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. 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?

Traditional explanations for differences in compensation structure often rely on monitoring costs, product quality, or worker shirking. In my proposed study, I investigate an alternative hypothesis—adverse selection. If less productive workers are willing to accept lower hourly wages than their observably equivalent peers, firms might post exclusively piece-rate positions to avoid attracting the wrong type of worker. Distinguishing this unraveling phenomenon from alternative theories of compensation structure is important for determining the welfare impacts of various labor policies. For example, hourly wage subsidies are more likely to improve welfare in an adversely selected labor market than in one where the compensation structure was driven purely by monitoring costs.

Identifying the effects of adverse selection in labor markets poses three empirical challenges. First, it requires estimating how workers' contract decisions respond to exogenous variation in wages. For example, comparing workers across wage changes caused by shifts in labor supply or composition would severely bias estimates. 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 labor contracts that do not exist due to unraveling (Einav et al., 2010b). Finally, detecting selection on worker productivity is difficult because that productivity is ex-ante unobserved. Researchers often compare ex-post outcomes across individuals choosing different contracts, but such comparisons combine selection with the potential treatment effects of contracts themselves (Chiappori and Salanie, 2000)—hourly workers may have lower output than piece-rate workers because they have private knowledge of poor productivity, or because they face weaker incentives to exert effort. In short, a credible empirical strategy must estimate selection on unobservables into hypothetical labor contracts across a range of exogenously varied wages. Methods using observational data offer little hope of meeting these requirements.

In this paper, I use a field experiment to estimate the welfare impact of adverse selection and moral hazard in short-term labor markets. The experiment offers online workers a choice between a randomized hourly wage and a standardized piece rate in exchange for performing a simple data-entry task. By randomizing the menu of wage contracts offered to online workers, my experimental design allows me to separately identify selection and behavioral effects for a range of compensation schemes. Comparing realized output across workers who decline different hourly wage offers in favor of a standardized piece rate isolates a selection effect—both groups work under the same form of compensation but faced different ex-ante menus of contracts. At the same time, a standard treatment-on-the-treated estimation allows me to separately identify the behavioral effects of each contract. 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 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.

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 6, 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 identify how workers with different unobserved productive potentials self-select into a range of hypothetical hourly wage contracts. However, the potential treatment effects of such contracts pose an empirical challenge—differences in realized output between workers who opted into different wage offers 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 empirical 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 treatment-on-the-treated estimation allows me to separately identify treatment effects of hourly wages among those who accept the offer.

2.1 Average Treatment and Selection

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_{0i} denote i's output if they work under the piece rate, and let Y_{0i} denote their output if they instead work under the hourly wage. 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:

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

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 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 piece rate and hourly wages, 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):

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

where $\pi \equiv Pr\left(D_i = 1 | Z_i = 1\right)$, the probability an individual takes the contract conditional on offer assignment.

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:

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

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 in the treatment group ($D_i = 0, Z_i = 1$) who chose to remain on the piece rate.

[1] Randomized assignment implies $E\left[Y_{0i} | Z_i = 1\right] = E\left[Y_{0i} | Z_i = 0\right] = E\left[Y_i | Z_i = 0\right]$, so $E\left[Y_{0i} | D_i = 1, Z_i = 1\right] = \frac{E[Y_i | Z_i = 0] - (1-\pi) E[Y_i | D_i = 0, Z_i = 1]}{\pi}$. 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, $E\left[Y_i | D_i = 1, Z_i = 1\right] - E\left[Y_i | D_i = 0, Z_i = 1\right]$.

2.2 Marginal Selection into Continuous Offers

The single-offer example above provides the intuition behind my experimental design, showing how one can estimate treatment-on-the-treated (TOT) and average selection into treatment ($\Delta\mu_0$) for a single treatment-assignment variable, Z_i. With multiple treatment assignments, however, I can extend this intuition to identify *marginal* treatment and selection across a range of wage offers. As I demonstrate in Section 5, this ability to estimate these distributions is crucial for quantifying the welfare losses from asymmetric information.

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 monotonicity ($S(w_1) \geq S(w_0)$ for all $w_1 > w_0$), I index workers by a type parameter, $\theta \in [0,1]$, equal to the share of the population willing to accept a lower wage than worker i's reservation wage, $\theta_i \equiv S(\overline{w}_i)$.

I define marginal potential outcomes, $\mu_0(\theta)$ and $\mu_1(\theta)$, as the conditional means of potential outcomes without and with treatment, respectively, for type θ:

$$\mu_0(\theta) \equiv E\left[Y_{0i}|\theta_i = \theta\right] \tag{6}$$

$$\mu_1(\theta) \equiv E\left[Y_{1i}|\theta_i = \theta\right]. \tag{7}$$

Equations (6) and (7) capture counterfactual mean outcomes under piece rate p and hourly wage $w = S^{-1}(\theta)$ for the worker who is indifferent between the two contracts. Differencing these conditional means yields the marginal treatment effect, $MTE(\theta) \equiv E[Y_{1i} - Y_{0i}|\theta_i = \theta]$—the parameter of interest in a variety of studies (Björklund and Moffitt, 1987; Heckman and Vytlacil, 1999, 2005; Carneiro et al., 2011; Arnold et al., 2022). As separate parameters, however, $\mu_0(\theta)$ and $\mu_1(\theta)$ capture marginal selection on counterfactual outcomes into the treatment condition (Heckman, 1990).

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

$$\begin{aligned}
\mu_0(\theta^w) &= -\frac{\partial\left(E\left[Y_{0i}|\theta_i > \theta^w\right](1-\theta^w)\right)}{\partial\theta^w} \\
&= -\frac{\partial\left(E\left[Y_i|w_i = w, D_i = 0\right](1-S(w))\right)}{\partial w}\left(\frac{\partial S(w)}{\partial w}\right)^{-1} \qquad (8)\\
\mu_1(\theta^w) &= \frac{\partial\left(E\left[Y_{1i}|\theta_i \leq \theta^w\right]\theta^w\right)}{\partial\theta^w} \\
&= \frac{\partial\left(E\left[Y_i|w_i = w, D_i = 1\right]S(w)\right)}{\partial w}\left(\frac{\partial S(w)}{\partial w}\right)^{-1}. \qquad (9)
\end{aligned}$$

Intuitively, Equations (8) and (9) 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, (8) and (9) 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.[2] Specifically, I write 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:

$$Y_i = \gamma_0 + \gamma_1 D_i + \delta_0 w_i + \delta_1(w_i \times D_i) + \epsilon_i. \qquad (10)$$

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 (10) 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:

$$D_i = \alpha + \beta w_i + \nu_i. \qquad (11)$$

[2]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.

The coefficient β in Equation (14) captures change in the share of workers on hourly contracts associated with a one-dollar increase in the hourly wage offer.

With estimates of δ_0 and β in hand, I can calculate $\mu_0(w)$ and $\mu_1(w)$ as

$$\mu_0(\theta) = \gamma_0 + \frac{\delta_0(2\theta - \alpha)}{\beta} \quad (12)$$

$$\mu_1(\theta) = \gamma_0 + \gamma_1 + \frac{(\delta_0 + \delta_1)(2\theta - \alpha)}{\beta} \quad (13)$$

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 MTurk 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 MTurk job posting is provided in Figure 2A.

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 work on the platform 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.[3] After clicking this link, workers are randomized into one of four experimental groups.[4] 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 2B. 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) 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.[5] 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'

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

[4]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.

[5]Figure 2C 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.

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. For example, online workers' selection into wage contracts by typing ability 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 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 offer wage contracts that firms would deem unprofitable. However, even if I offer a range of potentially unprofitable contracts, I only observe selection into these contracts among those who agreed to participate in the task. If my job posting only attracted low-productivity workers, my estimates would exclude selection among high-types who never even receive wage offers. I mitigate this concern by advertising a generous up-front fee for simply 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 3 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 4, 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 (10), 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 4 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 Adverse Selection 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 and used to quantify potential welfare loss from adverse selection in wage contracts.

Consider a perfectly competitive labor market in which firms face a population of observably equivalent workers.[6] Once hired, workers can produce some level of hourly output, q, which is a function of both effort and noise, $q = f(e, \nu)$, where ν is the realization of a random variable and e is individual effort. Firms value labor this labor product, q, at a constant price, p, and compete for workers through two types of contracts—an hourly contract that pays the worker wage w in exchange for their labor product q, and a piece-rate contract that pays an hourly wage of zero but lets the worker keep some share γ of the value generated by their labor product (i.e., γpq).

Assuming $\overline{w}_i$ has continuous support, I can rewrite the reservation wage as a function of worker type:

$$\overline{w}(\theta) \equiv S^{-1}(\theta). \tag{14}$$

Facing a population of observably identical workers with unknown types, employers set wages to maximize profits. For any hourly wage, w, let θ_w denote the marginal type willing to accept the hourly contract, (i.e., $\theta_w \equiv S(w)$). I define the *marginal value* of type θ_w as

$$MV(\theta_w) \equiv E[y|\theta = \theta_w], \tag{15}$$

where $y = \gamma pq$, the incremental value of output q produced under an hourly contract.[7] Note that $MV(\theta_w)$ equals type θ_w's expected earnings under the market piece rate, γp. If θ_w were risk averse, we would expect their reservation wage to fall below this "actuarially fair"

[6] 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.

[7] Analogous to the incremental cost of insurance defined in Einav et al. (2010a), y represents the incremental value to the firm of output q produced by an hourly worker relative to a piece-rate worker. Under the hourly contract, a worker producing q generates pq of value for the firm. Under the piece-rate contract, the value of a worker producing q is $(1-\gamma)pq$—the share that firms would keep after paying piece rates. The incremental value of q under the hourly contract is, therefore, $y = pq - (1-\gamma)pq = \gamma pq$—i.e., the amount the firm saves by not paying the piece rate. Note that, because the piece-rate contract amounts to pure revenue sharing at no hourly cost, the incremental cost of the hourly contract is simply equal to the hourly wage, $w - 0 = w$.

wage (i.e., $\overline{w}(\theta_w) < MV(\theta_w)$). 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 $w \equiv \overline{w}(\theta_w)$ exclusively to type θ_w.

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

$$AV(\theta_w) \equiv E[y|\theta \leq \theta_w]. \tag{16}$$

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

$$\Pi(w) = S(w)(AV(\theta_w) - w). \tag{17}$$

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

$$\overline{w}(\theta^{EQ}) = AV(\theta^{EQ}). \tag{18}$$

Figure 5 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

$$DWL = \frac{1}{2}(\theta_{EF} - \theta_{EQ})(w_{EQ} - w_{EF}) \tag{19}$$

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.

6 Welfare Estimation: Mapping the Model to Experimental Results

Under minimal assumptions, my framework allows me to compare equilibrium contracts in the online freelancer market relative to a perfectly competitive benchmark without adverse selection. I can use this comparison to estimate the welfare losses arising from the inefficient provision of hourly contracts under asymmetric information.

First, note that I can estimate the supply curve for hourly workers $S(w)$ as

$$S_i = \alpha + \beta w_i + \varepsilon_i, \tag{20}$$

where S_i is an indicator for whether an individual in my experimental sample accepted their treatment wage offer $w_i \in \{\$3, \$5, \$8\}$.

Because I can observe each worker's output under different contract wages, I can estimate $AV(w)$ by regressing the value of that output against offered wages among the subsample of invited workers who accepted the position.

$$y_i = \gamma + \delta w_i + \epsilon_i. \tag{21}$$

Equation (21) gives the relationship between the average value worker output and the marginal worker's hourly reservation wage. Note that this relationship can be estimated for different subsamples of workers in each offer group—those whose contract wage was equal to their offer wage versus those whose contract wage was increased to \$8 per hour. Comparing results from these specifications would identify how the welfare loss from adverse selection would change if there was no behavioral response to wages.

With estimates of $S(w)$ and $AV(w)$ in hand, I can calculate $MV(w)$ without further estimation. To see how, note the following:

$$MV(w) = \frac{dTV(w)}{dS(w)} = \frac{\partial\left(AV(w) * S(w)\right)}{\partial S(w)} = \left(\frac{\partial S(w)}{\partial w}\right)^{-1} \frac{\partial\left(AV(w) * S(w)\right)}{\partial w}, \tag{22}$$

where $TV(w)$ denotes the total value of all hourly contracts exchanged at wage w. Using the linear parameterizations in equations (20) and (21), the marginal value curve can be computed as $MV(w) = \frac{\alpha\delta}{\beta} + \gamma + 2\delta w$. The efficient equilibrium price and quantities are given by $w^{EF} = 1/(1-2\delta)(\frac{\alpha\delta}{\beta} + \gamma)$ and $\theta^{EF} = \alpha + 1/(1-2\delta)(\alpha\delta + \beta\gamma)$, while the equilibrium with adverse selection is given by $w^{EQ} = \frac{\gamma}{1-\delta}$ and $\theta^{EQ} = \alpha + \beta(\frac{\gamma}{1-\delta})$. Applying these estimates to equation (19), I can calculate welfare loss as the area of the region corresponding to the triangle in Figure 5. This calculated area provides an estimate of the deadweight loss from adverse selection.

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.

7 Conclusion

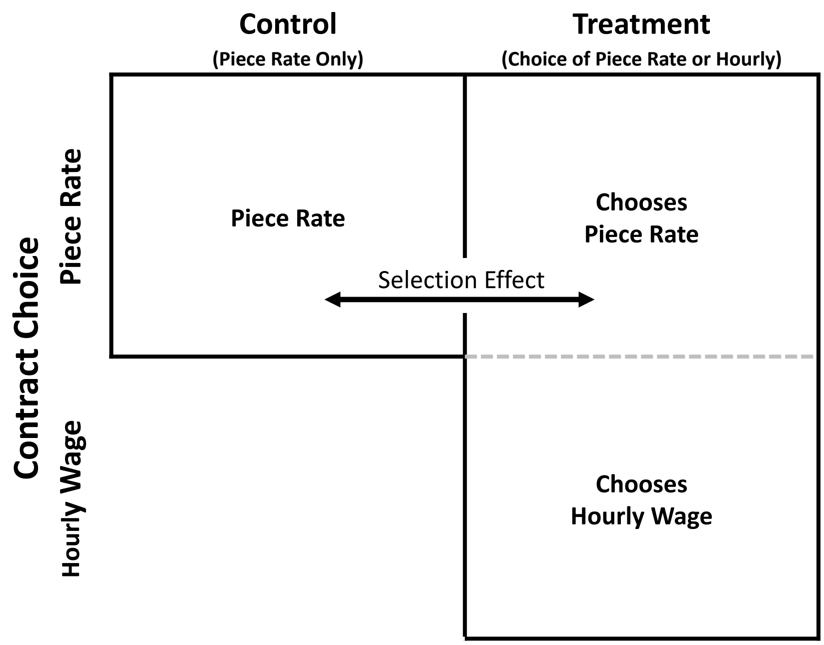
This paper uses a novel experimental approach to investigate information asymmetries in short-term labor markets. The experiment offers participants a choice between a performance-based piece rate and a randomized hourly wage, allowing me to separately identify selection and treatment effects of wage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

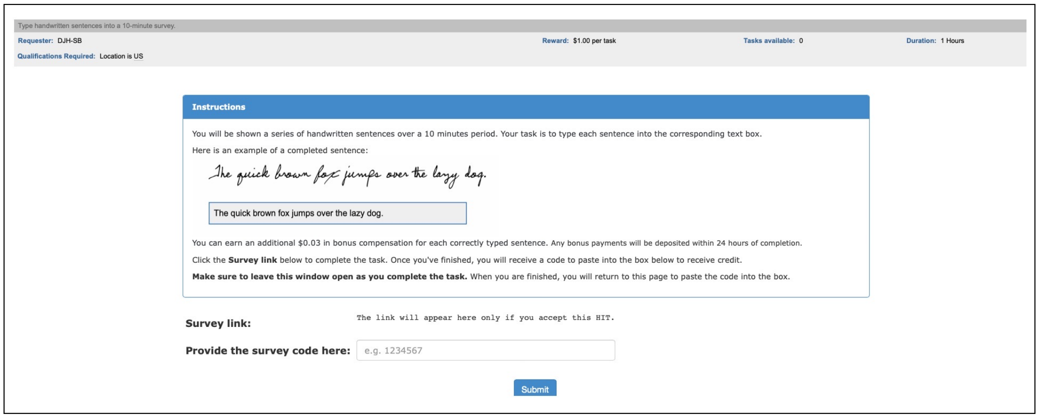
Figures and Tables

Figure 1: Experimental Design: Single Treatment

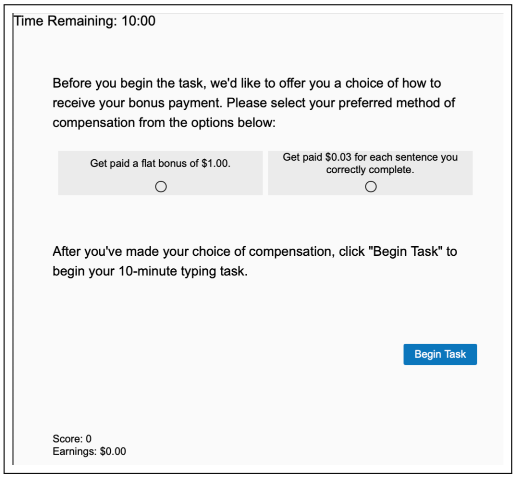


Note: This figure provides a graphical representation of a single-treatment version of my experimental design. Columns denote experimental groups with different menus of wage options, and rows denote the realized wage contracts chosen by workers within each group. The control group, represented by the 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.

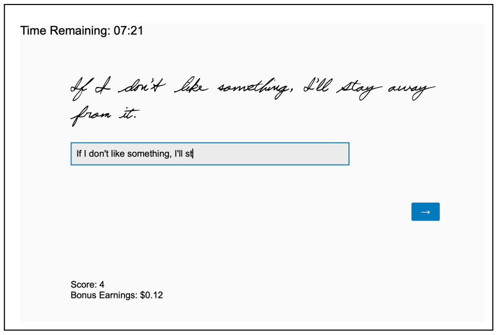
Figure 2: Example Job Posting



(A) Job Posting



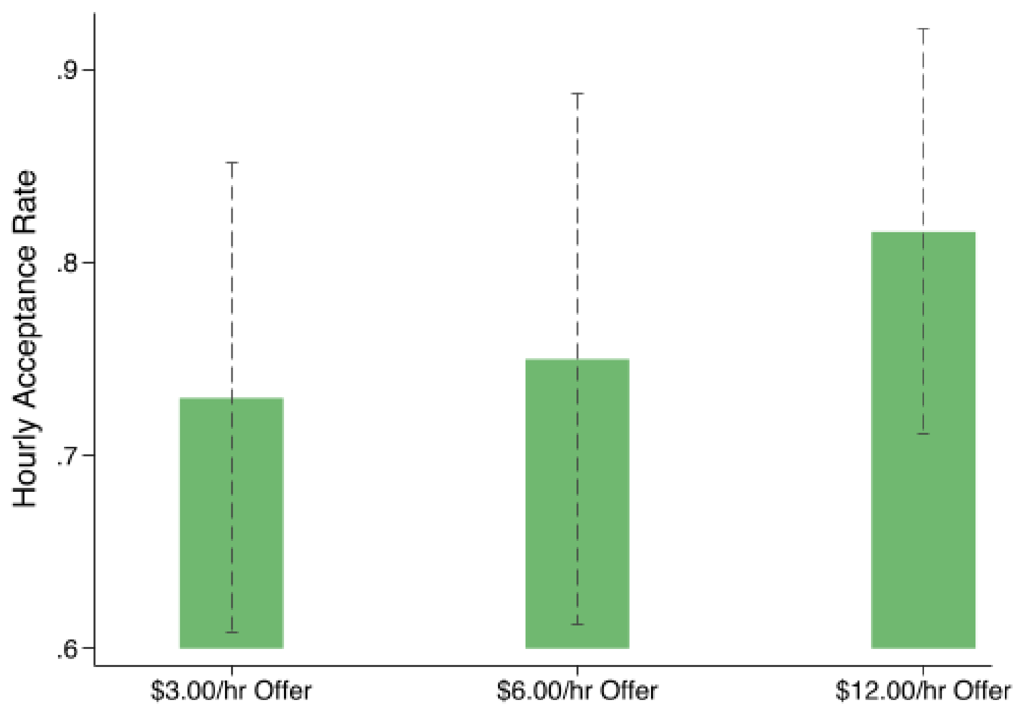
(B) Example Wage Offer



(C) Typing Task

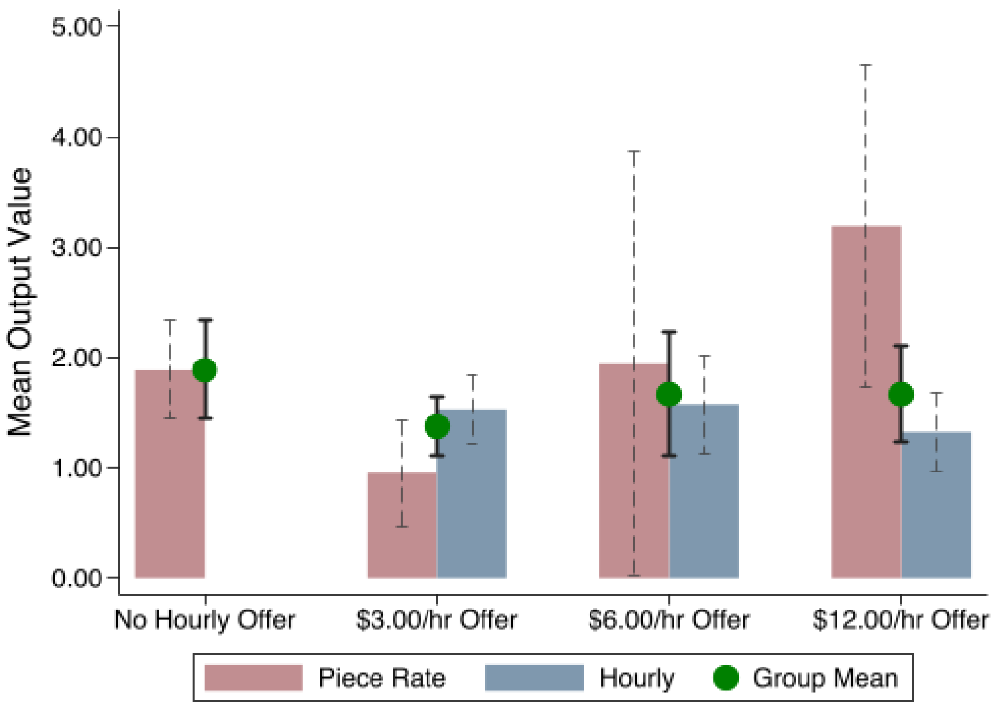
Note: This figure provides screenshots of the experimental intervention. Panel A shows the experimental job posting on MTurk. Panel B shows an example wage offer participants see before they begin the task. Panel C shows the sentence-typing task while it is being performed.

Figure 3: Hourly Wage Take-Up



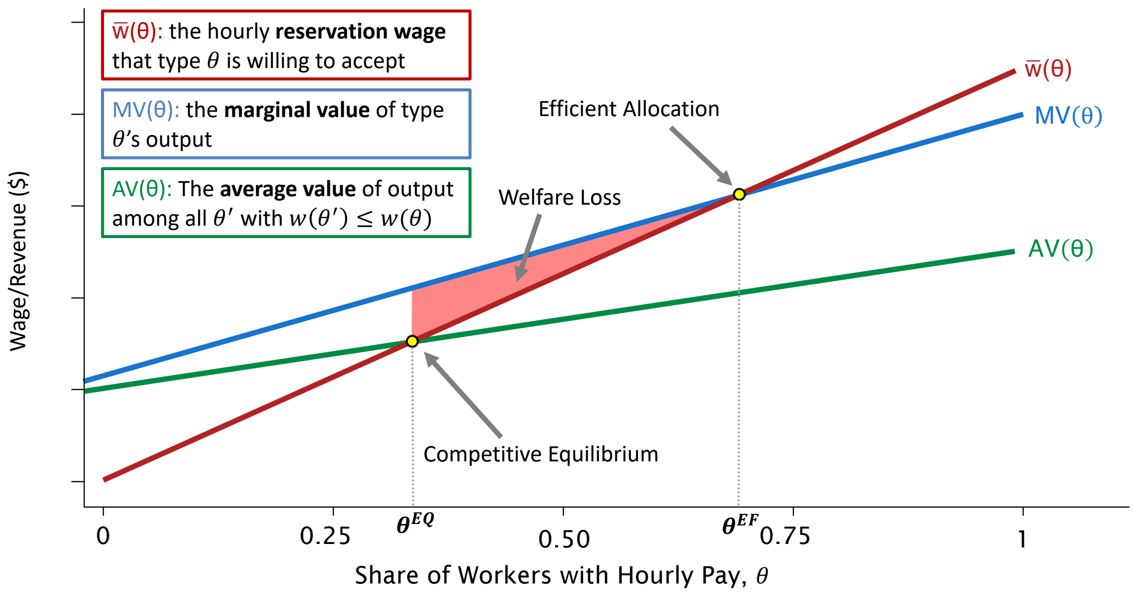
Note: This figure reports hourly-wage acceptance rates by treatment group. The y-axis measures the share of borrowers in each group who declined the $0.03 piece rate in favor of the hourly wage offer displayed on the x-axis. Dotted bands indicate 90% confidence intervals.

Figure 4: 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 5: 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	31
Treatment 2	\$6.00	\$0.03 per sentence	27
Treatment 3	\$12.00	\$0.03 per sentence	34

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.

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