexisting piece rate. Empirically, however, it requires separating the selection from treatment effects for the "pure" hourly wage offers in my experiment.

To separate the incentive response of the contract from selection on underlying unobservables, I must consider a given worker's counterfactual output both with *and without* the hourly wage contract. Adopting the potential outcomes notation from Section 2, I split Equations (7) and (8) into two pairs of curves. First, I define marginal values of a type θ as the conditional means of potential output value with (Y_{1i}) and without (Y_{1i}) the hourly wage:

$$MV_1(\theta) \equiv E[Y_{1i}|\theta_i = \theta] \tag{12}$$

$$MV_0(\theta) \equiv E[Y_{0i}|\theta_i = \theta] \tag{13}$$

$$\tag{14}$$

Note that $MV_1(\theta)$ is simply a relabeling of $MV(\theta)$ from Equation (7)—it captures the expected output value under hourly wage $w = S^{-1}(\theta)$ for the worker who is indifferent between accepting or declining the offer. $MV_0(\theta)$, on the other hand, captures the expected output value of that same worker if they had instead rejected wage offer w and remained on the piece rate.

Equations (12) and (13) have a useful mapping to the causal-inference literature. Treating the wage offer w as a continuous instrument and worker type $\theta \equiv S(w)$ as propensity score reveals how the difference in marginal values $MV_1(\theta)$ and $MV_0(\theta)$ is equivalent to the marginal treatment effect, $MTE(\theta) \equiv E[Y_{1i} - Y_{0i}|\theta_i = \theta]$ (Björklund and Moffitt, 1987; Heckman and Vytlacil, 1999, 2005, 2007). In my context, this $MTE(\theta)$ can be interpreted as the incentive effect of hourly wages for the marginal worker θ.

Similar to the marginal value curve, the average value curve can be split into two counterfactuals—the average value of output among hourly-pay workers with lower reservation wages, and the average value among those same workers if they had instead worked under a piece rate:

$$AV_1(\theta_w) \equiv E[Y_{1i}|\theta_i \leq \theta] \tag{15}$$

$$AV_0(\theta_w) \equiv E[Y_{0i}|\theta_i \leq \theta]. \tag{16}$$

In a loose sense, these two curves can be thought of as bounds. If firms have some way of mitigating moral hazard, the true marginal value curve would lie somewhere between $MV_0(\theta)$ and $MV_1(\theta)$.

5.2 Estimating Model Parameters

With a continuum of instruments (i.e., wage offers, w), marginal value can be identified by separately differentiating take-up weighted conditional means for decliners and accepters of each offer:

$$\begin{aligned}
MV_1(\theta^w) &= \frac{\partial\left(E\left[Y_{1i}|\theta_i \leq \theta^w\right]\theta^w\right)}{\partial\theta^w} \\
&= \frac{\partial\left(E\left[Y_i|w_i = w, D_i = 1\right]S(w)\right)}{\partial w}\left(\frac{\partial S(w)}{\partial w}\right)^{-1} \qquad (17)\\
MV_0(\theta^w) &= -\frac{\partial\left(E\left[Y_{0i}|\theta_i > \theta^w\right](1-\theta^w)\right)}{\partial\theta^w} \\
&= -\frac{\partial\left(E\left[Y_i|w_i = w, D_i = 0\right](1-S(w))\right)}{\partial w}\left(\frac{\partial S(w)}{\partial w}\right)^{-1}. \qquad (18)
\end{aligned}$$

Intuitively, Equations (18) and (17) identify marginal piece-rate hourly output as the change in total output from adding the marginal worker θ^w to the (no-)treatment condition.

With a sufficiently wide range of experimental wage offers, (17) and (18) could be estimated non-parametrically (Heckman and Vytlacil, 2007). With only three treatment offers, however, I instead estimate selection as a linear function of continuous-valued hourly wage offers.[8] Specifically, I estimate $AV_1(w)$ by writing Y_i as a linear function of hourly wage offers, w_i, interacted with an indicator, D_i, for whether participants accept those offers over the piece rate:

$$Y_i = \gamma_0 + \gamma_1 D_i + \delta_0 w_i + \delta_1(w_i \times D_i) + \epsilon_i. \qquad (19)$$

In the reduced form model above, the coefficient δ_0 captures the average change in Y_i among the pool of "decliners" ($D_i = 0$) associated with a one-dollar increase in the hourly wage offer. Similarly, $\delta_0 + \delta_1$ captures the corresponding change in Y_i among the pool of "accepters" ($D_i = 1$). I can estimate the coefficients in (19) using OLS regression on the sample of workers receiving experimental wage offers. I can also use OLS to estimate the supply curve for hourly labor:

$$D_i = \alpha + \beta w_i + \nu_i. \qquad (20)$$

The coefficient β in Equation (20) captures change in the share of workers on hourly contracts associated with a one-dollar increase in the hourly wage offer.

[8] The full-scale experiment, expected to complete in early summer of 2024, includes several additional treatment arms and should allow for a more flexible functional form.

With estimates of δ_0 and β in hand, I can calculate $AV_1(\theta)$ and $AV_0(\theta)$ as

$$AV_1(\theta) = \gamma_0 + \gamma_1 + (\delta_0 + \delta_1)\left(\frac{\theta - \alpha}{\beta}\right) \tag{21}$$

$$AV_0(\theta) = \frac{E[Y_0] - \left(\gamma_0 + \delta_0\left(\frac{\theta-\alpha}{\beta}\right)\right)(1-\theta)}{\theta}, \tag{22}$$

where $E[Y_0]$ is estimated by taking the mean output value of the control group (piece-rate only).

Finally, using Equations (17) and (18), I can estimate $MV_1(\theta)$ and $MV_0(\theta)$ as

$$MV_1(\theta) = \gamma_0 + \gamma_1 + \frac{(\delta_0 + \delta_1)(2\theta - \alpha)}{\beta} \tag{23}$$

$$MV_0(\theta) = \gamma_0 + \frac{\delta_0(2\theta - \alpha - 1)}{\beta} \tag{24}$$

With estimates of $AV(\theta)$, $MV(\theta)$, and $\overline{w}(\theta)$, it is straightforward to calculate deadweight loss from Equation (11). However, due to the lack of statistical precision in estimates from my small-scale pilot experiment, I have deferred welfare calculations until after completion of the large-scale experiment in late spring.

6 Conclusion

Short-term labor contracts provide a valuable benefit to workers. Gig work can offer valuable flexibility to workers with time constraints (Mas and Pallais, 2017). They can also provide liquidity to credit-poor individuals facing income shocks (Garin et al., 2020; Koustas, 2018). However, these benefits come at a cost—a gig worker can choose their own hours, but they often face more uncertainty over what they'll earn during those hours. This trade off is likely not a coincidence—traditional employers can profitably sustain hourly wage contracts because their repeated interactions with workers mitigate information asymmetries. Short-term employment relationships, on the other hand, offer less opportunity to reveal workers' latent productivity, making the implicit insurance of hourly wages more prone to moral hazard and adverse selection on worker productivity.

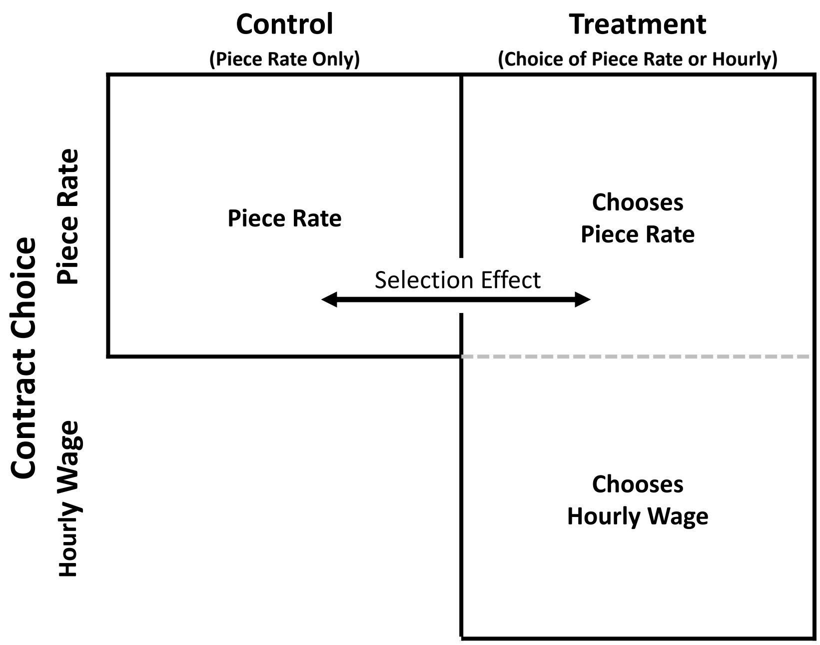
This paper uses an experimental approach to investigate information asymmetries in short-term labor markets. The experiment offers participants a choice between a performance-based piece rate and a randomized hourly wage, allowing me to separately identify selection and treatment effects of wage contracts.

Findings from a preliminary pilot experiment reveal significant selection effects—a one-dollar increase in the offered hourly wage correlates with a \$0.25 (SE=0.101) increase in hourly output among those who prefer the piece rate. This result provides evidence of adverse selection in contract preference, wherein workers with higher latent productivity are more likely to forego guaranteed wages in favor of performanced-based compensation.

I place these experimental estimates into a theoretical framework that shows how the provision of hourly employment contracts is determined by two factors: a worker's reservation wage—the minimum compensation they will accept in exchange for an hour of labor—and the average output of workers with comparatively lower reservation wages. These objects can be straightforwardly identified for workers in my experimental sample—first by comparing the shares of workers opting into hourly wages across offer treatments, then by comparing the average output among hourly workers in each group. I then show how to use these model estimates to quantify the welfare loss associated with inefficiently low provision of hourly positions.

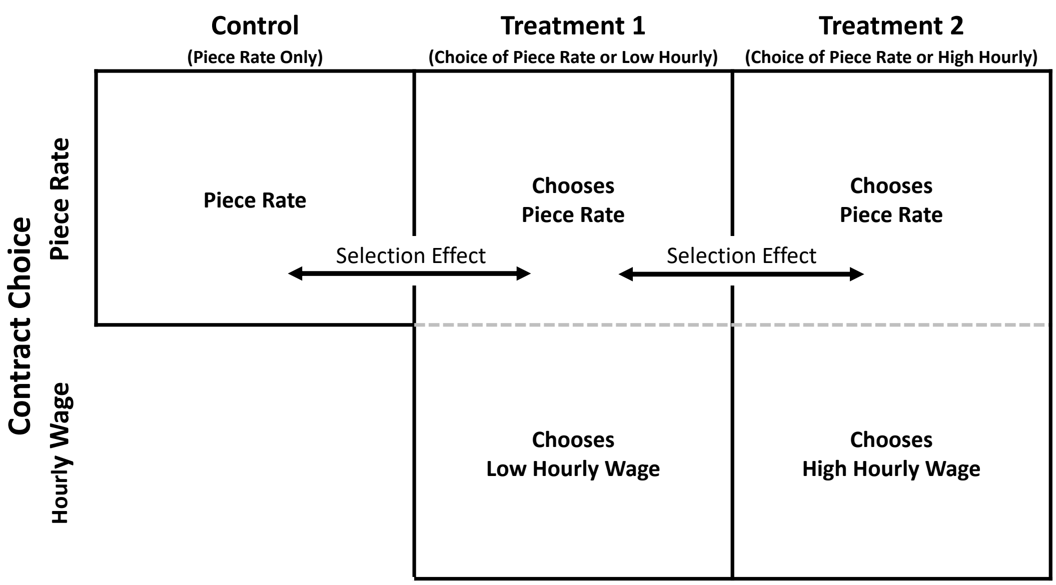
Figures and Tables

Figure 1: Experimental Design: Single Treatment



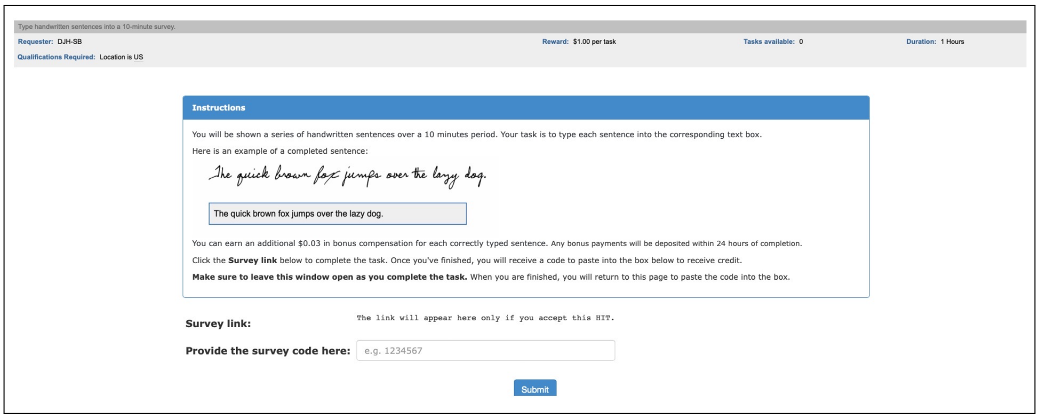
Note: This figure provides a graphical representation of a single-treatment version of my experimental design. Columns denote experimental groups with different menus of wage options, and rows denote the realized wage contracts chosen by workers within each group. The control group, represented by the left column, is not offered an hourly wage option and is compensated entirely through the piece-rate contract (upper box). The treatment group, represented by the right column, is separated into those who accept the piece-rate contract (upper box) and those who accept the hourly contract (lower box). The solid arrow denotes comparison groups to measure adverse selection—groups that were offered different menus of contracts but ultimately face the same repayment terms.

Figure 2: Experimental Design: Multiple Treatments

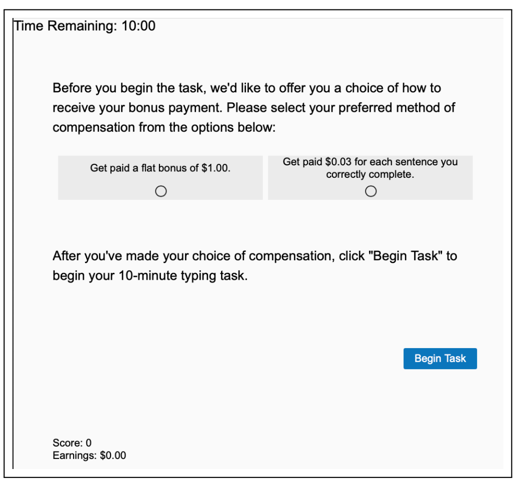


Note: This figure provides a graphical illustration of my experimental design. Columns denote initial wage offers, and rows denote the contract wages that workers are paid. The solid arrow denotes comparison groups to measure adverse selection—groups that were offered different menus of contracts but ultimately face the same repayment terms.

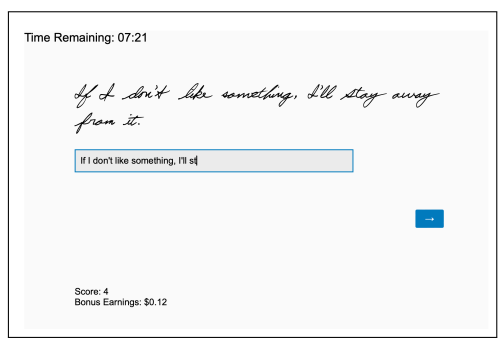
Figure 3: Example Job Posting



(A) Job Posting



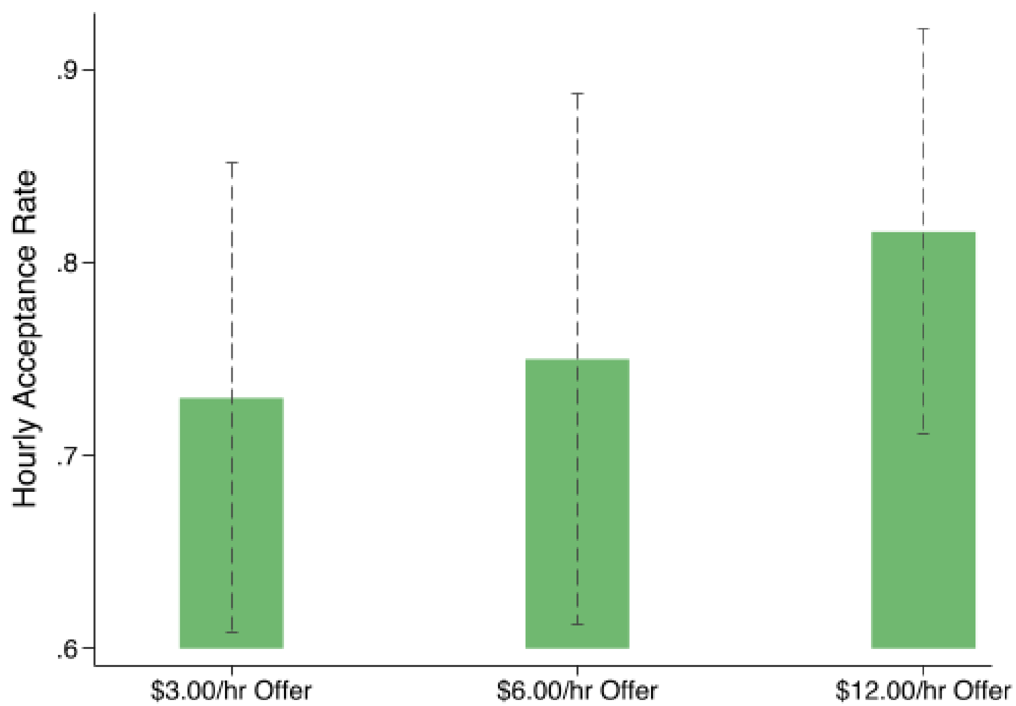
(B) Example Wage Offer



(C) Typing Task

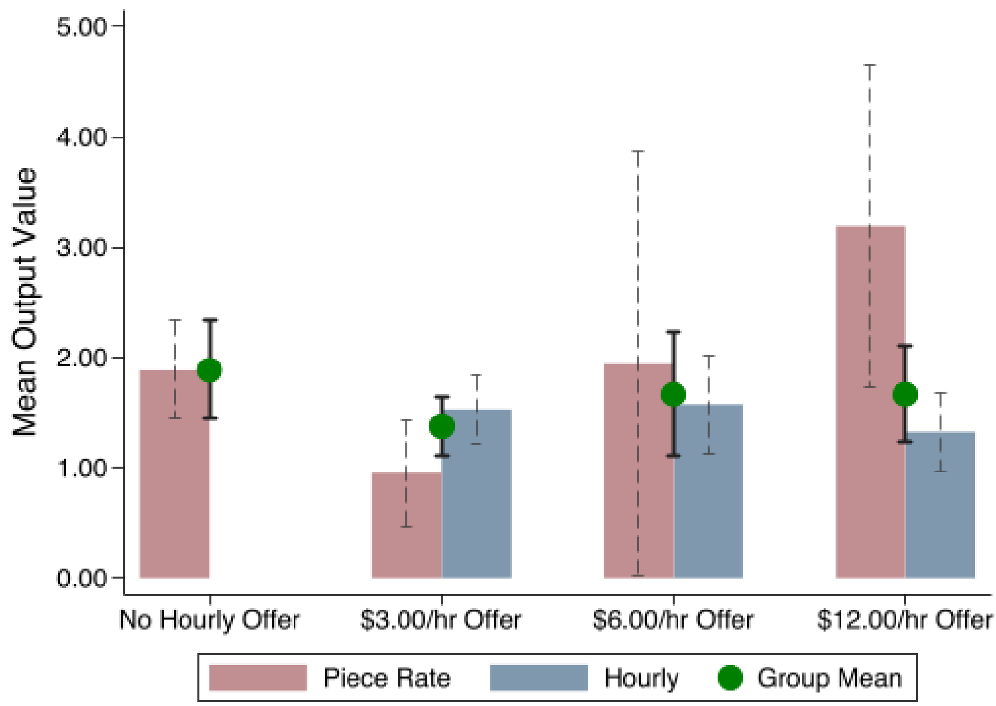
Note: This figure provides screenshots of the experimental intervention. Panel A shows the experimental job posting on MTurk. Panel B shows an example wage offer participants see before they begin the task. Panel C shows the sentence-typing task while it is being performed.

Figure 4: Hourly Wage Take-Up



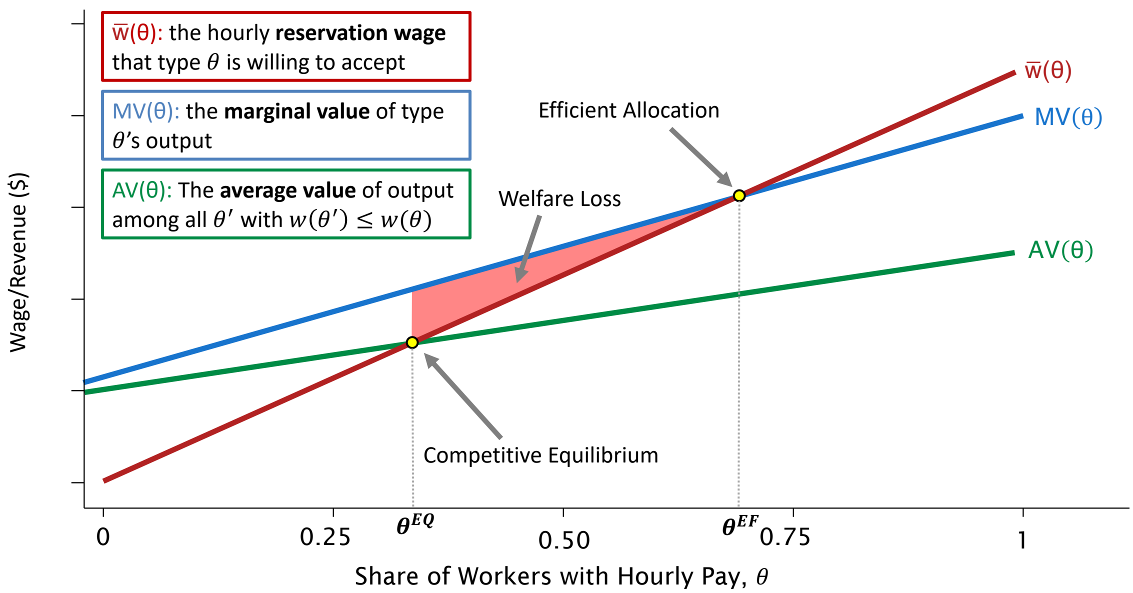
Note: This figure reports hourly-wage acceptance rates by treatment group. The y-axis measures the share of borrowers in each group who declined the $0.03 piece rate in favor of the hourly wage offer displayed on the x-axis. Dotted bands indicate 90% confidence intervals.

Figure 5: Worker Output by Treatment Offer and Compensation Choice



Note: This figure shows mean worker output value by wage-offer groups and compensation choice. "Output value" is defined as the number of correctly typed sentences per hour multiplied by $0.03. Control and treatment groups are labeled on the x-axis. Green circles measure mean outcomes among all individuals in each experimental group. Vertical bars measure mean outcomes among those who choose hourly wages (blue) and those who choose piece rates (red). Bold and dotted bands indicate 90% confidence intervals for overall and hourly/piece-rate group means, respectively.

Figure 6: Model of Adverse Selection in Wage Contracts



Note: This figure provides a graphical representation of market unraveling for hourly wages. The blue line plots the $MV(\theta)$ curve, which is equal to the quantiles of expected worker output conditional on private information, $E[Y|\theta]$. The red line plots inverse labor supply (i.e., reservation wage), $\overline{w}(\theta)$. The green line plots the average value curve, $AV(\theta)$, which corresponds to the average expected output among workers with reservation wages below θ. On the horizontal axis, types θ are enumerated in ascending order based on their reservation wage, $\overline{w}(\theta)$.

Table 1: Pilot Experiment Group Assignment

Experimental Group	Hourly Wage Offer	Piece-Rate Offer	Number of Participants
Control	N/A	$0.03 per sentence	45
Treatment 1	$3.00	$0.03 per sentence	37
Treatment 2	$6.00	$0.03 per sentence	28
Treatment 3	$12.00	$0.03 per sentence	38

Note: This table summarizes the treatment conditions and sample sizes for each experimental group in the pilot. *Piece-rate offer* denotes the performance-based bonus offer, which is awarded on a per-sentence basis and common across all experimental groups. *Hourly wage offer* denotes the time-based rate of compensation offered to participants for the 10-minute task, prorated to one hour.

Table 2: OLS Estimates of Selection by Wage Offer

	(1) Output Value
Hourly Wage Offer	0.246**
	(0.101)
Accepted	1.354**
	(0.678)
Accepted × Hourly Wage Offer	-0.272**
	(0.106)
Constant	0.293
	(0.630)
Mean Dep. Var.	1.56
R-squared	0.110
N	103

Note: This table reports estimated coefficients from OLS regressions of output value (sentences ×\$0.03) against hourly wage offers interacted with a dummy for whether an individual accepted the hourly offer ("Accept") over the piece rate. The coefficient on "Hourly Wage Offer" captures the dollar change in output value among piece-rate workers for each dollar increase in their hourly wage offer. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 3: 2SLS Estimates of Treatment Effects of Hourly Wages Relative to Piece Rates

	(1) Output Value
Accepted Hourly Offer	-0.396
	(0.400)
Constant	1.870***
	(0.269)
Mean Dep. Var.	1.66
R-squared	0.018
N	148

Note: This table reports estimated coefficients from two-stage least-squares regressions of output value against hourly wages, where I instrument for hourly wage with treatment-group assignment. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

References

Abraham, Katharine, John Haltiwanger, Kristin Sandusky, and James Spletzer (2017) "Measuring the gig economy: Current knowledge and open issues," *Measuring and Accounting for Innovation in the 21st Century.*

Akerlof, George A (1970) "The Market for Lemons: Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics*, 84 (3), 488–500.

Angrist, Joshua D, Sydnee Caldwell, and Jonathan V Hall (2021) "Uber Versus Taxi: A Driver's Eye View," *American Economic Journal: Applied Economics*, 13 (3), 272–308.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2010) "Social incentives in the workplace," *The review of economic studies*, 77 (2), 417–458.

Björklund, Anders and Robert Moffitt (1987) "The estimation of wage gains and welfare gains in self-selection models," *The Review of Economics and Statistics*, 42–49.

Black, Dan A, Joonhwi Joo, Robert LaLonde, Jeffrey A Smith, and Evan J Taylor (2022) "Simple tests for selection: Learning more from instrumental variables," *Labour Economics*, 79, 102237.

Brune, Lasse, Eric Chyn, and Jason Kerwin (2022) "Peers and motivation at work: evidence from a firm experiment in Malawi," *Journal of Human Resources*, 57 (4), 1147–1177.

Bureau of Labor Statistics (2024) "Occupational Requirements in the United States," Website, `https://www.bls.gov/web/ors.supp.toc.htm` Accessed: 2024-03-28.

Chiappori, Pierre-André and Bernard Salanie (2000) "Testing for Asymmetric Information in Insurance Markets," *Journal of Political Economy*, 108 (1), 56–78.

Collins, Brett, Andrew Garin, Emilie Jackson, Dmitri Koustas, and Mark Payne (2019) "Is gig work replacing traditional employment? Evidence from two decades of tax returns," *Unpublished paper, IRS SOI Joint Statistical Research Program.*

Cook, Cody, Rebecca Diamond, Jonathan V Hall, John A List, and Paul Oyer (2021) "The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers," *The Review of Economic Studies*, 88 (5), 2210–2238.

DellaVigna, Stefano and Devin Pope (2018) "What motivates effort? Evidence and expert forecasts," *The Review of Economic Studies*, 85 (2), 1029–1069.

——— (2022) "Stability of Experimental results: Forecasts and evidence," *American Economic Journal: Microeconomics*, 14 (3), 889–925.

Difallah, Djellel, Elena Filatova, and Panos Ipeirotis (2018) "Demographics and dynamics of mechanical turk workers," in *Proceedings of the eleventh ACM international conference on web search and data mining*, 135–143.

Einav, Liran, Amy Finkelstein, and Mark R Cullen (2010a) "Estimating Welfare in Insurance Markets Using Variation in Prices," *The Quarterly Journal of Economics*, 125 (3), 877–921.

Einav, Liran, Amy Finkelstein, and Jonathan Levin (2010b) "Beyond testing: Empirical models of insurance markets," *Annu. Rev. Econ.*, 2 (1), 311–336.

Emanuel, Natalia and Emma Harrington (2023) "Working remotely? Selection, treatment, and the market for remote work," *Selection, Treatment, and the Market for Remote Work (June 2023). FRB of New York Staff Report* (1061).

Garin, Andrew, Emilie Jackson, Dmitri K Koustas, and Carl McPherson (2020) "Is new platform work different from other freelancing?" in *AEA Papers and Proceedings*, 110, 157–161, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Garin, Andrew, Emilie Jackson, Dmitri K Koustas, and Alicia Miller (2023) "The Evolution of Platform Gig Work, 2012-2021,"Technical report, National Bureau of Economic Research.

Gibbons, Robert and Lawrence F Katz (1991) "Layoffs and lemons," *Journal of labor Economics*, 9 (4), 351–380.

Greenwald, Bruce C (1986) "Adverse selection in the labour market," *The Review of Economic Studies*, 53 (3), 325–347.

Heckman, James J and Edward Vytlacil (2005) "Structural equations, treatment effects, and econometric policy evaluation," *Econometrica*, 73 (3), 669–738.

Heckman, James J and Edward J Vytlacil (1999) "Local instrumental variables and latent variable models for identifying and bounding treatment effects," *Proceedings of the national Academy of Sciences*, 96 (8), 4730–4734.

——— (2007) "Econometric evaluation of social programs, part II: Using the marginal treatment effect to organize alternative econometric estimators to evaluate social programs, and to forecast their effects in new environments," *Handbook of econometrics*, 6, 4875–5143.

Hendren, Nathaniel (2013) "Private Information and Insurance Rejections," *Econometrica*, 81 (5), 1713–1762.

——— (2017) "Knowledge of Future Job Loss and Implications for Unemployment Insurance," *American Economic Review*, 107 (7), 1778–1823.

Herbst, Daniel and Nathaniel Hendren (2021) "Opportunity Unraveled: Private Information and the Missing Markets for Financing Human Capital,"Technical report, National Bureau of Economic Research.

Herbst, Daniel and Alexandre Mas (2015) "Peer effects on worker output in the laboratory generalize to the field," *Science*, 350 (6260), 545–549.

Huber, Martin (2013) "A simple test for the ignorability of non-compliance in experiments," *Economics letters*, 120 (3), 389–391.

Jackson, Emilie, Adam Looney, and Shanthi P Ramnath (2017) "The rise of alternative work arrangements: Evidence and implications for tax filing and benefit coverage."

Jovanovic, Boyan (1982) "Favorable selection with asymmetric information," *The Quarterly Journal of Economics*, 97 (3), 535–539.

Kantarevic, Jasmin and Boris Kralj (2016) "Physician payment contracts in the presence of moral hazard and adverse selection: the theory and its application in Ontario," *Health economics*, 25 (10), 1326–1340.

Karlan, Dean and Jonathan Zinman (2009) "Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment," *Econometrica*, 77 (6), 1993–2008.

Katz, Lawrence F and Alan B Krueger (2019) "Understanding trends in alternative work arrangements in the United States," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 5 (5), 132–146.

Koustas, Dmitri (2018) "Consumption insurance and multiple jobs: Evidence from rideshare drivers," *Unpublished working paper*.

Kowalski, Amanda E (2023) "How to examine external validity within an experiment," *Journal of Economics & Management Strategy*, 32 (3), 491–509.

Kugler, Adriana D and Gilles Saint-Paul (2004) "How do firing costs affect worker flows in a world with adverse selection?" *Journal of Labor Economics*, 22 (3), 553–584.

Kuziemko, Ilyana, Michael I Norton, Emmanuel Saez, and Stefanie Stantcheva (2015) "How elastic are preferences for redistribution? Evidence from randomized survey experiments," *American Economic Review*, 105 (4), 1478–1508.

Lazear, Edward P (1986) "Salaries and piece rates," *Journal of business*, 405–431.

——— (2000) "Performance pay and productivity," *American Economic Review*, 90 (5), 1346–1361.

Levine, David I (1991) "Just-cause employment policies in the presence of worker adverse selection," *Journal of Labor Economics*, 9 (3), 294–305.

Mas, Alexandre and Enrico Moretti (2009) "Peers at work," *American Economic Review*, 99 (1), 112–145.

Mas, Alexandre and Amanda Pallais (2017) "Valuing alternative work arrangements," *American Economic Review*, 107 (12), 3722–3759.

Moen, Espen R and Åsa Rosen (2005) "Performance Pay and Adverse Selection," *Scandinavian Journal of Economics*, 107 (2), 279–298.

Pallais, Amanda (2014) "Inefficient hiring in entry-level labor markets," *American Economic Review*, 104 (11), 3565–3599.

Pallais, Amanda and Emily Glassberg Sands (2016) "Why the referential treatment? Evidence from field experiments on referrals," *Journal of Political Economy*, 124 (6), 1793–1828.

Paolacci, Gabriele and Jesse Chandler (2014) "Inside the Turk: Understanding Mechanical Turk as a participant pool," *Current directions in psychological science*, 23 (3), 184–188.

Shearer, Bruce (1996) "Piece-rates, Principal-agent Models, and Productivity Profiles: Parametric and Semi-parametric Evidence from Payroll Records," *Journal of Human Resources*, 275–303.

——— (2004) "Piece Rates, Fixed Wages and Incentives: Evidence from a Field Experiment," *The Review of Economic Studies*, 71 (2), 513–534.

Spence, Michael (1973) "Job Market Signaling," *The Quarterly Journal of Economics*, 87 (3), 355–374.

Wald, Abraham (1940) "The fitting of straight lines if both variables are subject to error," *The annals of mathematical statistics*, 11 (3), 284–300.

Weiss, Andrew (1980) "Job Queues and Layoffs in Labor Markets with Flexible Wages," *Journal of Political economy*, 88 (3), 526–538.