Asymmetric Information in Labor Contracts: Evidence from an Online Experiment

Daniel Herbst*
University of Arizona

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Abstract

For workers facing uncertain output, hourly wage contracts provide implicit insurance compared to self-employment or task-based pay. But like any insurance product, these contracts are prone to market distortions through moral hazard and adverse selection. Using a model of wage contracts under asymmetric information, I show how these distortions can be identified as potential outcomes in a marginal-treatment-effects framework. I apply this framework to a field experiment in which data-entry workers are offered a choice between a randomized hourly wage and a standardized piece rate. Using experimental wage offers as an instrument for hourly wage take-up, I find evidence of both moral hazard and adverse selection. Hourly wage contracts reduces worker productivity by an estimated 6.32 percent relative to the mean. Meanwhile, a 10 percent increase in the hourly wage offer attracts a marginal worker whose productivity is higher by 1.44 percent of mean worker output. I estimate the welfare loss associated with asymmetric information and calculate marginal values of public funds (MVPFs) across a range of hourly wage subsidies. My estimates imply a socially optimal hourly wage subsidy of $1.00 per hour or less, depending on the cost of public financing.

*Department of Economics, University of Arizona, McClelland Hall 401QQ, Tucson, AZ 85721 (email: dherbst@arizona.edu, website: www.danjherbst.com). I am thankful to Will Dobbie, Nathan Hendren, Hide Ichimura, Juan Pantano, and Evan Taylor for their helpful comments in the development of this paper. Financial support was provided by the University of Arizona Eller College of Management.

1 Introduction

Labor contracts often provide some degree of insurance—a fixed-wage worker knows what they will earn from a day's work, even when their labor product is unpredictable. But like any insurance product, these contracts are prone to market distortions through moral hazard and adverse selection. An hourly wage contract might induce less effort or attract lower productivity workers than freelance hiring or task-based pay. The potential for these distortions is especially high in short-term "gig" labor markets, where employers have less opportunity to observe workers' latent productivity.

Identifying the effects of moral hazard and adverse selection on labor markets has important implications for a variety of policies. Hourly wage subsidies, employment classification rules, portable benefits programs, and even the minimum wage can mitigate welfare loss from these distortions by promoting insurance-like provisions in labor contracts. However, the social value of these policies depends the relative magnitudes of moral hazard and adverse selection. For example, hourly wage subsidies might attenuate adverse selection by inducing more productive workers into fixed-wage contracts but are unlikely to discourage workers from shirking due to moral hazard.

Separately identifying the effects of moral hazard and adverse selection is difficult for two reasons: First, both moral hazard and adverse selection predict lower observed productivity among fixed-wage workers, making them difficult to distinguish empirically. Second, the potential for market unraveling makes it difficult to quantify the welfare effects these phenomena using real-world data—wage contracts threatened by adverse selection may be too unprofitable for employers to offer and thus impossible to observe in competitive labor markets.

In this paper, I experimentally estimate the distortionary effects of moral hazard and adverse selection in fixed wage contracts. To separately identify these forces, I conduct an online field experiment with two stages of randomization: First, I offer workers a choice between a randomized hourly wage and a standardized piece rate in exchange for performing a data-entry task. Then, after workers choose a payment option but before they begin the task, I increase hourly wages for a randomized subset of those who accepted hourly offers, bringing them to parity with higher hourly wage offers. Holding paid wages constant, using the initial wage offer as an instrument for accepting an hourly contract allows me to identify the moral hazard effect of fixed-rate compensation. Meanwhile, comparing output across workers on the same contract who faced different ex-ante offers identifies adverse selection. Importantly, experimental wage offers include contracts that may not be profitable to a real-world employer, avoiding the "under-the-lamppost" problem inherent to many empirical studies of information asymmetries (Einav et al., 2010b).

Results from my experiment provide evidence of both moral hazard and adverse selection into hourly wage contracts. Using experimental wage offers as an instrument for hourly wage take-up, I find that hourly wage contracts reduce worker output value by 6.32 percent relative to the mean. But while working under an hourly wage appears to reduce output, the level of that wage has no discernible effect on effort—among workers who chose hourly contracts, I find no significant differences in performance between those who worked under their advertised wage and those whose effective wage had been randomly increased prior to working on the task. Meanwhile, comparisons across advertised wages provides strong evidence of selection on unobserved productivity. A ten-percent increase in the hourly wage offer attracts a marginal worker with 1.44 percent higher productivity compared to the mean.

To investigate the labor market implications of these findings, I develop a model of labor markets under asymmetric information. Using this framework, I show how the provision of fixed-wage employment contracts is determined by two curves: a worker's reservation wage—the minimum payment they will accept for an hour of labor—and the average value of output among workers with comparatively lower reservation wages. An hourly worker can be profitably hired only if the average value of their contract exceeds their reservation wage. Relative to an efficient equilibrium with full information, this profit condition leads to an underprovision of hourly work—some freelance workers would like to forfeit a portion of their expected earnings in exchange for the implicit insurance of fixed wages, but the threat of adverse selection prevents employers from offering hourly positions at those workers' reservation wages.

To quantify welfare losses from inefficient wage contracts, I show how both moral hazard and adverse selection can be expressed as functions of "marginal values"—the potential outputs of workers with a given reservation wage under fixed-wage and piece-rate counterfactuals. These marginal values are equivalent to potential outcomes in a marginal-treatment effects (MTE) framework, allowing me to estimate their distributions using semi-parametric methods (Björklund and Moffitt, 1987; Heckman and Vytlacil, 1999, 2005, 2007). My estimates imply that 59 percent of workers would benefit from hourly contracts. This share reflects the efficient allocation that would exist if employers were fully informed of workers' potential output under fixed-wage contracts. By contrast, only 54 percent of workers can find hourly positions in a competitive equilibrium with asymmetric information. The resulting welfare loss from this attenuation in hourly work is \$0.03 per hour of labor.

If adverse selection results in a suboptimal provision of fixed-wage positions, the government might consider subsidizing hourly wages to induce workers and firms into these contracts. To measure the welfare impact of such subsidies, I construct their marginal values of public funds (MVPFs). I estimate marginal values of public funds (MVPFs) between .95 and 1.15 across a range of hourly wage subsidies. An hourly subsidy maximizes welfare when the MVPF of a marginal increase to the subsidy equals the government's marginal cost of public financing. My estimates imply this socially optimal hourly wage subsidy would be \$1.00 per hour or less, depending on the cost of public financing.

This study relates to several streams of existing research. A large literature in labor theory demonstrates how information asymmetries can lead to worker shirking and self-sorting, resulting in inefficient hiring or wage setting (Holmström, 1979; Grossman and Hart, 1983; Jovanovic, 1982; Greenwald, 1986; Lazear, 1986; MacLeod and Malcomson, 1989; Levine, 1991; Kugler and Saint-Paul, 2004; Moen and Rosen, 2005; Shimer, 2005).[1]

[1]Several studies build upon this theory to show how "efficiency wages"—wages paid above the market-

Relatedly, several papers build upon Spence (1973) to investigate how signaling mechanisms like education (Hungerford and Solon, 1987; Tyler et al., 2000; Bedard, 2001; Arcidiacono et al., 2010; Weiss, 1995), work experience (Farber and Gibbons, 1996; Gibbons and Katz, 1991), job recruitment (Marinescu and Wolthoff, 2020), or performance reviews (Pallais, 2014; Pallais and Sands, 2016) might narrow the informational gap between firms and workers.

This paper also builds upon several studies of adverse selection and moral hazard effects in insurance markets. In particular, my model borrows from Einav et al. (2010a) and Herbst and Hendren (2024), who develop models of asymmetric information in health insurance markets and college financing markets, respectively. Methodologically, my approach complements Kowalski (2023b), who uses a marginal-treatment effects framework to reconcile estimates of moral hazard effects from the Oregon health insurance experiment and the Massachusetts health reform.

This study also closely relates to a several empirical papers documenting incentive effects and differential sorting into job characteristics or compensation schemes. Lazear (2000) compares productivity of windshield-repair workers before and after switching to a performance-based payment scheme. He finds an increased productivity among both existing workers and newly hired workers. Other studies show how different compensation schemes influence productivity and selection among teachers (Brown and Andrabi, 2021; Johnston, 2024), ride-share drivers (Angrist et al., 2021), miners (Shearer, 1996), and physicians (Kantarevic and Kralj, 2016). More recently, Emanuel and Harrington (2024) estimate treatment and selection into another aspect of labor contracts—remote work. They find both negative negative productivity effects and negative selection into remote work among call-center workers following the COVID-19 pandemic.

While many studies use observational data to estimate selection and incentive effects in various contract markets, comparatively few have used experimental methods. Two notable exceptions are DellaVigna and Pope (2018), which uses an online experiment to

clearing rate—may also be a consequence of information asymmetries between firms and workers (Weiss, 1980; Krueger and Summers, 1988; Weiss, 2014; Yellen, 1984; Malcomson, 1981; Katz, 1986).

investigate the effects of monetary and non-monetary incentives on worker performance, and Shearer (2004), which estimates the productivity differences between piece-rate and fixed-wage tree-planters in British Columbia. Another example is Karlan and Zinman (2009), which randomizes contract offerings on microfinance loans in South Africa. Using a design similar to the second stage of my experiment, the authors isolate selection on unobservables by comparing borrowers who faced different menus of options but ultimately faced the same contract terms. They find strong evidence of moral hazard and weaker evidence of adverse selection.

Relative to existing work, my study offers several contributions. First, I provide an experimental framework that can be applied to a variety of contract markets to separately estimate adverse selection and moral hazard effects. Building upon methods from the insurance literature (Einav et al., 2010a), my framework shows how the welfare impact of these information asymmetries can be identified through marginal-treatment effects estimation. Second, my application of this framework to an online market of data-entry workers provides new evidence of both adverse selection and moral hazard in wage contracts. Importantly, my estimates rely upon 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. Finally, this paper estimates the MVPFs for hourly wage subsidies, providing guidance on policies aimed at reducing workers' earning risk through wage contracts.

The rest of this paper proceeds as follows: In Section 2, I describe my experiment and underlying empirical strategy. In Section 3, I discuss the results of the experiment. Section 4 presents a model of hourly wage contracts under asymmetric information, and Section 5 estimates that model using marginal treatment effects. Section 6 uses estimated information asymmetries to investigate the welfare effects of hourly wage subsidies. In Section 7, I discuss my findings and potential threats to external validity. Section 8 concludes.

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 experiment offers data-entry 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 work under the same contract identifies adverse selection—both groups ultimately face the same compensation scheme but made decisions under different menus of options. At the same time, using wage offers as an instrument for take-up of the hourly contract allows me to separately identify treatment effects of hourly wages among those who accept the offer.

2.1 Example using a Single Wage Offer

To formalize this intuition, consider a potential outcomes framework in which a worker i chooses one of two mutually exclusive contracts—a piece rate and an hourly wage. Let Y_{1i} denote i's output if they work under the hourly wage, and let Y_{0i} denote their output if they work under 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. Differencing realized outputs between hourly ($D_i = 1$) and piece-rate ($D_i = 0$) workers would yield the following:

$$
\begin{aligned}
& E[Y_i|D_i = 1] - E\left[Y_i|D_i = 0\right] \\
&\quad = \underbrace{E\left[Y_{1i} - Y_{0i}|D_i = 1\right]}_{\text{Average Treatment on the Treated}} + \underbrace{E\left[Y_{0i}|D_i = 1\right] - E\left[Y_{0i}|D_i = 0\right]}_{\text{Average Selection on } Y_0}
\end{aligned}
\tag{2}
$$

This difference is the sum of two components. The first is the average treatment-on-the-treated effect, which equals the average effect of hourly pay among those who accept the hourly wage offer over the piece rate. The second is average selection on untreated outcomes, 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 facing the same menu of compensation options, workers are randomly assigned to two different offer conditions, $W_i \in \{0, 1\}$. Only workers assigned to $W_i = 1$ are offered the choice between the piece rate ($D_i = 0$) and hourly wage ($D_i = 1$), while workers assigned to $W_i = 0$ are paid the piece rate with no alternative. Assume the offer condition W_i can only affect Y_i through the choice of contract, so $W_i \perp\!\!\!\perp (Y_{1i}, Y_{0i})$. Finally, let D_i^1 denote worker i's potential take-up of the hourly wage if given the option ($W_i = 1$), so observed take-up D_i is given by $D_i = W_i D_i^1$.

Comparing worker output across these two treatment-offer groups and scaling by the hourly-wage take-up rate yields the classic treatment-on-the-treated estimator from Wald (1940):

$$
\underbrace{E\left[Y_{1i} - Y_{0i}|D_i^1 = 1\right]}_{\text{Average Treatment on the Treated}} = \frac{E\left[Y_i|W_i = 1\right] - E\left[Y_i|W_i = 0\right]}{\pi}, \tag{3}
$$

where $\pi \equiv Pr\left(D_i = 1|W_i = 1\right)$, the share of hourly contracts accepted among those offered a choice ($W_i = 1$).

In the context of this paper, however, the selection component 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 ($W_i = 0$) and piece-rate workers in the hourly-offer group ($W_i = 1$), who declined the hourly wage offer:

$$\underbrace{\left(E\left[Y_{0i}|D_i^1 = 1\right] - E\left[Y_{0i}|D_i^1 = 0\right]\right)}_{\text{Average Selection on } Y_0} = \frac{E\left[Y_i|W_i = 0\right] - E\left[Y_i|D_i = 0, W_i = 1\right]}{\pi}, \quad (4)$$

where equality follows from randomized assignment.[2]

Graphical Illustration Figure 1 illustrates 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 ($D_i = 0, W_i = 0$) to those in the treatment group ($D_i = 0, W_i = 1$) who chose to remain on the piece rate. This selection-on-unobservables estimator captures the average difference in potential untreated outcomes for "compliers" versus "never-takers" (Black et al., 2022; Kowalski, 2023a; Mogstad et al., 2018; Huber, 2013).

2.2 Multiple Wage Offers and Second Stage Randomization

The example above simulates a simplified version of my experimental design with a binary treatment assignment, $W_i \in \{0, 1\}$. In practice, however, my experiment features several treatment groups facing different hourly wage offers. Including multiple wage offers with incomplete take-up allows me to identify selection on potential outcomes under both the piece rate (i.e., the untreated state, Y_0) and hourly wages (i.e., the treated state, Y_1).

To see how, consider an example experiment with three offer conditions, $W_i \in \{0, L, H\}$. As in the previous example, control workers assigned to $W_i = 0$ are offered the piece rate with no alternative. But in this example, the remaining workers are randomly separated

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

into two groups—workers assigned to $W_i = L$ are offered the choice between the piece rate and low hourly wage, while workers assigned to $W_i = H$ are offered the choice between the piece rate and a high hourly wage. Let D_i^L and D_i^H be in indicator for individual i's potential take-up of contracts L and H, respectively, and assume $D_i^H \geq D_i^L$ for all i.

As in Equation (4), comparing the decliners of either wage offer with control workers identifies unconditional selection on Y_0. I can also identify selection on Y_0 into offer H among those who would reject the less generous offer (L):

$$\underbrace{E\left[Y_{0i}|D_i^H = 1, D_i^L = 0\right] - E\left[Y_{0i}|D_i^H = 0\right]}_{\text{Average Selection on } Y_0} = \frac{1-\pi^L}{\pi^H - \pi^L}\left(E[Y_i|D_i = 0, W_i = L] - E\left[Y_i|D_i = 0, W_i = H\right]\right). \quad (5)$$

At the same time, a comparison between *accepters* of high- and low-offer treatment offers identifies average selection on Y_1 into offer L among those who would accept the more generous offer (H):

$$\underbrace{E\left[Y_{1i}|D_i^L = 1\right] - E\left[Y_{1i}|D_i^H = 1, D_i^L = 0\right]}_{\text{Average Selection on } Y_1} = \frac{\pi^H}{\pi^H - \pi^L}\left(E[Y_i|D_i = 1, W_i = L] - E\left[Y_i|D_i = 1, W_i = H\right]\right), \quad (6)$$

In short, because both high- and low-offer treatment arms contain a mix of hourly and piece-rate workers, this multiple-treatment design allows me to identify worker selection on *both* potential outcomes—productivity under the piece rate (Y_0) and productivity under hourly wages (Y_1).

Wage Effects So far, I have assumed that a worker's assigned offer condition can only affect their outcome through the choice of hourly versus piece-rate contract, $W_i \perp\!\!\!\perp (Y_{1i}, Y_{0i})$. If hourly workers are paid their offered wages, this exclusion restriction could be violated through wage effects—higher pay might induce greater effort through increased motivation or satisfaction, biasing my estimates of both selection and treatment effects.

To separate the potential behavioral response of higher effective wages from the incentive effects of hourly contract structure, my experiment incorporates an additional dimension of randomization in the spirit of Karlan and Zinman (2009). Specifically, after workers choose their compensation option, but before they begin the task, I increase hourly wages for a random subset of those accepting lower wage offers, bringing them to parity with higher treatment-offer groups. This design creates random variation in *offered* wages among workers of a given *effective* wage, allowing me to separate potential wage effects from moral hazard and adverse selection.

Graphical Illustration Figure 2 illustrates my experimental design with three offer conditions and a second stage of randomization. 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 on productivity under the piece rate, Y_0. The bottom two boxes represent workers who opted into low and high hourly wages, respectively. In the second stage of the experiment, a random subset of those accepting the low hourly wage are promised an additional top-up compensation before they begin working on the task. This surprise top-up equalizes their effective wage with that of the high-offer group, allowing me to separate wage effects (diagonal arrow) from selection on productivity under hourly wages, Y_1 (horizontal arrow).[3]

2.3 Setting and Implementation

The design and recruitment details for this experiment were pre-registered on the AEA RCT Registry under ID AEARCTR-0000714, titled "Asymmetric Information in Labor Contracts: Evidence from an Online Experiment" (Herbst, 2024).

Participants in my experiment were recruited on Prolific, an online platform that al-

[3]A formal proof of wage effects is provided in Appendix B.1

lows clients to hire online workers for short-term tasks.[4] The experimental job posting offered participants a $1.00 reward for transcribing handwritten text into typed form for five minutes. Such transcription tasks are commonly requested on Prolific and other online platforms. The posting also informed participants they "can earn an additional $0.03 in bonus compensation for each correctly typed sentence."

Workers could only see my experimental job posting if they met the following screening criteria: (1) were located in the United States, (2) spoke fluent English, (3) successfully completed 10 or more previous tasks, and (4) earned an approval rate above 98 percent on previous tasks. These screening criteria allow me remove casual users who may take the tasks less seriously than "professional" online workers who regularly perform tasks to earn income.

Workers who accept the job posting are taken to an external link to perform the task.[5] After clicking this link, workers are randomized into one of eighteen experimental groups. 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 $0.10 for completing the task or a piece rate of $0.03 per correctly typed sentence.[6] In the second treatment group, participants are offered a choice between a flat $0.15 bonus or the same $0.03 piece rate. Additional treatment groups follow the same structure, increasing the flat bonus offer by multiples of $0.05, up to a maximum of $1.75. A control group is offered the $0.03 piece rate for each correctly typed sentence, with no alternative option. Experimental conditions are summarized in Table 1.

After receiving detailed instructions on the data-entry task, treated workers are presented with their group's bonus options in randomized order, as shown in Appendix Figure A1, Panel A. Once workers choose their compensation scheme, they are brought to a

[4] Douglas et al. (2023) finds that the Prolific platform compares favorably to Amazon Mechanical Turk ("MTurk") and other platforms across several dimensions of data quality.

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

[6] A piece rate of $0.03 per sentence was chosen to roughly align with the market rate for online text-to-text transcription services (GMR Transcription, 2024; GoTranscript, 2024; Ditto Transcripts, 2024; Transcription Services, 2024).

new page that states, "For performing this task, you will receive \$1.00, plus your chosen bonus of [*bonus choice*]." A random 50 percent of workers who chose lower-valued bonus options receive a modified message that increases their base payment by enough to equalize their total compensation with the most generous offer (\$1.00 + \$1.75 = \$2.75). For example, half of those who select the \$0.25 bonus are told "you will receive \$2.50, plus your chosen bonus of \$0.25."

Once participants are notified of their bonus compensation and click "Begin Task," they are presented with 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 five 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.[7] When the timer reaches zero, the screen refreshes to an end-of-task page displaying a performance summary and a completion link to redeem their earnings.[8] Workers are paid the \$1.00 reward plus any bonus earnings within 24 hours of completing the task. Figure 3 provides a timeline of the experimental protocol.

Importantly, clients on the Prolific 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 a salient concern among workers on Prolific and similar platforms (u/ProlificAc, 2024).As in most labor markets, this threat of rejection threat creates an incentive for online workers to maintain a minimum standard of performance, even if they are paid a flat hourly wage.

The experiment took place in ten waves of three-hundred job postings launched over the

[7] Appendix Figure A1, Panel B 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—the maximum score achieved was 52.

[8] A small number of participants exited the task or failed to click the completion link within thirty minutes of accepting the task. Those who exit before observing their experimental wage offers are dropped from the experimental sample. Participants who progress far enough to learn their wage offers remain in the sample, and their output is measured using task performance up until the point of exit.

course of two weeks beginning August 31, 2024. Waves were launched at a broad range of times to make the sample more representative of the general population of online workers; if workers who accept tasks at night differ from those who prefer mornings, a hypothetical employer could screen on time-of-day preferences by strategically posting positions at targeted times.

At the conclusion of each wave, I collected data on task performance. The primary outcome of interest is hourly output value, defined as

$$\text{Output Value} \equiv \frac{\text{Completed Sentences} \times \$0.03}{{}^{1}\!/_{12}\ \text{Hours}}. \tag{7}$$

I also construct a measure of quality-adjusted output value, which is defined the same as above but includes only sentences that were typed with no errors. Both measures of output value are linked to self-reported background information from participants' Prolific profiles. Specifically, I observe each workers' gender, ethnicity, age, employment status, and whether they are a student. I also observe the prior number of tasks they have successfully completed through the Prolific platform. Because the goal of my experiment is to identify selection on *private* information, conditioning on these potentially screenable characteristics allows me to simulate a sample of workers who would be observably equivalent to a hypothetical employer.

3 Experimental Results

This section describes results from the experiment. Sample size for each experimental group is provided in the third column of Table 1, and balance tests are reported in Appendix Table A1.[9] Table 2 reports summary statistics for this experimental sample. 44 percent of participants accepted hourly wage offers. On average, participants completed 21.98

[9]When a participant begins the task but exits early or fails to complete, the Prolific task scheduler automatically re-assigns treatment conditions to a new participant, even while the incomplete submission remains in my sample (see Footnote 8). These re-assigned treatments result in an observation count (3,030) that exceeds my pre-registered sample size of 3000.

sentences within five minutes (17.79 without error), resulting in a mean hourly output value of $7.91.

Hourly Labor Supply 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. On average, only 0.21 of wage offers below $3.00 were accepted, while wage offers of $10.80 and above were accepted at a rate of 0.74. Moving from group-specific means to a continuous supply curve, Table 3 reports estimated coefficients from a logistic regression of a binary indicator hourly acceptance against log wage offers, excluding the control group. Column 1 reports estimates from a univariate specification, while Columns 2 through 4 successively add controls for task timing, employment, and demographics. In each specification, I find a statistically significant effect of log wage offer on hourly take-up, with estimates ranging from 1.20 (SE=0.06) to 1.25 (SE=0.06) depending on the inclusion of controls.

Selection into Wage Contracts The results above demonstrate how the supply of hourly workers increases with the wage rate. In what follows, I show the average hourly worker's productivity changes with that increased supply by comparing realized output between workers who faced different hourly wage offers but ultimately worked under the same contract. 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, and those who accept lower hourly wages should perform worse than those who hold out for a higher hourly rate.

In Figure 5, I examine how output value varies between piece-rate and hourly workers across four groups—those in the control group who received no hourly offer, those receiving a wage offer below $3.00, those receiving a wage offer between $3.60 and $9.60, and those receiving a wage offer of $10.80 or higher. "Output value" is defined as the number of 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 self-selected subgroups across each treatment category in this figure provides insight into participants' selection on output potential under counterfactual contracts. First, I examine selection by workers' piece-rate productivity by comparing piece-rate workers' output value (those declining hourly wage offers) across treatment groups. I find that those declining offers below \$3.00 produce \$8.53 of output value, those declining offers between \$3.60 and \$9.60 produce \$8.81 of output value, and those declining offers of \$10.80 and above produce \$8.86 of output value. By comparison, piece-rate workers in the control group, who received no hourly wage offer, produce \$8.12 of output value. Similarly, I can examine selection by productivity under hourly wages by comparing those who *accepted* each treatment's wage offer, then restricting attention to hourly workers who were randomly paid the maximum rate of \$21.00 per hour. Among these workers, I find that those accepting offers below \$3.00 produce \$5.65 of output value, those accepting offers between \$3.60 and \$9.60 produce \$6.93 of output value, and those accepting offers of \$10.80 and above produce \$7.47 of output value.

Next, I fit the selection patterns seen in Figure 5 to the following linear model:

$$Y_i = \alpha D_i + \beta_0(1 - D_i) \times W_i + \beta_1 D_i \times W_i + \gamma D_i \times W_i^P + \boldsymbol{\xi X_i} + \epsilon_i, \tag{8}$$

where W_i is worker i's log hourly wage offer, D_i is a binary indicator whether they accept the hourly wage, W_i^P is the log wage hourly workers are actually paid (equal to zero for piece-rate workers), and X_i represents a vector of covariates and a constant term.[10]

Table 4, reports OLS estimates of coefficients from Equation (8). The estimated coefficient on "Declined × Log Hourly Wage Offer" implies that increasing wage offers by one log point corresponds to a \$0.17 (SE=\$0.10) increase in output value among those declining the offer in favor of the piece rate. Likewise, the coefficient on "Accepted × Log Hourly Wage

[10]Rather than include a common W_i term and only one interaction term, Equation (8) includes full interactions of wage offers with acceptance status, $(1 - D_i) \times W_i$ and $D_i \times W_i$. While the two models are equivalent, parametrization of the β_0 and β_1 in the fully interacted specification is easier to interpret. Note that $(1 - D_i) \times W_i^P$ is excluded because $W_i^P = 0$ for all $D_i = 0$.

Offer" implies that productivity among hourly workers increases by \$0.62 (SE=\$0.12) per log point. By comparison, the estimated coefficient on "Accepted × Log Effective Hourly Wage" are small and statistically insignificant, suggesting wage effects are not particularly important in this setting. Adding controls for task experience, employment, and demographics in Columns 2 through 4 produces estimates that are more precise and similar in magnitude, suggesting worker selection on ex-ante productivity is not well captured by observable characteristics.

Figure 6 plots estimated coefficients from an OLS regression of output value against the full set of dummy variables for each experimental wage offer, controlling for log effective wages among hourly workers and task timing. Red dots represent coefficients on hourly wage offers interacted with an indicator for remaining on the piece rate. Blue diamonds represent coefficients on hourly wage offers interacted with an indicator for accepting the offer. The upward slope in both of the two series indicates adverse selection into hourly wages—as wage offers decrease, the most productive workers opt out of hourly work and into the piece rate, resulting in lower average productivity among both hourly and piece-rate workers.

Treatment Effect of Hourly Wages Table 5 reports reduced-form treatment effects of hourly wages after removing the potential influence of wage effects.[11] Across all three specifications, hourly contracts induce a statistically significant reduction in worker productivity. Absent controls, accepting an hourly contract reduces a worker's output value by 0.51 (SE=0.21) or 6.40 percent of the sample mean. Adding controls for task specifics changes this estimate to 0.50 (SE=0.20), while adding employment and demographic controls reduces the estimate to 0.49 (SE=0.20) and 0.37 (SE=0.19), respectively. Table 5 reports estimates from the same exercise, but adjusts the outcome measure to include only correctly typed sentences.

[11] I partial-out wage effects in Table 5 by regressing output value against treatment offers and log effective hourly wages among hourly workers, then subtracting the demeaned wage effect implied by the coefficient on log effective hourly wages. I then instrument for hourly wage take-up with dummy variables for each treatment offer in a two-stage least-squares regression.

To summarize, experimental results provide evidence of both adverse selection and moral hazard in hourly wage contracts. In the following section, I develop a model to investigate the labor market implications of these information asymmetries.

4 Model of Asymmetric Information in Wage Contracts

In this section, I present model of short-term labor markets under asymmetric information. The model borrows from Einav et al. (2010a) and Herbst and Hendren (2024), who develop models of asymmetric information in health insurance markets and college financing markets, respectively. I then show how the parameters of this model can be mapped into marginal-treatment effects framework, allowing me to estimate welfare loss and policy counterfactuals with minimal parametric assumptions.

Consider a perfectly competitive labor market in which risk-neutral firms face a population of workers.[12] Assume this population has already been pre-screened on observable characteristics, so that workers are observably equivalent to potential employers.[13] 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 worker output at a constant market price of p per unit.[14] Alternatively, they can offer a flat, up-front wage of their own choosing, w, in exchange for a claim on a worker's hourly output, q_i.[15]

For individual i, I define the reservation wage, $\overline{w}_i$, as the minimum w at which they

[12]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.

[13]In my empirical analysis, I allow employers to set wages using public information about each individual, X. Omitting these "X" terms from the model simulates a market for the subpopulation of workers with observables matching a particular value, $X = x$. I also assume employers know the data generating process, so that they can form unbiased beliefs about the distribution of q conditional on X.

[14]Directly purchasing a worker's product of labor can be thought of as either piece-rate employment or hiring a self-employed contractor. This model is also equivalent to one in which workers sell their product directly to consumers and firms serve as (potential) insurers of their labor product. While I assume firms can freely measure worker output, one could easily incorporate a monitoring cost of observing q_i.

[15]While a worker's output, q_i, can vary between hourly and piece-rate contracts (e.g., through moral hazard effects), I assume an hourly worker's output does not vary with the wage, w (i.e., no wage effects). While the absence of wage effects in my empirical results would seem to validate this assumption, I include a model with wage effects in Appendix B.3 for completeness.

would accept an hourly contract. The relative supply of hourly workers is given by

$$S(w) \equiv \Pr\left(\overline{w}_i \leq w\right). \tag{9}$$

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, $\theta_i \equiv S(\overline{w}_i)$. I can then rewrite a worker's reservation wage as a function their type, $\overline{w}_i = \overline{w}(\theta_i)$, where

$$\overline{w}(\theta) \equiv S^{-1}(\theta). \tag{10}$$

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

$$MV(\theta) \equiv E\left[Y_i|\theta_i = \theta\right], \tag{11}$$

where $Y_i = pq_i$, the incremental value of output q_i produced under an hourly contract.[16] Absent any behavioral response to the hourly contract, $MV(\theta)$ 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 $w = \overline{w}(\theta)$ 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_i such that $\overline{w}(\theta_i) \leq w(\theta)$. So instead of obtaining type θ's marginal

[16] Y_i reflects the market value of q_i units of output, or, equivalently, the amount the firm saves by not buying hourly worker i's output at the piece rate. This measure of incremental value is analogous to the incremental cost of insurance defined in Einav et al. (2010a). Note that any monitoring costs of observing worker output would increase this incremental value, making hourly wages more likely.

value, $MV(\theta)$, the employer would obtain their *average value*, defined as

$$AV(\theta) \equiv E[Y_i|\theta_i \leq \theta]. \tag{12}$$

The average value, $AV(\theta)$, of type θ is given by the average value of output produced among all types $\theta_i \leq \theta$. When we account for this selection into contracts, the employer's expected profits from hiring a worker at wage w are given by

$$\Pi(w) = S(w)\left(AV(\theta^w) - w\right), \tag{13}$$

where $\theta^w \equiv S(w)$, the worker type with reservation wage equal to w.

I assume that at least one worker's marginal value exceeds their reservation wage, ($\overline{w}(\underline{\theta}) > MV(\underline{\theta})$ for some $\underline{\theta} > 0$). This assumption will hold unless all workers are risk-loving, risk-neutral, or hold over-optimistic beliefs about their productivity. I further assume that $MV(\theta)$ crosses the supply curve at most once (if $\overline{w}(\overline{\theta}) > MV(\overline{\theta})$ for some $\overline{\theta}$, then $\overline{w}(\theta) > MV(\theta)$ for all $\theta > \overline{\theta}$). With these simplifying assumptions in hand, the equilibrium condition for the share of workers under hourly contracts, θ^{EQ}, is given by

$$\overline{w}(\theta^{EQ}) = AV(\theta^{EQ}). \tag{14}$$

In equilibrium, firms offer wage contracts up the point where the marginal worker's reservation wage, $\overline{w}(\theta^{EQ})$, is exactly equal to the average value of their hourly employees' output, $AV(\theta^{EQ})$.

Figure 7 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) 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

$$DWL = \int_{\theta^{EQ}}^{\theta^{EF}} (MV(\theta) - \overline{w}(\theta))\, d\theta. \tag{15}$$

In summary, private knowledge of productivity can create a gap between the marginal and average values of labor, preventing Pareto-improving exchanges of hourly wage contracts—workers are paid by the hour if and only if their reservation wage is no higher than the average value of those with lower reservation wages. This information asymmetry reduces total welfare below what it would be under a full-information benchmark.

Monitoring Costs Existing research shows how relative costs of monitoring worker inputs and outputs can influence payment schemes in different occupations (Lazear, 1986, 2000; Goldin, 1986). My paper seeks to complement this literature by identifying the market implications of asymmetric information holding these monitoring costs fixed. As such, worker time and productivity is costlessly observed in both my model and experimental setting. Nonetheless, one could easily extend my framework to incorporate a monitoring cost of measuring worker output (q_i). Such output-monitoring costs would, all else equal, making hourly wage contracts more likely.[17] Likewise, I could incorporate a time-monitoring cost of observing workers' time spent on the job, making hourly wages less likely. I could also allow firms to observe worker effort (e_i) at some additional cost, placing an effective ceiling on the costs of asymmetric information. However, allowing firms to observe an additional worker

[17]Note that hourly wages typically require some degree of output monitoring as well, as it allows firms to credibly threaten low-performing workers with dismissal, rejection, or damaged reputation.

input other than time would likely lead to multi-dimensional wage contracts, complicating my analysis.

4.1 Incorporating Moral Hazard

Note that the model above allows for moral hazard effects, even if those effects are not explicitly discussed. To see how, consider worker i's potential output values under counterfactual contracts. Specifically, let Y_{1i} denote i's output value if they work under the hourly wage, and let Y_{0i} denote their output value if they work under the piece rate. The moral hazard effect for worker i is given by their individual treatment effect of the hourly wage, $MH_i \equiv Y_{1i} - Y_{0i}$.[18] However, since piece-rate workers sell their output at a constant price per unit, their productivity per hour has no affect on firm profits. So while firms care about a worker's output under the hourly contract (Y_{1i}), they don't care how this output compares to the piece-rate counterfactual (Y_{0i}). As a result, $AV(\theta)$ and $MV(\theta)$ are defined conditional on accepting the hourly contract, and thus depend only on output under hourly wages, Y_{1i}. The profit condition (13) and welfare calculation (15) are therefore inclusive of any incentive effects.

While not strictly necessary to calculate welfare loss, explicitly modeling and estimating moral hazard effects is nonetheless important, especially for policy counterfactuals. As I show in Section 6, moral hazard effects are necessary to assess the social value of policies like hourly wage subsidies, as the public cost of these subsidies must include the reduced tax revenue from potentially lower earnings among those induced into hourly wage contracts. Moreover, separately identifying moral hazard is important if firms have ways of mitigating the incentive 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 the disincentive effects of hourly pay but do little to prevent adverse selection—low-productivity workers would still prefer the partial insurance of mixed compensation

[18] Strictly speaking, $Y_{1i} - Y_{0i}$ captures worker i's overall output response to the hourly wage contract. This response could result from behavioral phenomena not traditionally classified as "moral hazard."

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. However, to identify the model under this counterfactual, I must explicitly separate selection from treatment effects under the "pure" hourly wage offers in my experiment.

To separate the incentive response of the contract from selection on underlying unobservables, I must consider the value of worker output across types under hourly wage and both with *and without* the hourly wage contract. To do so, I split Equations (11) and (12) 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_{0i}) the hourly wage:

$$MV_1(\theta) \equiv E\left[Y_{1i}|\theta_i = \theta\right] \tag{16}$$

$$MV_0(\theta) \equiv E\left[Y_{0i}|\theta_i = \theta\right]. \tag{17}$$

Note that $MV_1(\theta)$ is simply a relabeling of $MV(\theta)$ from Equation (11)—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.[19] The difference between these two marginal value curves identifies the moral hazard effect for a given type:

$$MH(\theta) \equiv MV_1(\theta) - MV_0(\theta). \tag{18}$$

Similarly, the average value curve can be split into two counterfactuals:

$$AV_1(\theta) \equiv E\left[Y_{1i}|\theta_i \leq \theta\right] \tag{19}$$

$$AV_0(\theta) \equiv E\left[Y_{0i}|\theta_i \leq \theta\right]. \tag{20}$$

[19] 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 $MV_1(\theta)$.

$AV_1(\theta)$ is equivalent to $AV(\theta)$ from Equation (12); it equals the average value of output among hourly-pay workers with lower reservation wages than type $\overline{w}(\theta)$. $AV_1(\theta)$, on the other hand, equals the average value among those same workers if they had instead worked under a piece rate.

5 Estimating the Model using Marginal Treatment Effects

The model above demonstrates how the welfare effects of asymmetric information rely on the distribution of marginal values across a range of wages. In this section, I show how treating multiple experimental wage offers as continuous instrument in a marginal-treatment-effects (MTE) framework identifies these marginal values.

Adopting the parlance of the causal inference literature, I let experimental wage offers w serve as an instrument for taking up an hourly contract. I can then characterize a worker's quantile reservation wage, $\theta_i \equiv S(\overline{w}_i)$, as their "resistance to treatment" (Björklund and Moffitt, 1987; Heckman and Vytlacil, 1999, 2005, 2007). Under this framing, the marginal values defined in Equations (16) and (17) are equivalent to mean potential outcomes, and the moral hazard effect in Equation (18) is equivalent to the marginal treatment effect of the hourly contract, $MTE(\theta) \equiv E[Y_{1i} - Y_{0i}|\theta_i = \theta] \equiv MH(\theta)$. As Figure 8 illustrates, this marginal treatment effect measures the average effect of treatment (hourly contract) among those whose resistance to treatment (quantile reservation wage, θ_i) is equal to a given propensity score (share of hourly workers, $\theta = S(w)$).[20]

The correspondence above means I can apply insights from the MTE literature to identify the model with minimal parametric assumptions. First, note that the supply curve in Equation (9) can be straightforwardly identified as the share of accepters across wage offers:

$$S(w) \equiv \Pr(\overline{w}_i \leq w) = \Pr(D_i = 1|w_i = w). \tag{21}$$

[20] Kowalski (2023b) uses similar insights from the MTE literature to show how adverse selection on potential outcomes can explain differences in the estimated treatment effects of health insurance in Oregon and Massachusetts.

Using predicted hourly worker shares from $S(w)$, average value under both hourly and piece-rate contracts can be identified from the conditional means of outcomes across worker propensity scores, $\theta = S(w)$, among respective accepters and decliners of the corresponding wage offer, w. So the (potential) average value curve under the hourly wage equals the average output value among those who accept the hourly wage offer that induces θ-share of workers into the hourly contract:

$$AV_1(\theta) \equiv E[Y_{1i}|\theta_i \leq \theta] = E[Y_i|S(w_i) = \theta, D_i = 1]. \tag{22}$$

Likewise, the (potential) average value curve under the piece rate can be identified using average output value among workers *declining* the wage offer that is accepted by θ-share of workers:

$$AV_0(\theta) \equiv E[Y_{0i}|\theta_i \leq \theta] = \frac{E[Y_i|S(w_i) = 0] - (1-\theta)E[Y_i|S(w_i) = \theta, D_i = 0]}{\theta}, \tag{23}$$

where $E[Y_i|S(w_i) = 0]$ is the average output value of workers in the control group, who all work under the piece rate.

Marginal values can then be identified by separately differentiating take-up weighted conditional means for decliners and accepters of each offer:

$$MV_1(\theta) = \frac{\partial (E[Y_{1i}|\theta_i \leq \theta]\,\theta)}{\partial \theta} = \frac{\partial (E[Y_{1i}|S(w_i) = \theta, D_i = 1]\,\theta)}{\partial \theta} \tag{24}$$

$$MV_0(\theta) = -\frac{\partial (E[Y_{0i}|\theta_i > \theta]\,(1-\theta))}{\partial \theta} = -\frac{\partial (E[Y_i|S(w_i) = \theta, D_i = 0]\,(1-\theta))}{\partial \theta}. \tag{25}$$

Equations (22) through (25) depend on $E[Y_i|S(w_i) = \theta, D_i = 1]$, $E[Y_i|S(w_i) = \theta, D_i = 0]$, and their derivatives with respect to θ.

5.1 Estimation

To estimate hourly supply as a function of hourly wage offers, I use the logistic regressions in Section 3. This specification is attractive for two reasons: First, the logit model ensures estimates of θ are bound between zero and one. Second, measuring hourly wage offers in logs, as opposed to levels, prevents negative reservation wages among low-θ workers.

Once I've estimated the supply curve, $S(w)$, I use the local polynomial regression approach from Carneiro et al. (2011) to estimate average and marginal values. First, I separately residualize covariates from Y_i for hourly and piece-rate workers using double-residual regression methods (Robinson, 1988), assuming these covariates are additively separable from $MV_1(\theta)$ and $MV_0(\theta)$.[21] To simulate potential screening or (legal) wage discrimination of hypothetical employers, these covariates include controls for number of previous tasks, task start time, and employment status.[22] For hourly workers, I also include the effective wage paid after any randomized top-up payments in the second round of my experiment. As in Section 3, this residualization prevents potential wage effects from violating the exclusion restriction for the wage-offer instrument. I then estimate marginal and average values using local polynomial regression of the residualized Y_i on $S(w_i)$ with a bandwidth of 0.2. Using this semi-parametric method allows me to estimate value curves as flexibly as possible, which is critical to accurately estimate welfare consequences of asymmetric information. Standard errors are calculated using five-hundred bootstrap replications.

Welfare Impact Once I have estimated $\overline{w}(\theta)$, $MV(\theta)$, and $AV(\theta)$ curves, it is straightforward to calculate the welfare loss from Equation (15). First, I calculate equilibrium (θ^{EQ}) and efficient (θ^{EF}) shares of hourly wages using the intersection of $\overline{w}(\theta)$ with $AV(\theta)$ and $MV(\theta)$, respectively. Then, I calculate the cumulative difference in $\overline{w}(\theta)$ and $MV(\theta)$ over the region $\theta \in \left(\theta^{EQ}, \theta^{EF}\right)$. This calculation measures lost welfare as the implied "risk discount" workers would be willing to accept for the implicit insurance provided by hourly wages.

[21] More formally, I assume $E\left[Y_{Ji}|X_i = x, \theta_i = \theta\right] = \xi_J \widetilde{X}_i + MV_J(\theta)$ for $J \in \{0, 1\}$, where $\widetilde{X}_i$ is a vector of covariates normalized to mean zero. In other words, X_i can affect the levels of $MV_1(\theta)$ and $MV_0(\theta)$, but not their slopes.

[22] Race, gender, and age were excluded because employers cannot legally use these characteristics in employment or wage-setting decisions.

5.2 Results

Figure 9 plots semiparametric estimates of supply and value curves under both hourly wage and piece-rate counterfactuals. On the horizontal axis, types θ are enumerated in ascending order. The red line plots hourly reservation wage, $\overline{w}(\theta)$, which equals the inverse of the labor supply curve estimated in Table 3, $\overline{w}(\theta) \equiv S^{-1}(\theta)$. In Panel A, the green line and blue lines plot the average and marginal value curves under hourly wages, $AV_1(\theta) \equiv E[Y_{1i}|\theta_i \leq \theta]$ and $MV_1(\theta) \equiv E[Y_{1i}|\theta_i = \theta]$. In Panel B, green line and blue lines plot the average and marginal value curves under the piece rate, $AV_0(\theta) \equiv E[Y_{0i}|\theta_i \leq \theta]$ and $MV_0(\theta) \equiv E[Y_{0i}|\theta_i = \theta]$.

In both panels, the majority of workers produce labor at marginal values, $MV(\theta)$, that exceed their hourly reservation wages, $\overline{w}(\theta)$. Because a worker's marginal value is equivalent to their expected output times the piece rate, we can use the relationship between $\overline{w}(\theta)$ and $MV(\theta)$ to draw inferences about their risk preferences. Workers with $MV_1(\theta) > \overline{w}(\theta)$ are either risk averse or systematically undervalue their productive potential; a risk-neutral worker of type θ would not accept hourly wage w knowing they can produce $MV_1(\theta) > w$ on average because they could earn more (in expectation) by applying the same effort under the piece rate. $MV_0(\theta) > \overline{w}(\theta) > MV_1(\theta)$, on the other hand, could be explained by selection on moral hazard—even risk-neutral workers might be willing to give up $MV_0(\theta) - \overline{w}(\theta)$ in exchange for the utility of decreased effort under the hourly wage.

Despite workers' willingness to sacrifice some of their expected earnings for the insurance of hourly wages, this implied risk premium is not enough to prevent some degree of market unraveling. In both panels, the divergence between the marginal and average value curves reflects the inefficiency created by adverse selection in hourly wage contracts. If firms were fully informed of workers' productivities, they could profitably offer hourly positions up to the point where the marginal value curve, $MV(\theta)$, intersects with the supply curve, $\overline{w}(\theta)$. Taking workers' behavioral responses to hourly contracts as given, this efficient allocation would imply that 59 (SE=0.08) percent of workers would work under hourly contracts. With adverse selection, however, only 54 (SE=0.06) percent of workers can find hourly positions. If we remove the moral hazard effects of hourly contracts, the efficient share of hourly workers would instead be 61 (SE=0.08) percent, which lowers to 55 (SE=0.08) percent in a competitive equilibrium with adverse selection. The resulting welfare loss from this attenuation in hourly work is \$0.03 (SE=0.0006) per hour of labor inclusive of moral hazard effects, or \$0.04 (SE=0.0014) per hour of labor excluding moral hazard effects. This loss corresponds to 1.4 percent of the total potential welfare that would be achieved in an efficient equilibrium.

Figure 10 plots the marginal treatment effect of hourly wages—the difference in estimated marginal values under hourly and piece-rate contracts, $MV_1(\theta) - MV_0(\theta)$. In the context of the model, this curve represents the (marginal) moral hazard effect of an hourly wage contract. The downward slope suggests some degree of selection on moral hazard, but in the opposite direction of what one might expect—those more prone to shirking have relatively higher hourly reservation wages, indicating a preference for *less* insurance. This pattern can be explained by heterogenous risk preferences. If preferences for payoff risk and reputational risk are correlated, those who avoid the insurance of hourly wages may also be more likely to shirk once they have it, as they don't fear rejection or damaged reputation from poor performance. It would also be consistent with a model in which hourly workers lower their effort to meet some minimum threshold to avoid dismissal—the most productive workers have the largest gap between this threshold and their potential output, resulting in a larger behavioral response to hourly contracts.

6 Policy Impliciations: MVPF of Hourly Wage Subsidies

If adverse selection results in a suboptimal provision of hourly positions, the government might consider subsidizing hourly wages to induce workers and firms into these contracts. In this section, I measure the welfare impact of such subsidies by constructing their marginal values of public funds (MVPFs). The MVPF measures the social value of a policy per dollar of net cost to the government (Hendren and Sprung-Keyser, 2020). It's defined as

$$MVPF = \frac{WTP}{Cost - FE}, \tag{26}$$

where WTP is the aggregate willingness-to-pay for the policy, $Cost$ is the government's direct costs of the policy, and FE captures any fiscal externalities the government might incur as a result of the policy.

Consider an hourly wage subsidy of \$$\delta$ per hour worked. The effect of such a subsidy would be to lower reservation wages by \$$\delta$, inducing an increase in hourly supply share from θ^{EQ} to $\theta^{\delta} \equiv S(w^{EQ} + \delta)$, where θ^{EQ} and w^{EQ} denote hourly supply share and wages in a competitive equilibrium. The welfare effects are twofold: First, it provides a direct transfer of \$$\delta$ to all workers with $\theta \leq \theta^{\delta}$. Second, it generates $MV_1(\theta) - \overline{w}(\theta)$ of additional welfare from hiring worker types $\theta \in \left(\theta^{EQ}, \theta^{\delta}\right]$, corresponding to the risk premium these workers place on the implicit insurance of hourly wages. The aggregate willingness-to-pay is therefore given by

$$WTP(\delta) = \underbrace{\delta\theta^{\delta}}_{\text{Transfer}} + \underbrace{\int_{\theta^{EQ}}^{\theta^{\delta}} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}_{\text{Insurance Benefit}}, \tag{27}$$

which captures the subsidy's net transfer to beneficiaries as well as its insurance benefits to risk-averse workers induced into hourly pay.

How do these benefits compare to the costs of the subsidy? The direct cost of the subsidy is simply given by the government's hourly transfer to all workers hired under the subsidy, $\delta\theta^{\delta}$. In addition to these direct costs, the policy's moral hazard effects impose an indirect cost—those induced into hourly pay through the subsidy may reduce their output, resulting in lower earnings and decreased tax revenue.[23] I capture this fiscal externality using estimates of moral hazard (marginal treatment effects) for types $\theta \in \left(\theta^{EQ}, \theta^{\delta}\right)$ from

[23]The fiscal externality I calculate assumes tax rates are invariant to contract structure. In reality, however, taxes on earnings often vary by worker classification and compensation type. Incorporating these differences across the myriad of potential contracts paying hourly wages, freelance fees, and/or piece-rate payments lies beyond the scope of this paper.

Section 5.2, so that the total cost of the subsidy is given by

$$Cost(\delta) \quad = \quad \underbrace{\delta\theta^{\delta}}_{\text{Direct Cost of Transfer}} \quad + \quad \underbrace{\int_{\theta^{EQ}}^{\theta^{\delta}} \tau MH(\theta)d\theta}_{\text{Fiscal Externality from Moral Hazard}} \quad . \tag{28}$$

With Equations (27) and (28) in hand, I can write $MVPF_{\text{Sub}}(\delta)$—the MVPF of a \$$\delta$ subsidy—as

$$MVPF_{\text{Sub}}(\delta) = \frac{\delta\theta^{\delta} + \int_{\theta^{EQ}}^{\theta^{\delta}} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}{\delta\theta^{\delta} - \int_{\theta^{EQ}}^{\theta^{\delta}} \tau MH(\theta)d\theta}. \tag{29}$$

Equation (29) reveals the trade-off faced by policymakers promoting hourly wage contracts. The marginal social benefit of an additional hourly contract depends on the relative magnitudes of its insurance value to the marginal worker and that worker's propensity to shirk. More generally, this trade-off highlights the importance of separating adverse selection from moral hazard in markets with asymmetric information—misattributing one for the other can lead to suboptimal policy decisions.

Figure 11A plots estimates $MVPF_{\text{Sub}}(\delta)$. Estimated MVPFs decline with the size of the subsidy because first worker induced into hourly pay has the highest risk premium among non-hourly workers. The vertical line denotes the subsidy that achieves the hourly supply share found in an full-information equilibrium. This "efficient" level of subsidy is equal to \$1.09 (SE=0.011), and results in an MVPF equal to 1.04 (SE=0.001).

6.1 Optimal Subsidies

While the above analysis helps identify the range of potential MVPFs associated with hourly wage subsidies, it does not solve for the welfare-maximizing level of subsidy.[24] To determine the optimal subsidy, I use Equations (27) and (28) above to maximize aggregate net welfare as follows:

$$\max_{\delta} \left\{ WTP(\delta) - \lambda Cost(\delta) \right\}, \tag{30}$$

[24] Comparisons of MVPFs between mutually-exclusive policies that endogenously differ in scale can lead to suboptimal policy choices. In this instance, the highest-MVPF subsidy would be the one with the smallest number of beneficiaries.

where λ reflects the marginal cost of public financing—the cost of raising one dollar of revenue through taxation, or the MVPF of some alternative policy from which funds are redirected.

The first order conditions for (30) imply

$$MVPF_{d\text{Sub}}(\delta^*) \equiv \frac{\theta^{\delta^*} + (MV_1(\theta^{\delta^*}) - \overline{w}(\theta^{\delta^*}))\frac{d\theta^\delta}{d\delta}}{\theta^{\delta^*} - \tau MH(\theta^{\delta^*})\frac{d\theta^\delta}{d\delta}} \quad = \quad \lambda. \tag{31}$$

$MVPF_{d\text{Sub}}(\delta)$ is the MVPF for a *marginal increase* in hourly wage subsidy. Equation (31) provides a prescription for achieving the optimal hourly wage subsidy—the one that maximizes net aggregate welfare. Policymakers should increase the subsidy until the MVPF of a marginally higher subsidy equals the marginal cost of acquiring public funds.

Figure 11B plots estimates of $MVPF_{d\text{Sub}}(\delta)$. The MVPF of marginally higher subsidies declines with the subsidy level, reaching one at a subsidy of \$1.00 (SE=0.014) per hour. Note that, in the absence of the fiscal externality imposed by the moral hazard effects of hourly wages, the subsidy at which the MVPF equals one would coincide with the \$1.09 subsidy that achieves the full-information benchmark. The attenuation to \$1.00 reflects the small added cost the reduced tax revenue from lower earnings. If we allow for a non-zero marginal cost of acquiring public financing ($\lambda > 1$), the optimal subsidy would decrease from \$1.00 to the value of δ at which $MVPF_{d\text{Sub}}(\delta) = \lambda$.

7 Discussion and Robustness

In my experiment, I find that a worker's choice of wage contract correlates with their potential productivity and has a causal effect on their performance in a simple data-entry task. In this section, I discuss my interpretation of these results and how they might extrapolate to other settings.

A vast number of jobs are characterized by some degree of self-employment, freelance work, or piece-rate compensation. Restaurant servers, barbers, salespeople, and delivery workers are just a few of the occupations where, rather than clocking their hours, workers derive most of them earnings from selling their labor product directly to an employer or customer.

External Validity As a theoretical matter, any job with an uncertain labor product that depends on worker effort is susceptible to the forces of moral hazard and adverse selection. Many of these jobs are characterized by some degree of self-employment, freelance work, or piece-rate compensation. While this paper suggests that suboptimal labor contracts are plausible in these settings, my estimates cannot speak to the magnitudes of potential welfare loss from asymmetric information in all of these markets. For example, the pattern of selection on data-entry skills likely differs from how workers would sort on driving ability or salesmanship. But given the economy-wide 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, 2000), parameter estimates concerning worker productivity are usually difficult to generalize beyond narrowly defined labor markets.[25] While my study is not exempt from these limitations, several elements of my experiment are designed to mitigate these concerns.

First, my experimental typing task requires a dimension of effort and skill that is highly demanded by a variety of employers. In the narrowest sense, human text-to-text transcription is a task commonly requested by clients and offered by workers on online platforms (Khan, 2024; Ahmad, 2024). And more generally, "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 are relevant to a variety of labor markets. Second, workers in my experiment are recruited using a widely used and well-established freelancing platform with over 100,000 workers. The ubiquity of such platforms (e.g., MTurk, Up-

[25] 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.

work, Fiverr) means that even the most conservative interpretation of my estimates holds non-trivial welfare implications. Finally, workers are not aware that they are part of an experiment until after they perform the task, so estimates are biased by their potential desire to generate a particular result.[26]

Despite efforts to generalize the experimental task, its short-term nature might raise concerns about workers' choices or performance under small stakes. In particular, one might worry that workers see the task more as a game than as a job, biasing them towards riskier behavior. Some of my results alleviate this concern. On average, workers in my sample have already completed over 1,200 tasks, suggesting they regularly perform tasks to earn income and are concerned with their reputation on the Prolific platform. Moreover, my results imply that workers' contract choices are consistent with risk aversion—for the majority of the sample, the output value of the marginal worker exceeds their reservation wage. Finally, note that most of the behavior changes one would expect to arise from the task's short duration or small stakes would bias my results towards zero. For example, inattention or risk-loving behavior would make the hourly supply less elastic or shift it leftwards, resulting in a smaller estimates of welfare loss.

Selection Into the Task To credibly estimate welfare effects of information asymmetries, the observed variation in wage offers must cover the entire range of contracts that might exist under a benchmark counterfactual where firms are fully informed. This empirical hurdle is difficult to overcome in observational studies because adverse selection might limit the set of contracts in existing markets. As a result, methods using real-world wage contracts are likely to understate the consequences of asymmetric information (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 due to market unraveling.

However, even if I can observe selection into unprofitable contracts, I still only ob-

[26]Rather than elicit consent prior to the task, I debriefed participants on the nature of the experiment after its conclusion. The experimental task resembles those commonly requested for non-research purposes.

serve outcomes for those who initially agreed to my experimental task. For example, 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-entry piece rate offered to all treatment groups, I am likely to attract a broad swath of workers who meet my screening criteria. Indeed, in communities of online workers, the Profilic platform is known to be the most renumerative, where workers rarely turn down a task for which they are eligible (u/ProlificAc, 2024).

Generalizing the Outside Option Workers in my experiment accepted or rejected hourly wage offers relative to a standardized \$0.03-per-entry piece rate. If this rate does reflect the true market value of workers' labor product, it could bias my estimates. For example, my estimates of reservation wages and marginal values are higher than what one would expect if workers' outside options was to sell their typed data entries at \$0.10 per entry.

I mitigate this concern in two ways. First, to price workers' outside option as realistically as possible, I set the experimental piece rate to roughly correspond to observed rates for online text-to-text transcription services (Khan, 2024; Ahmad, 2024; GMR Transcription, 2024; GoTranscript, 2024; Ditto Transcripts, 2024; Transcription Services, 2024). Second, in Appendix B.4, I show that under fairly benign assumptions concerning worker utility, estimates of reservation wages and value curves are proportional to the per-unit price at which workers can sell their labor product. In particular, if workers' contract preferences exhibit constant relative risk aversion, I can normalize these objects to a piece rate of \$1, allowing me to express welfare loss on a per-dollar basis.

Experimental Trade-offs Having acknowledged its shortcomings, it's important to note the benefits of my experimental setting, which would likely be lost under an alternative design. To accomplish the goals of this paper, an empirical approach would have to satisfy the following criteria: First, the researcher must elicit workers' preferences over a range of hypothetical contracts, including those that would be unprofitable to a real-world employer. This requirement is difficult to satisfy with observational studies, as restricting attention to observed variation in wages would likely fail to identify welfare losses from unraveled contracts. Second, it requires a measure of worker output that unambiguously maps to a potential employer's profit function. This output would be difficult to define in many of the professions dominated by self-employment or task-based pay, where a given worker's value can be difficult to measure (e.g., restaurant servers). Third, output must be measured not only among workers who accept a given contract, but also those who decline it. Most administrative data sources would be constrained to the former, as they would exclude workers who decline a firm's contract offer in favor of self-employment or a competing offer. In short, the nature of the information asymmetries makes it difficult to improve upon my existing design without sacrificing its most desirable features.

8 Conclusion

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.

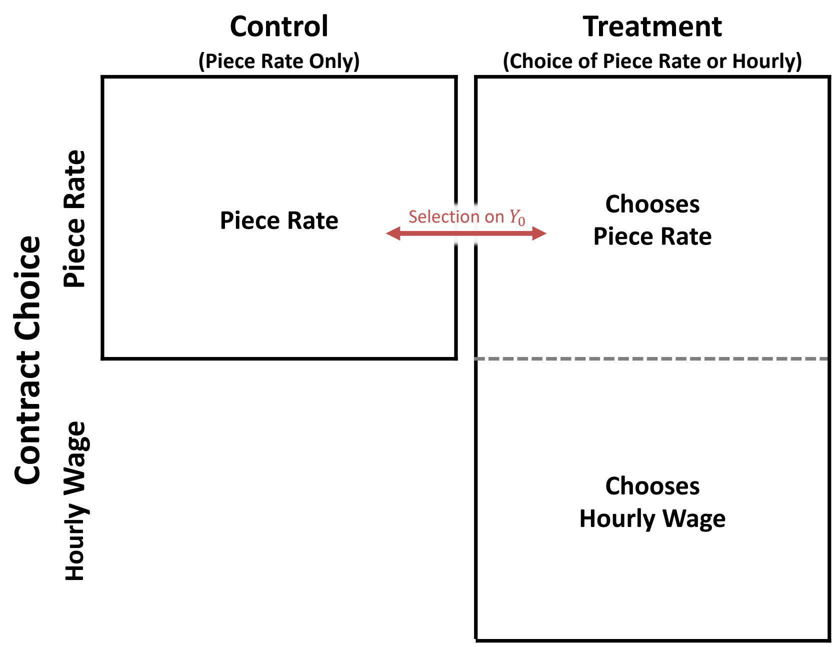
I place these experimental estimates into a theoretical framework that shows how the provision of hourly employment contracts is determined by two factors: a worker's reservation wage—the minimum compensation they will accept in exchange for an hour of labor—and the average output of workers with comparatively 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.

I find that hourly wage contracts reduce average worker output value by 6.32 percent. At the same time, I find evidence of adverse selection on productivity—a 10 percent increase in the hourly wage offer attracts a marginal worker with 1.44 percent higher productivity relative to the mean. I estimate the welfare loss associated with asymmetric information and calculate marginal values of public funds (MVPFs) across a range of hourly wage subsidies. My estimates imply a socially optimal hourly wage subsidy of $1.00 per hour or less, depending on the cost of public financing.

While this study advances our understanding of information asymmetries in labor contracts, my empirical results are limited to a specific task and population of workers. In reality, a vast number of labor markets are characterized by some degree of self-employment, freelance work, or piece-rate compensation. Future research might apply my framework to these settings. For example, asymmetric information might explain why a growing number of self-employed gig workers are compensated by the number of miles driven, pages written, or tasks completed (Garin et al., 2023; Collins et al., 2019; Katz and Krueger, 2019; Abraham et al., 2017; Jackson et al., 2017). It could also lead to welfare losses among salespeople, barbers, or restaurant servers—occupations in which, rather than clocking their hours, workers derive most of them earnings from selling their labor product directly to an employer or customer. In fact, any job with some dimension of unobserved effort or productivity is subject to the forces of adverse selection and moral hazard. Gaining better knowledge of potential market failures in these settings could meaningfully improve the lives of millions of workers.

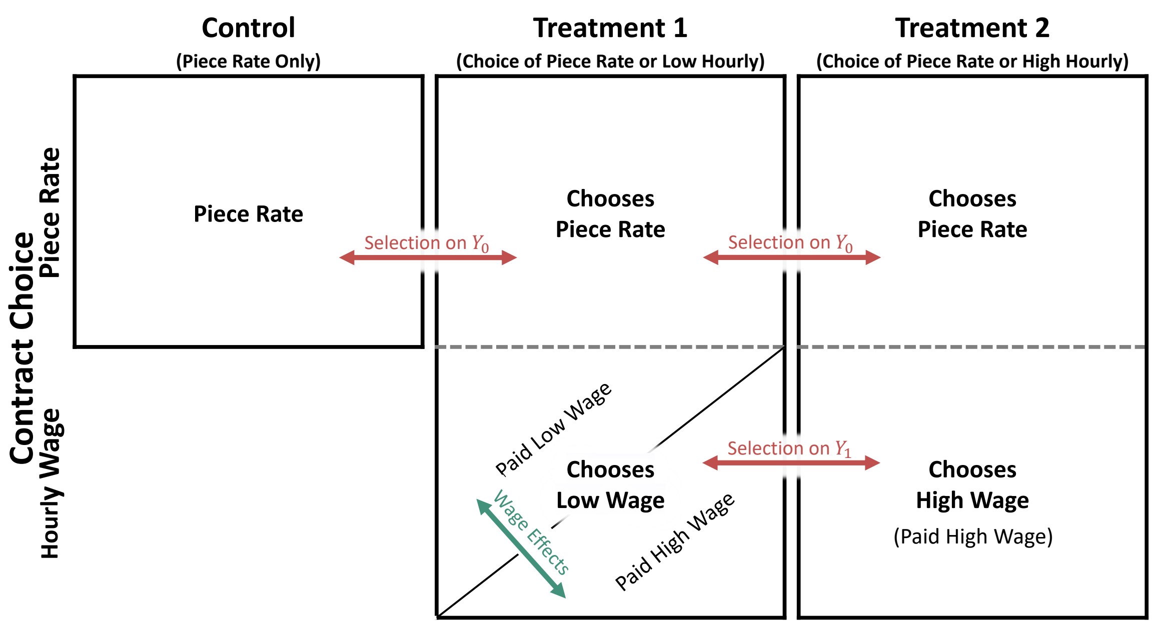
Figures and Tables

Figure 1: Experimental Design: Single Treatment



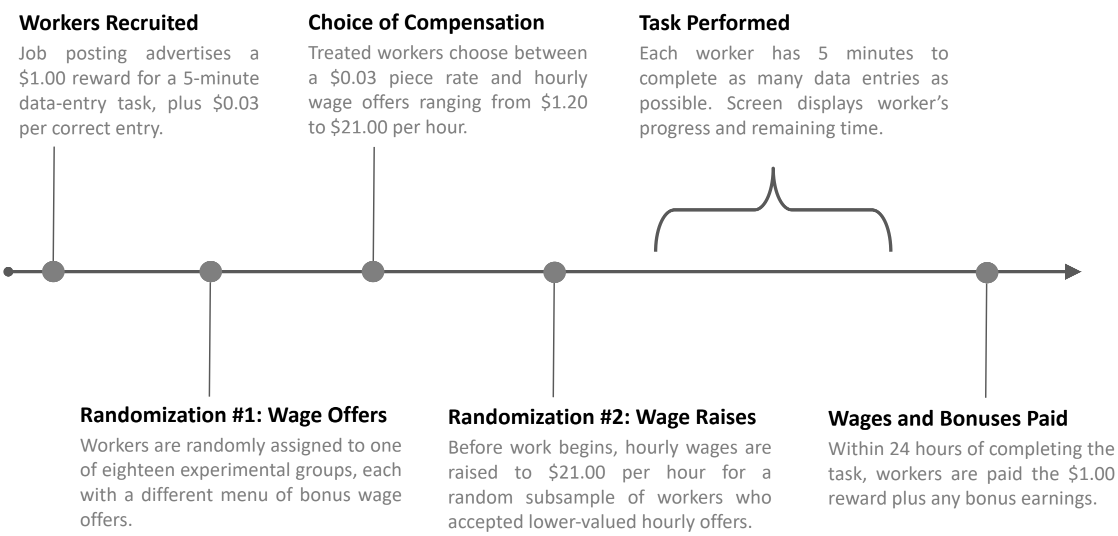
Note: This figure provides a graphical representation of a single-offer version of my experimental design. Columns denote experimental groups with different menus of wage options, and rows denote the realized wage contracts chosen by workers within each group. The control group, represented by the left column, is not offered an hourly wage option and is compensated 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



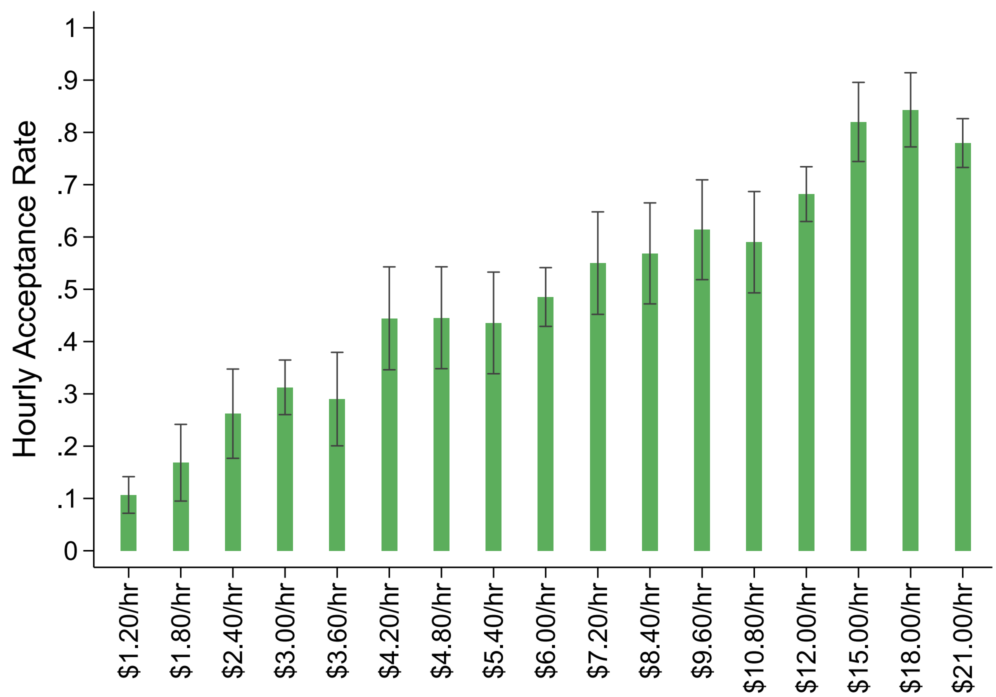
Note: This figure provides a graphical illustration of my two-stage experimental design with two treatment offers. Columns denote initial hourly wage offers, and rows denote the type of contract that workers choose. The diagonal split in the bottom box of Treatment 1 (low-wage offer) represents the second stage of randomization, in which some workers accepting the low hourly wage are promised the higher wage before they begin the task. Horizontal arrows denotes comparison groups to measure adverse selection—groups that were offered different menus of contracts but ultimately face the same repayment terms. The diagonal arrow denotes comparison groups to measure wage effects. The treatment effect of a hourly wages relative to piece rates (moral hazard) is identified by instrumenting for a given (paid) hourly wage with initial wage offers.

Figure 3: Experiment Timeline



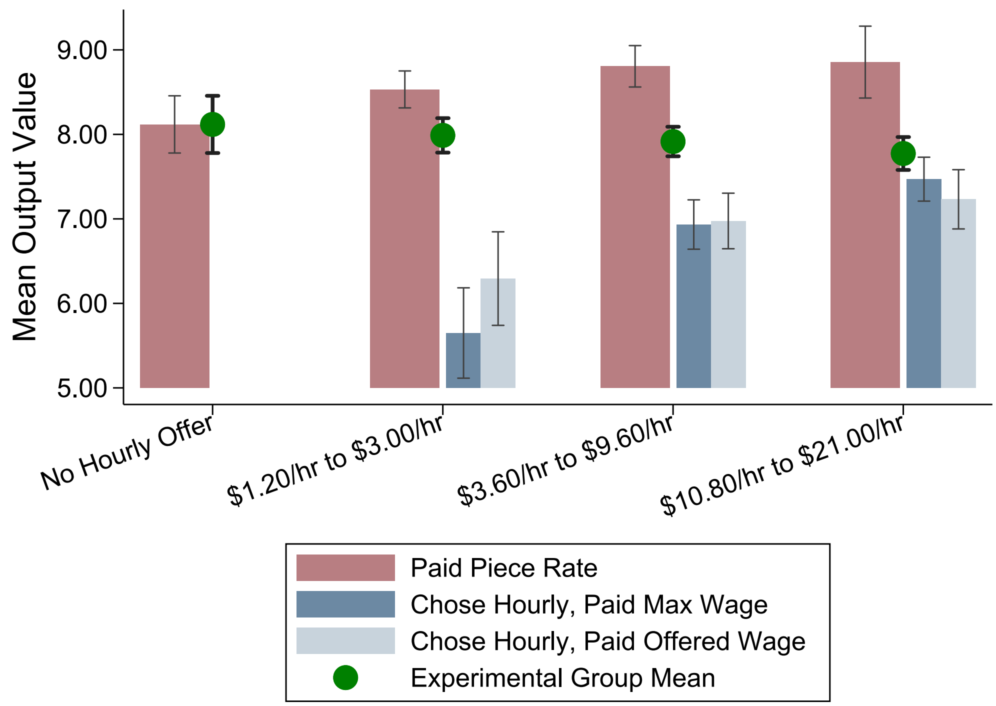
Note: This figure provides a timeline for a single wave of the experiment.

Figure 4: Hourly Wage Take-Up



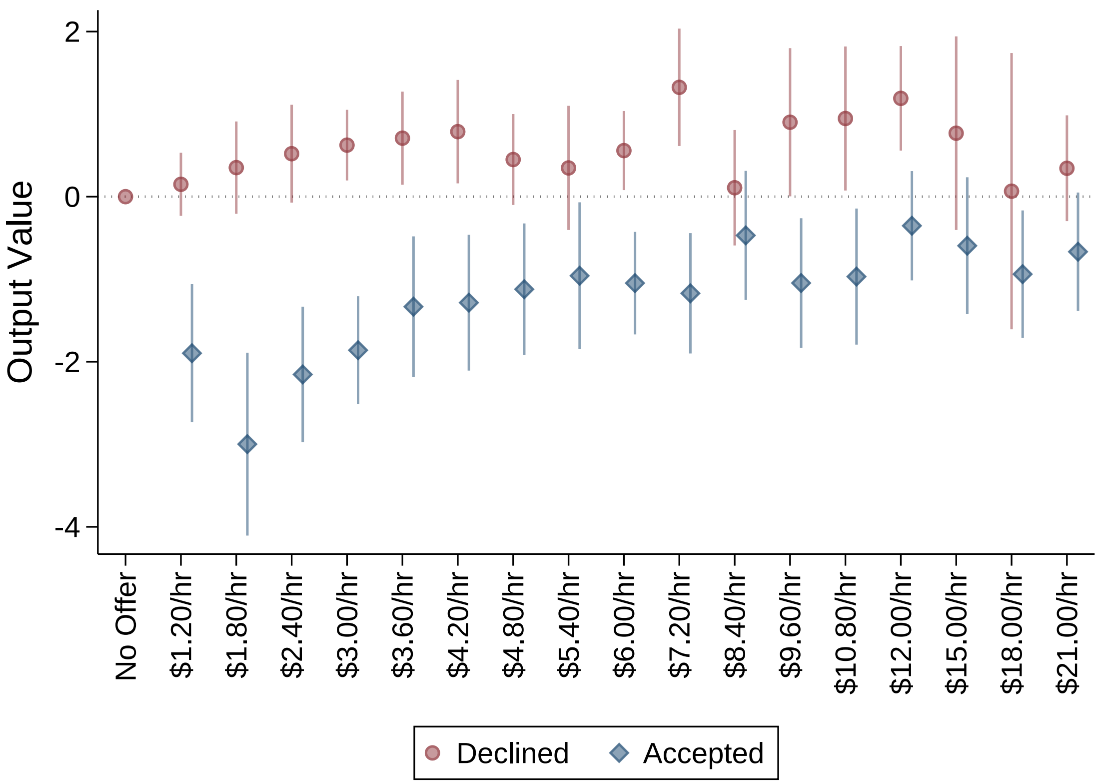
Note: This figure reports hourly-wage acceptance rates by treatment group. The y-axis measures the share of borrowers in each group who declined the $0.03 piece rate in favor of the hourly wage offer displayed on the x-axis. Note that both piece rate and hourly wage options are offered as supplements to a base wage of $12.00 per hour. Bands indicate 95% confidence intervals.

Figure 5: Worker Output Value by Treatment Offer and Acceptance Status



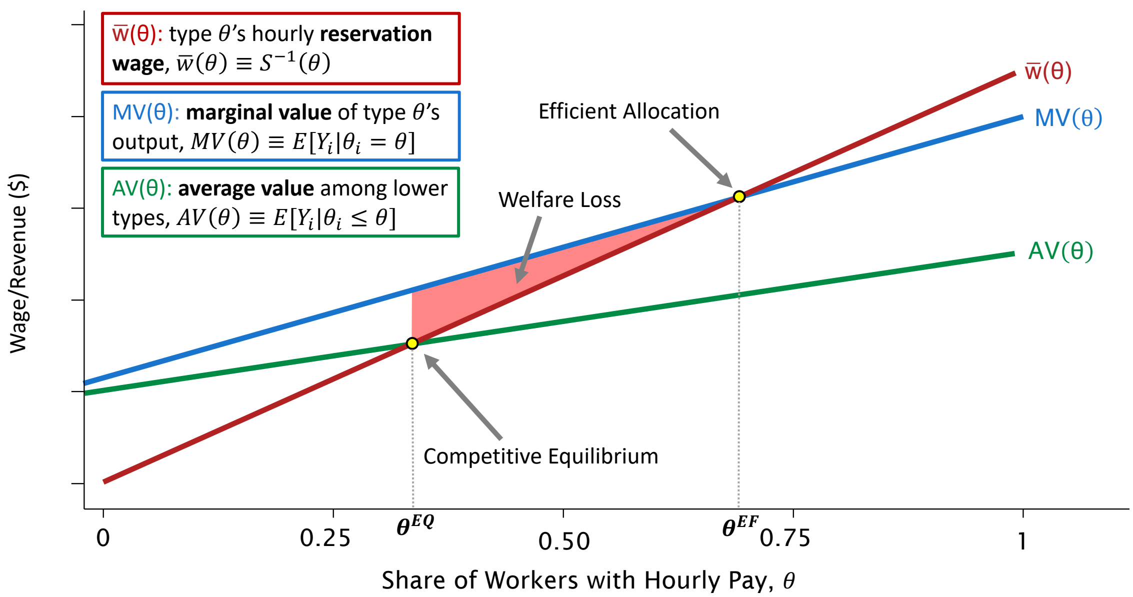
Note: This figure shows mean worker output value by wage-offer groups and compensation choice. "Output value" is defined as the number of typed sentences per hour multiplied by $0.03. Control and treatment groups are labeled on the x-axis. Green circles measure mean outcomes among all individuals in each group. Red bars measure mean output value among those who were paid the $0.03 piece rate. Dark blue bars measure mean output value among those who chose the hourly wage offer and received a randomized top-up above the offered rate, bringing their hourly wages to the $21.00 per hour maximum. Dark blue bars measure mean output value among those who chose the hourly wage offer and did not receive a top-up. Note that both piece rate and hourly wage options are offered as supplements to a base wage of $12.00 per hour. Bold and dotted bands indicate 95% confidence intervals for overall and hourly/piece-rate group means, respectively.

Figure 6: OLS Estimates of Selection on Output Value by Wage Offer



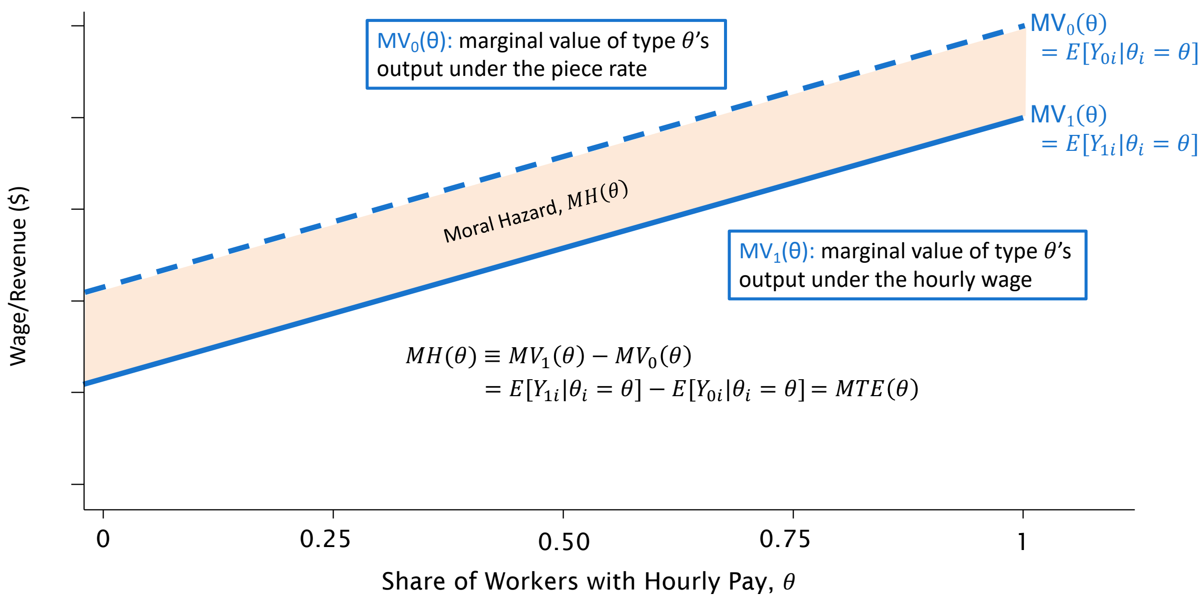
Note: This figure plots coefficients from an OLS regression of output value against the full set of dummy variables for each experimental wage offer, controlling for log effective wages among hourly workers (inclusive of top-ups) as well as task timing. Red dots represent coefficients on hourly wage offers interacted with an indicator for remaining on the piece rate. Blue diamonds represent coefficients on hourly wage offers interacted with an indicator for accepting the offer. Lines represent 95% confidence intervals.

Figure 7: Model of Asymmetric Information in Wage Contracts



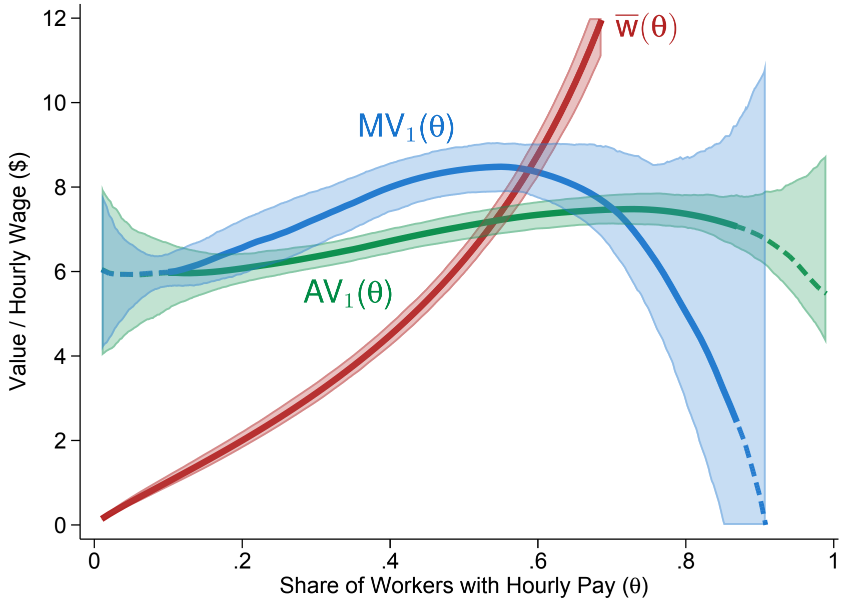
Note: This figure provides a graphical representation of market unraveling for hourly wages. On the horizontal axis, types θ are enumerated in ascending order based on their hourly reservation wage, $\overline{w}_i$. The blue line plots the marginal value curve, $MV(\theta)$, which is equal to expected worker output value conditional on their type, $MV(\theta) \equiv E[Y_i|\theta_i = \theta]$. The red line plots hourly reservation wage, $\overline{w}(\theta)$, which equals the inverse of labor supply, $\overline{w}(\theta) \equiv S^{-1}(\theta)$. The green line plots the average value curve, $AV(\theta)$, which corresponds to the average expected output among lower-type workers, $AV(\theta) \equiv E[Y_i|\theta_i \leq \theta]$.

Figure 8: Model of Asymmetric Information in Wage Contracts: Moral Hazard Effects

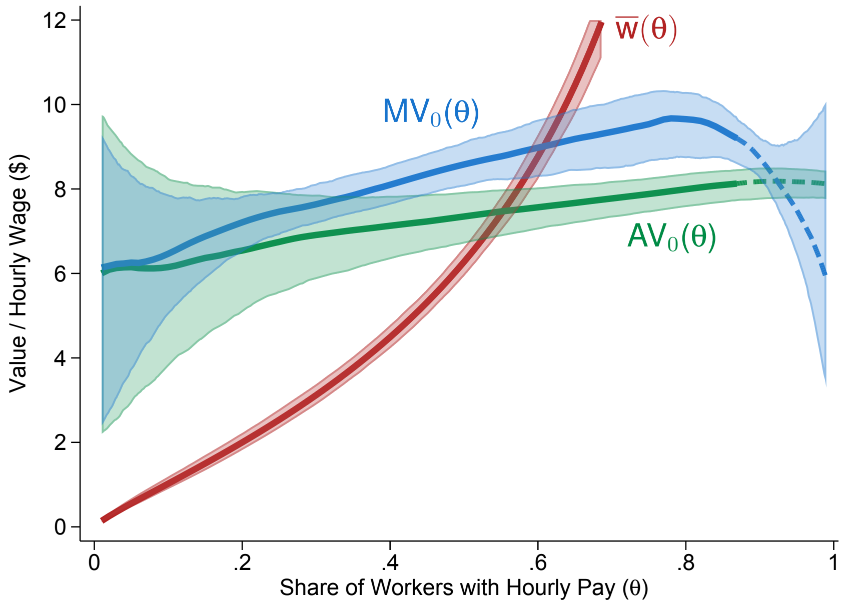


Note: This figure provides a graphical representation of moral hazard in my model. On the horizontal axis, types θ are enumerated in ascending order based on their hourly reservation wage, $\overline{w}_i$. The solid blue line plots $MV_1(\theta)$, which is equal to the expected output value among workers of type θ under the hourly wage, $MV_1(\theta) \equiv E[Y_{1i}|\theta_i = \theta]$. The shaded blue line plots $MV_0(\theta)$, which is equal to the expected output value among the same workers if they were instead paid a piece rate, $MV_0(\theta)\, E[Y_{0i}|\theta_i = \theta]$. The difference between the two marginal value curves identifies the moral hazard effect for a given type, $MH(\theta) \equiv MV_1(\theta) - MV_0(\theta)$, which is equivalent to the marginal treatment effect of the hourly contract among those whose resistance to treatment (quantile reservation wage, $\theta_i \equiv S(\overline{w}_i)$) is equal to the propensity score (share of hourly workers, $\theta = S(w)$) for their assigned instrument (wage offer, w_i).

Figure 9: Estimates of Marginal and Average Value Curves



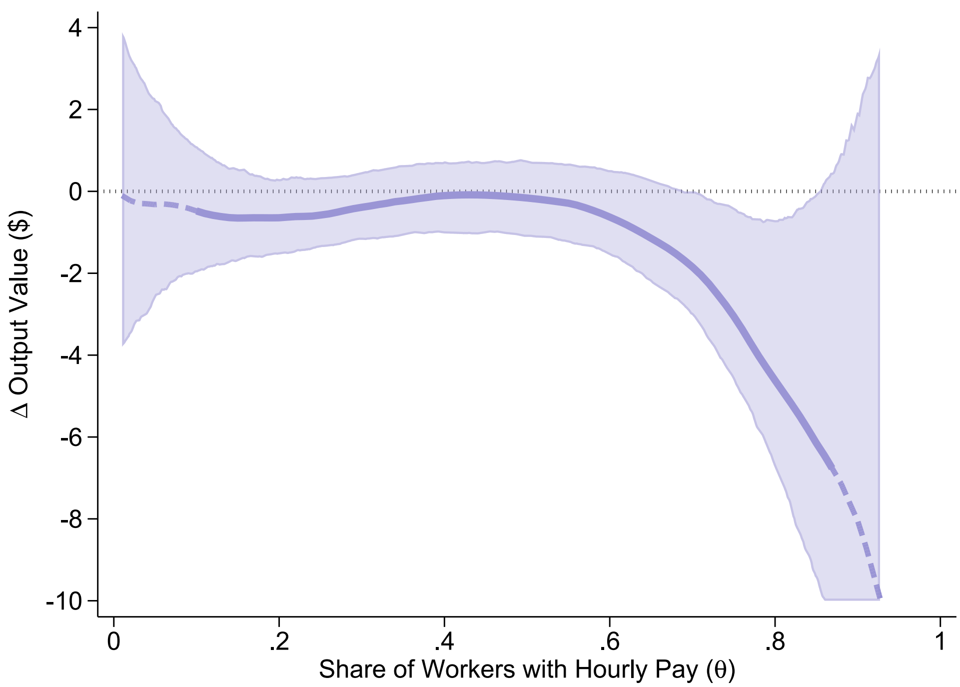
(A) Potential Value Under Hourly Wage



(B) Potential Value Under Piece Rate

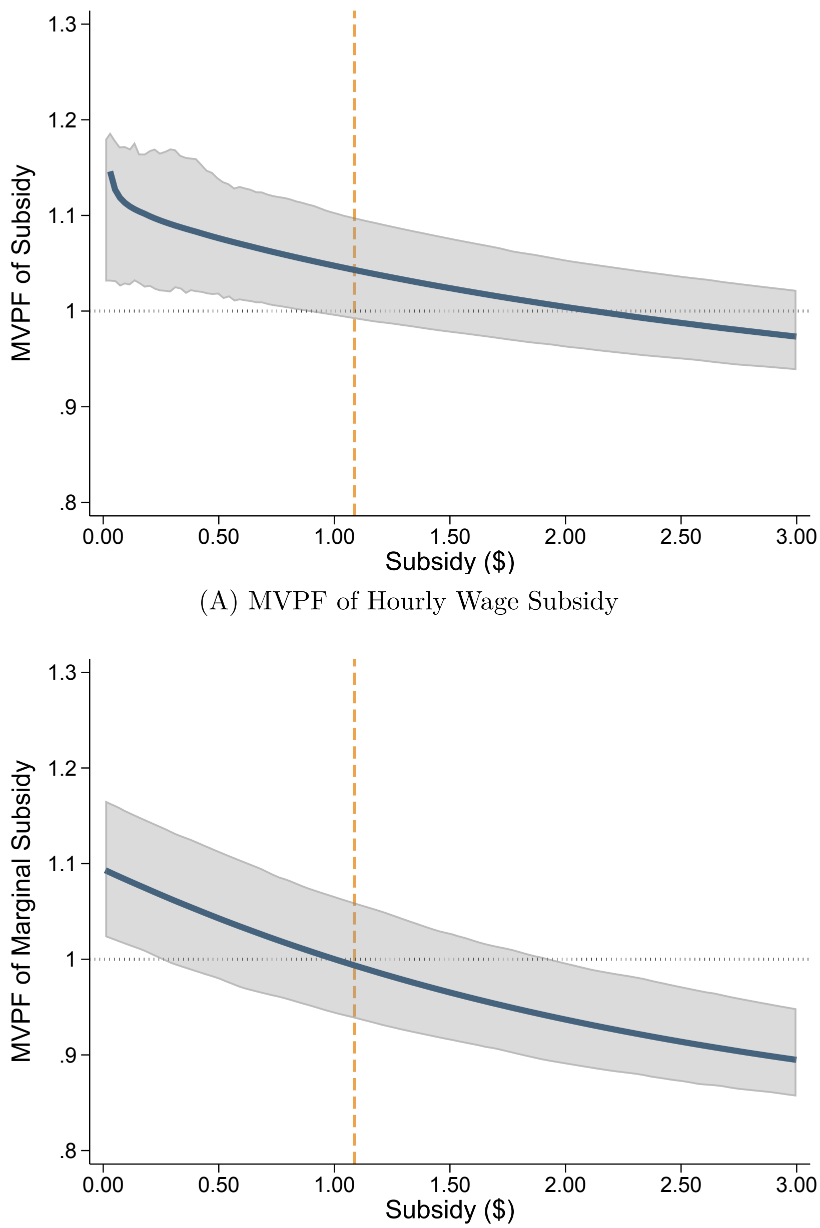
Note: This figure plots estimates supply and value curves, where output values reflect the number of typed sentences multiplied by the piece rate. In the left panel, the blue and green lines plot semiparametric estimates of the marginal value, $MV_1(\theta)$, and average value $AV_1(\theta)$, under hourly wages, as defined in Figure 7. In the left panel, blue and green lines plot these same curves ($MV_0(\theta)$ and $AV_0(\theta)$) under a piece-rate counterfactual. In both panels, the red line plots estimated hourly supply curve from a logit regression of hourly take-up against experimental wage offers. Value curves are estimated using a second-degree local polynomial regression of residualized hourly output value against predicted hourly supply. Dashed portions of each line represent regions outside the support of observed propensity scores over which local polynomials were extrapolated. Shaded regions represent 90% confidence intervals.

Figure 10: Estimates of Marginal Treatment Effects (Moral Hazard)



Note: This figure plots estimated marginal treatment effects of hourly wages on worker output value. Estimates are obtained using local polynomial regressions of worker output value against propensity score (i.e. hourly supply share), as described in Section 5. Solid lines denote $MH(\theta) \equiv MV_1(\theta) - MV_0(\theta)$—the difference in the marginal worker's potential output value under an hourly wage versus the piece rate. The left panel measures output value using the total number of sentences multiplied by the piece rate. The right panel uses *correctly* typed sentences multiplied by the piece rate. Value curves are estimated using a second-degree local polynomial regression of residualized hourly output value against predicted hourly supply. Dashed portions of each line represent regions outside the support of observed propensity scores over which local polynomials were extrapolated. Shaded regions represent 90% confidence intervals.

Figure 11: Estimates of MVPF by Hourly Wage Subsidy



(A) MVPF of Hourly Wage Subsidy

(B) MVPF of Marginal Increase in Hourly Wage Subsidy

Note: This figure plots estimated marginal value of public funds (MVPF) for hourly wage subsidies. In Panel A, the vertical axis plots estimated MVPFs associated with hypothetical hourly wage subsidies (in dollars per hour worked) denoted on the horizontal axis. In Panel B, the vertical axis plots estimated MVPFs associated with a marginal increase to the hourly wage subsidies on the horizontal axis. The vertical line denotes the subsidy that achieves the "efficient" hourly supply share found in an full-information equilibrium. MVPFs are constructed using marginal value and supply curve estimates applied to Equation (29) in the text. Shaded regions represent 90% confidence intervals.

Table 1: Experimental Group Assignment

Hourly Wage Offer	Piece-Rate Offer	Number of Participants
No Hourly Offer	\$0.03 per sentence	302
\$1.20/hr	\$0.03 per sentence	300
\$1.80/hr	\$0.03 per sentence	101
\$2.40/hr	\$0.03 per sentence	103
\$3.00/hr	\$0.03 per sentence	304
\$3.60/hr	\$0.03 per sentence	100
\$4.20/hr	\$0.03 per sentence	99
\$4.80/hr	\$0.03 per sentence	101
\$5.40/hr	\$0.03 per sentence	101
\$6.00/hr	\$0.03 per sentence	305
\$7.20/hr	\$0.03 per sentence	100
\$8.40/hr	\$0.03 per sentence	102
\$9.60/hr	\$0.03 per sentence	101
\$10.80/hr	\$0.03 per sentence	100
\$12.00/hr	\$0.03 per sentence	305
\$15.00/hr	\$0.03 per sentence	100
\$18.00/hr	\$0.03 per sentence	102
\$21.00/hr	\$0.03 per sentence	304
		Total: 3030

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 fixed-rate compensation offered to participants for the 5-minute task, prorated to one hour. Note that both piece rate and hourly wage options are offered as supplements to a base wage of \$12.00 per hour.

Table 2: Summary Statistics

Category	Variable	Mean	SD
Panel A: Task Performance	Accepted Hourly Offer	0.438	0.496
	Completed Sentences	21.98	8.148
	Correct Sentences	17.79	9.360
	Output Value	7.912	2.933
	Finished	0.986	0.118
Panel B: Demographics & Employment	Age	37.23	12.18
	Female	0.643	0.479
	Minority	0.357	0.479
	Employed	0.685	0.465
	Student	0.187	0.390
	Number of Previous Tasks	1281.6	1746.4

Note: This table reports summary statistics for the experimental sample. Panel A reports statistics on variables related to experimental task performance and experience. Panel B reports demographic information.

Table 3: Logit Estimates of Hourly Supply

	(1) Accepted Offer	(2) Accepted Offer	(3) Accepted Offer	(4) Accepted Offer
Log Hourly Wage Offer	1.198***	1.202***	1.212***	1.245***
	(0.0554)	(0.0554)	(0.0560)	(0.0578)
Number of Previous Tasks/1000			0.0138	−0.00295
			(0.0252)	(0.0261)
Age				0.0291***
				(0.00427)
Female				0.282***
				(0.0956)
Task Controls	No	Yes	Yes	Yes
Employment Controls	No	No	Yes	Yes
Demographic Controls	No	No	No	Yes
N	2728	2728	2728	2728

Note: This table reports estimated coefficients from logistic regressions of hourly contract acceptance against log wage offers, excluding control-group workers who were only offered a piece rate. Task controls include indicators for experimental wave and start time. Employment controls include unemployment and not-in-labor-force indicators, student enrollment status, and number of previous tasks completed on Prolific. Demographic controls include race, gender, and age. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 4: OLS Estimates of Selection on Output Value by Wage Offer

	(1) Output Value	(2) Output Value	(3) Output Value	(4) Output Value
Accepted Hourly Offer	-2.598^{***}	-2.481^{***}	-2.439^{***}	-2.256^{***}
	(0.329)	(0.319)	(0.320)	(0.300)
Declined × Log Hourly Wage Offer	0.167^{*}	0.193^{**}	0.210^{**}	0.230^{***}
	(0.0960)	(0.0932)	(0.0925)	(0.0855)
Accepted × Log Hourly Wage Offer	0.621^{***}	0.570^{***}	0.568^{***}	0.501^{***}
	(0.116)	(0.112)	(0.113)	(0.104)
Accepted × Log Effective Hourly Wage	-0.0608	-0.0443	-0.0444	-0.0000829
	(0.122)	(0.118)	(0.118)	(0.110)
Number of Previous Tasks/1000			0.166^{***}	0.173^{***}
			(0.0325)	(0.0309)
Age				-0.0454^{***}
				(0.00402)
Female				0.435^{***}
				(0.105)
Task Controls	No	Yes	Yes	Yes
Employment Controls	No	No	Yes	Yes
Demographic Controls	No	No	No	Yes
R-squared	0.082	0.123	0.139	0.273
N	3030	3030	3030	3030

Note: This table reports estimated coefficients from OLS regressions of output value (sentences × \$0.03) against hourly wage offers interacted with acceptance status, adjusting for log effective wages among hourly workers. The coefficient on "Declined × Log Hourly Wage Offer" captures the change in log output value among piece-rate workers for each unit increase in their log hourly wage offer. The coefficient on "Accepted × Log Hourly Wage Offer" captures the change in log output value among hourly workers for each unit increase in their log hourly wage offer. The coefficient on "Accepted × Log Effective Hourly Wage" captures the change in log output value hourly workers for each unit increase in the log hourly wage they are *paid*, conditional on the wage they are *offered*. Task controls include indicators for experimental wave and start time. Employment controls include unemployment and not-in-labor-force indicators, student enrollment status, and number of previous tasks completed on Prolific. Demographic controls include race, gender, and age. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 5: 2SLS Estimates of Treatment Effects of Hourly Wages on Output Value

	(1) Output Value	(2) Output Value	(3) Output Value	(4) Output Value
Accepted Hourly Offer	-0.506^{**}	-0.500^{**}	-0.488^{**}	-0.365^{**}
	(0.206)	(0.200)	(0.200)	(0.185)
Number of Previous Tasks/1000			0.164^{***}	0.174^{***}
			(0.0338)	(0.0322)
Age				-0.0527^{***}
				(0.00420)
Female				0.365^{***}
				(0.108)
Task Controls	No	Yes	Yes	Yes
Employment Controls	No	No	Yes	Yes
Demographic Controls	No	No	No	Yes
R-squared	0.037	0.080	0.096	0.232
N	3030	3030	3030	3030

Note: This table reports estimated coefficients from two-stage least-squares regressions of residual output value against an indicator for accepting an hourly wage offer. I partial-out wage effects by regressing output value against treatment offers and log effective hourly wages among hourly workers, then subtracting the demeaned wage effect implied by the coefficient on log effective hourly wages. I then instrument for hourly wage take-up with dummy variables for each treatment offer in a two-stage least-squares regression. Task controls include indicators for experimental wave and start time. Employment controls include unemployment and not-in-labor-force indicators, student enrollment status, and number of previous tasks completed on Prolific. Demographic controls include race, gender, and age. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 6: 2SLS Estimates of Treatment Effects of Hourly Wages on Quality-Adjusted Output Value

	(1) Output Value (Quality Adj.)	(2) Output Value (Quality Adj.)	(3) Output Value (Quality Adj.)	(4) Output Value (Quality Adj.)
Accepted Hourly Offer	-0.862^{***}	-0.856^{***}	-0.854^{***}	-0.739^{***}
	(0.232)	(0.227)	(0.225)	(0.214)
Number of Previous Tasks/1000			0.211^{***}	0.212^{***}
			(0.0365)	(0.0356)
Age				-0.0423^{***}
				(0.00483)
Female				0.251^{**}
				(0.125)
Task Controls	No	Yes	Yes	Yes
Employment Controls	No	No	Yes	Yes
Demographic Controls	No	No	No	Yes
R-squared	0.048	0.081	0.095	0.180
N	3030	3030	3030	3030

Note: This table reports estimated coefficients from two-stage least-squares regressions of residual quality-adjusted output value against an indicator for accepting an hourly wage offer. I partial-out wage effects by regressing quality-adjusted output value against treatment offers and log effective hourly wages among hourly workers, then subtracting the demeaned wage effect implied by the coefficient on log effective hourly wages. I then instrument for hourly wage take-up with dummy variables for each treatment offer in a two-stage least-squares regression. Task controls include indicators for experimental wave and start time. Employment controls include unemployment and not-in-labor-force indicators, student enrollment status, and number of previous tasks completed on Prolific. Demographic controls include race, gender, and age. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

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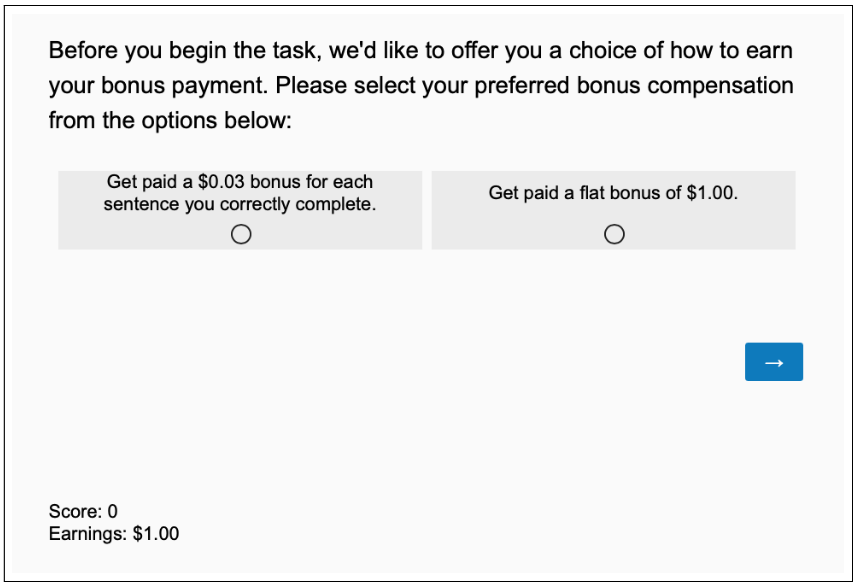
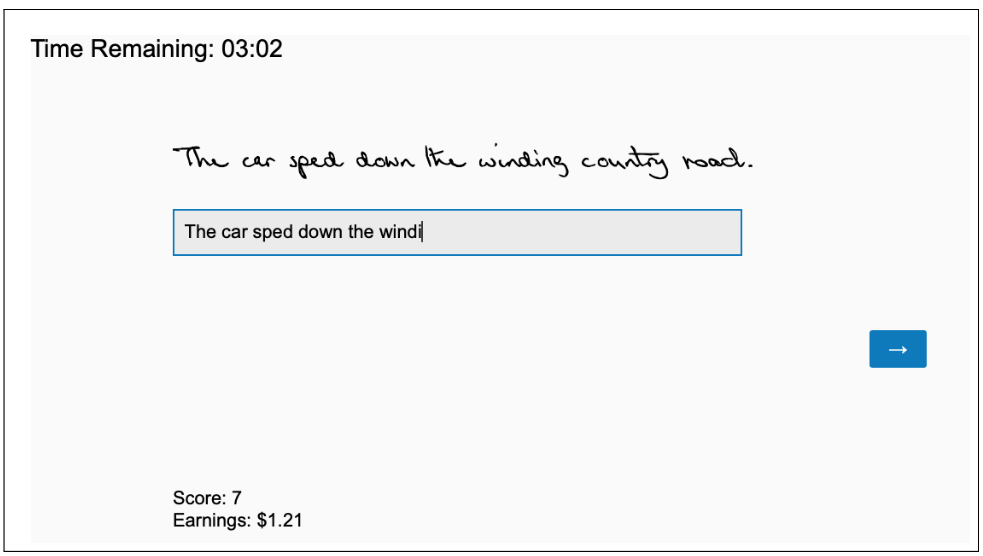
Appendix A Additional Figures and Tables

Figure A1: Example Job Posting



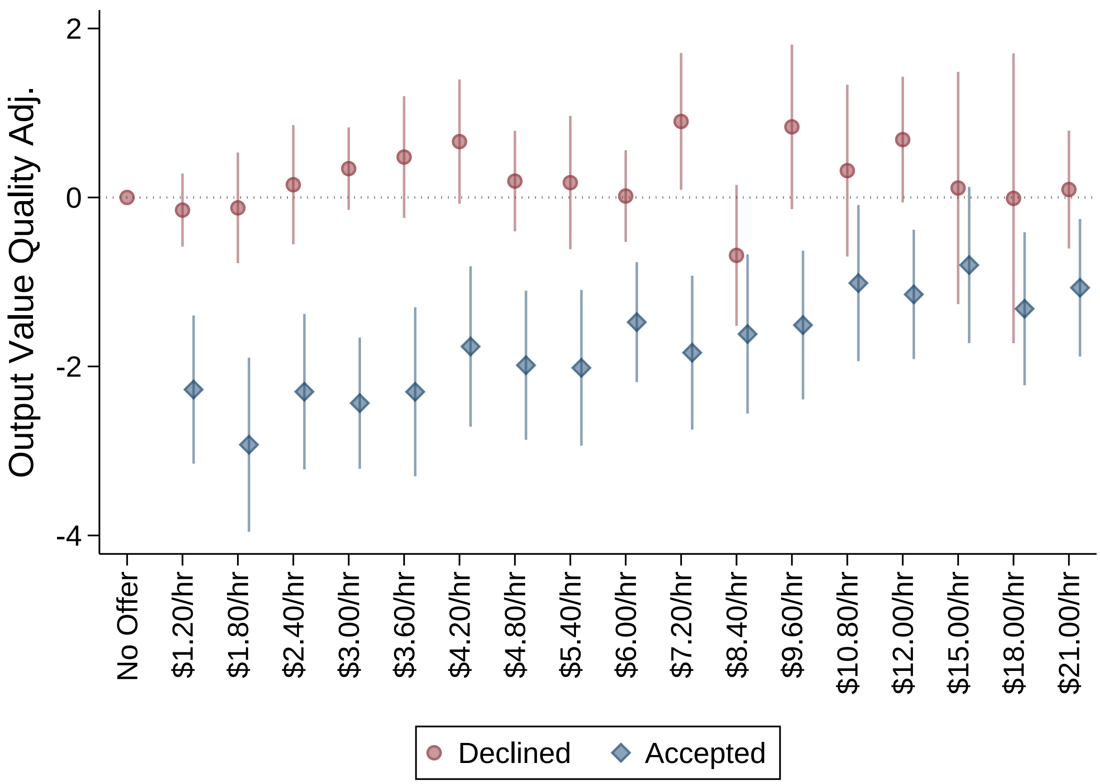
(A) Example Wage Offer



(B) Typing Task

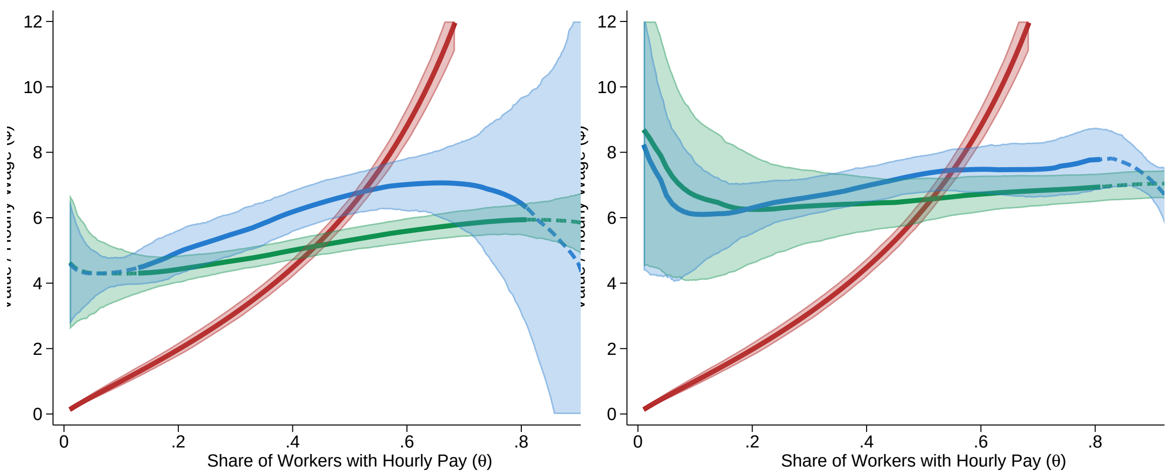
Note: This figure provides screenshots of the experimental intervention. Panel A shows an example wage offer participants see before they begin the task. Panel B shows the sentence-typing task while it is being performed.

Figure A2: OLS Estimates of Selection on Quality-Adjusted Output Value by Wage Offer



Note: This figure plots coefficients from an OLS regression of quality-adjusted output value against the full set of dummy variables for each experimental wage offer, controlling for log effective wages among hourly workers (inclusive of top-ups) as well as task experience and demographic characteristics. Red dots represent coefficients on hourly wage offers interacted with an indicator for remaining on the piece rate. Blue diamonds represent coefficients on hourly wage offers interacted with an indicator for accepting the offer. Lines represent 95% confidence intervals.

Figure A3: Estimates of Marginal and Average Value Curves: Quality Adjusted Output



(A) Potential Value Under Hourly Wage

(B) Potential Value Under Piece Rate

Note: This figure plots estimates supply and value curves, where output values reflect the number of *correctly* typed sentences multiplied by the piece rate. In the left panel, the blue and green lines plot semiparametric estimates of the marginal value, $MV_1(\theta)$, and average value $AV_1(\theta)$, under hourly wages, as defined in Figure 7. In the left panel, blue and green lines plot these same curves ($MV_0(\theta)$ and $AV_0(\theta)$) under a piece-rate counterfactual. In both panels, the red line plots estimated hourly supply curve from a logit regression of hourly take-up against experimental wage offers. Value curves are estimated using a second-degree local polynomial regression of residualized hourly output value against predicted hourly supply. Dashed portions of each line represent regions outside the support of observed propensity scores over which local polynomials were extrapolated. Shaded regions represent 90% confidence intervals.

Table A1: Balance Test

	(1) Experimental Wage Offer	(2) Output Value
Number of Previous Tasks/1000	-0.0478	0.191^{***}
	(0.0343)	(0.0305)
Age	0.00141	-0.0683^{***}
	(0.00529)	(0.00453)
Female	0.0909	0.366^{***}
	(0.124)	(0.108)
Minority	-0.0528	-0.896^{***}
	(0.125)	(0.109)
Employed	-0.202	0.142
	(0.138)	(0.121)
Student	0.0685	-0.474^{***}
	(0.169)	(0.149)
F-statistic	1.019	36.492
p-value	0.426	0.000
N	3030	3030

Note: This tables reports results from a test of balanced treatment for experimental hourly wage offers. Column 1 reports estimated coefficients from an OLS regression of hourly wage offers against the baseline demographic variables reported in the leftmost column. Column 2 reports estimated coefficients from the same specification, but with output value as the dependent variable. The bottom rows report F-statistics and p-values from a test of joint significance for all right-hand side variables.

Table A2: OLS Estimates of Selection on Quality-Adjusted Output Value by Wage Offer

	(1) Output Value (Quality Adj.)	(2) Output Value (Quality Adj.)	(3) Output Value (Quality Adj.)	(4) Output Value (Quality Adj.)
Accepted Hourly Offer	-2.947^{***}	-2.816^{***}	-2.782^{***}	-2.626^{***}
	(0.371)	(0.368)	(0.370)	(0.357)
Declined × Log Hourly Wage Offer	0.125	0.152	0.166	0.186^{*}
	(0.110)	(0.108)	(0.107)	(0.103)
Accepted × Log Hourly Wage Offer	0.663^{***}	0.611^{***}	0.612^{***}	0.564^{***}
	(0.131)	(0.127)	(0.127)	(0.124)
Accepted × Log Effective Hourly Wage	−0.0220	−0.00982	−0.0156	0.0168
	(0.137)	(0.135)	(0.135)	(0.132)
Number of Previous Tasks/1000			0.214^{***}	0.212^{***}
			(0.0356)	(0.0348)
Age				-0.0361^{***}
				(0.00477)
Female				0.307^{**}
				(0.123)
Task Controls	No	Yes	Yes	Yes
Employment Controls	No	No	Yes	Yes
Demographic Controls	No	No	No	Yes
R-squared	0.072	0.105	0.118	0.203
N	3030	3030	3030	3030

Note: This table reports estimated coefficients from OLS regressions of quality-adjusted output value (correct 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 "Log Hourly Wage Offer" captures the change in log output value among piece-rate workers for each unit increase in their log hourly wage offer. Task controls include indicators for experimental wave and start time. Employment controls include unemployment and not-in-labor-force indicators, student enrollment status, and number of previous tasks completed on Prolific. Demographic controls include race, gender, and age. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix B Mathematical Appendix

B.1 Identification of Wage Effects

Consider an individual i who receives a job offer, W_i, at one of two randomized wages: a high offer ($W_i = H$) or a low offer ($W_i = L$). Let D_{Wi} denote the individual's potential acceptance of a offer W, so that $D_{Hi} = 1$ if i would accept the high offer and $D_{Li} = 1$ if i would accept the low offer. Furthermore, let Y_{Hi} and Y_{Li} denote the potential output levels produced by i if they were paid hourly wages of H and L, respectively. Note that if realized wages reflected accepted offers, comparing output between those who accept H and those who accept L would yield the following:

$$
\begin{aligned}
&E\left[Y_i|W_i = H, D_i = 1\right] - E\left[Y_i|W_i = L, D_i = 1\right] \\
&= \underbrace{E\left[Y_{Hi} - Y_{Li}|D_{Li} = 1\right]}_{\text{Wage Effect}} + \underbrace{E\left[Y_{Hi}|D_{Hi} = 1\right] - E\left[Y_{Hi}|D_{Li} = 1\right]}_{\text{Selection}}. \qquad (32)
\end{aligned}
$$

This difference is the sum of both the wage effect and selection of H relative to L, which cannot be separated without observing $E\left[Y_{Hi}|D_{Li} = 1\right]$.

Now let W_i^P be an indicator whether individual i receives a surprise wage increase of $\Delta = H - L$ after accepting their contract. W_i^P is randomly assigned among those who received low offers ($W_i = L$) and accepted them ($D_{Li} = 1$) but is zero for everyone else. With this randomized wage raise, I can estimate wage effects by comparing output between low- and high-wage workers in the low-offer group:

$$
\begin{aligned}
\text{Wage Effect} &= E\left[Y_i|W_i = L, D_i = 1, W_i^P = 1\right] - E\left[Y_i|W_i = L, D_i = 1, W_i^P = 0\right] \\
&= E\left[Y_{Hi} - Y_{Li}|D_{Li} = 1\right] \qquad (33)
\end{aligned}
$$

And I can estimate selection by comparing output between low- and high-offer groups with high realized wages:

$$\begin{aligned}\text{Selection} &= E\left[Y_i|W_i=H, D_{Hi}=1\right] - E\left[Y_i|W_i=L, D_{Li}=1, W_i^P=1\right] \\ &= E\left[Y_{Hi}|D_{Hi}=1\right] - E\left[Y_{Hi}|D_{Li}=1\right]. \qquad (34)\end{aligned}$$

B.2 Marginal Value in a Linear Model

Drawing from Equations (5) and (6), consider the average potential outcomes among workers who reject over L but accept offer H.

$$E\left[Y_{1i}|D_i^H=1, D_i^L=0\right] = \frac{\pi^H E\left[Y_i|D_i=1, W_i=H\right] - \pi^L E\left[Y_i|D_i=1, W_i=L\right]}{\pi^H-\pi^L} \qquad (35)$$

$$E\left[Y_{0i}|D_i^H=1, D_i^L=0\right] = \frac{\left(1-\pi^L\right) E\left[Y_i|D_i=0, W_i=L\right] - \left(1-\pi^H\right) E\left[Y_i|D_i=0, W_i=H\right]}{\pi^H-\pi^L} \qquad (36)$$

Let $\overline{w}_i$ denote the lowest offer individual i is willing to accept. Let $H=w$ and $L=w-\eta$ in Equations (35) and (36). The limits of $E\left[Y_{1i}|D_i^H=1, D_i^L=0\right]$ and $E\left[Y_{0i}|D_i^H=1, D_i^L=0\right]$ as $\eta \to 0$ can be written as

$$E\left[Y_{1i}|\overline{w}_i=w\right] = \frac{\partial\left(E\left[Y_i|D_i(w)=1\right]S(w)\right)}{\partial S(w)} \qquad (37)$$

$$E\left[Y_{0i}|\overline{w}_i=w\right] = -\frac{\partial\left(E\left[Y_i|D_i(w)=0\right]\left(1-S(w)\right)\right)}{\partial S(w)}. \qquad (38)$$

Now suppose both $E[Y|D_i(w)=1]$, $E[Y|D_i(w)=0]$, and $S(w)\equiv \Pr\left(\overline{w}_i \le w\right)$, are all linear in the wage offer, w:

$$S(w) = \alpha+\beta w \qquad (39)$$

$$E[Y_i|D_i(w)=1] = \gamma_1+\delta_1 w \qquad (40)$$

$$E[Y|D_i(w)=0] = \gamma_0+\delta_0 w. \qquad (41)$$

We therefore have

$$
\begin{aligned}
E\left[Y_{1i}|\overline{w}_i = w\right] &= \frac{(\gamma_1 + \delta_1 w)\beta + (\alpha + \beta w)\delta_1}{\beta} &(42)\\
&= \frac{\alpha\delta_1}{\beta} + \gamma_1 + 2\delta_1 w. &(43)
\end{aligned}
$$

Likewise for $E\left[Y_{0i}|\overline{w}_i = w\right]$:

$$
\begin{aligned}
E\left[Y_{0i}|\overline{w}_i = w\right] &= \frac{-(\gamma_0 + \delta_0 w)\beta + (1 - \alpha - \beta w)\delta_0}{-\beta} &(44)\\
&= \frac{(\alpha - 1)\delta_0}{\beta} + \gamma_0 + 2\delta_0 w. &(45)
\end{aligned}
$$

We therefore have

$$
\begin{aligned}
\frac{\partial E\left[Y_{1i}|\overline{w}_i = w\right]}{\partial w} &= 2\delta_1 &(46)\\
\frac{\partial E\left[Y_{0i}|\overline{w}_i = w\right]}{\partial w} &= 2\delta_0 &(47)
\end{aligned}
$$

B.3 Model with Wage Effects

The theoretical framework in Section 4 allows workers' expected output to vary between hourly versus piece-rate compensation. It does not, however, allow that output to vary with the wage level under an hourly contract. In other words, it ignores any potential wage effects that higher hourly compensation might have on worker output. While the absence of wage effects in my empirical results would seem to validate this assumption, I include a model with wage effects in this appendix for completeness.

I can incorporate wage effects into the model by allowing each worker's potential output under the hourly contract to vary with the wage (i.e., $Y_{1i} = Y_{1i}(w)$). With this added dimension to potential outcomes, I rewrite $AV_1(\theta)$ as the average value of output among lower types *at θ's reservation wage*:

$$AV_1^E(\theta) \equiv E\left[Y_{1i}(\overline{w}(\theta))|\theta_i \leq \theta\right]. \tag{48}$$

Assuming wage effects are weakly positive and non-decreasing in θ, the equilibrium condition is given by $\overline{w}(\theta^{EQ}) = AV_1^E\left(\theta^{EQ}\right)$. In this case, firms pay an hourly wage equal to the average value of accepting workers' output *under that wage*, $AV^E(\theta^{EQ})$. Relative to the benchmark model, positive wage effects will therefore push the average value curve upwards and increase the share of hourly contracts under asymmetric information.

Note, however, that the efficient equilibrium—the one that would exist in a full-information counterfactual—is also complicated by the presence of wage effects. A fully-informed firm may benefit from paying a worker above their reservation wage if their expected increase in output exceeds the wage premium (i.e., if $E\left[Y_{1i}(w) - Y_{1i}(\overline{w_i})|\theta_i = \theta\right] > w - \overline{w}(\theta)$ for some w).[27] I thus rewrite $MV_1(\theta)$ as the marginal value of type θ's output *at their profit-maximizing wage*, so

$$MV_1^E\left(\theta\right) \equiv E\left[Y_{1i}(w^*(\theta))|\theta_i = \theta\right], \tag{49}$$

where

$$w^*(\theta) \equiv \underset{w}{\operatorname{argmax}}\, E\left[Y_{1i}(w) - w|\theta_i = \theta\right]. \tag{50}$$

Note that allowing for wage effects means I can no longer interpret Equation 18 as the marginal treatment effect of hourly-contract take-up—if the wage level influences worker output independently of the hourly compensation structure, the wage-offer instrument no longer satisfies the exclusion restriction. The randomized wage raises in my experimental design eliminate this concern. By equalizing the paid wages of low-offer accepters with those of high-offer accepters, these surprise wage increases isolate variation in *offered* wages conditional on a given *effective* wage. I can therefore identify the marginal treatment effect of being paid a given hourly wage among those indifferent to a particular wage offer. I discuss this instrument validity and estimation of wage effects in Section 2.2.

[27] I avoid the term "efficiency wages," which refers to a class of models explaining unemployment as a general-equilibrium consequence of firms' strategic wage-setting behavior (Weiss, 2014; Krueger and Summers, 1988; Yellen, 1984). In many efficiency-wage models, above-market wages are driven not by causal effects of wages on productivity, but by worker selection, firms' monitoring ability, or turnover costs (Salop, 1979; Weiss, 1980).

B.4 Welfare Under Alternative Piece Rates

Let $\overline{w}(\theta;p)$ denote type θ's hourly reservation wage from Equation (10) when their outside option is selling their labor product, q, at a per-unit price, p. Given some distribution of potential output, $F_\theta(q)$, $\overline{w}(\theta;p)$ equals the certainty equivalent of type θ's earnings under the piece rate p, $\overline{w}(\theta;p) = u^{-1}\left(E\left[u(pq)|\theta\right]\right)$. Assuming preferences exhibit constant relative risk aversion,

$$\begin{aligned}
\overline{w}(\theta;p) &= u^{-1}\left(E\left[u(pq)|\theta\right]\right) && (51)\\
&= \left((1-\rho)E\left[\frac{(pq)^{1-\rho}}{1-\rho}|\theta\right]\right)^{\frac{1}{1-\rho}} && (52)\\
&= pu^{-1}\left(E\left[u(q)|\theta\right]\right) && (53)\\
&= p\overline{w}(\theta;1), && (54)
\end{aligned}$$

where ρ is the coefficient of relative risk aversion.

Now let $MV(\theta;p)$ denote the marginal value of type θ's labor product from Equation (11) when its sold at a per-unit price of p:

$$\begin{aligned}
MV(\theta;p) &\equiv E\left[pq_i|\theta_i=\theta\right] && (55)\\
&= pE\left[q_i|\theta_i=\theta\right] = pMV(\theta;1). && (56)
\end{aligned}$$

Equations (54) and (56) allow me to rewrite welfare loss from Equation (15) for a given piece-rate, p, as

$$\begin{aligned}
DWL(p) &= \int_{\theta_{EQ}}^{\theta_{EF}} \left(MV(\theta;p) - \overline{w}(\theta;p)\right) d\theta && (57)\\
&= \int_{\theta_{EQ}}^{\theta_{EF}} \left(pMV(\theta;1) - p\overline{w}(\theta;1)\right) d\theta && (58)\\
&= pDWL(1). && (59)
\end{aligned}$$

Equation (59) shows how welfare loss from the under provision of hourly wage contracts is proportional to the per-unit value of workers' labor product. Under CRRA utility, I can therefore divide DWL by p to express welfare loss *per dollar earned* under the piece rate.

Note that these counterfactual welfare calculations assume worker production does not respond to different piece rates. This assumption might be violated if a higher piece rate (p) induces greater effort, resulting in higher output (q). To the extent the returns from this higher output exceeds the worker's disutility of effort, this incentive effect would attenuate counterfactual welfare estimates towards those calculated under the experimental piece rate.