Insurance and Asymmetric Information in Wage Contracts: Evidence from an Online Experiment

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August 1, 2025

Abstract

For workers facing uncertain output, fixed-wage contracts provide implicit insurance compared to self-employment or performance-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 (MTE) framework. I apply this framework to a field experiment in which data-entry workers are offered a choice between a randomized fixed hourly wage and a 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 reduce 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. Using semi-parametric MTE estimation, I calculate the welfare loss associated with asymmetric information and the marginal values of public funds (MVPFs) for a range of wage-based subsidy and tax policies. My estimates suggest that a 14-percent tax on performance-based pay can efficiently raise government revenue by mitigating adverse selection into fixed-wage contracts.

Keywords: compensation structure, wage insurance, performance pay, adverse selection, moral hazard, information asymmetries, marginal treatment effects.

JEL Classifications: J33, J38, M52, D82.

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1 Introduction

Fixed-wage contracts can provide implicit insurance against earnings risk—an hourly 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 vulnerable to moral hazard and adverse selection—fixed wages might induce less effort or attract less productive workers than freelance hiring or piece-rate pay. These information asymmetry problems can distort equilibrium wages, leaving workers underinsured and over-reliant on risky compensation or self-employment. They may, for example, explain why rideshare drivers are paid by the mile, why restaurant servers rely on tips, or why trial attorneys' earnings depend on case outcomes. Whether through performance bonuses, freelance fees, or sales commissions, millions of workers are paid in ways that expose them to earnings risk. Could asymmetric information be to blame?

The distortionary effects of moral hazard and adverse selection in labor markets have important implications for a variety of policies. Hourly wage subsidies, taxes on bonuses or tips, employment classification rules, and even the minimum wage can mitigate the welfare costs of asymmetric information by promoting insurance-like contracts between workers and firms. However, designing these policies requires knowledge of their treatment and selection effects across a wide range of workers. For example, an optimal hourly wage subsidy must balance the insurance benefits it provides to the marginal fixed-wage worker with the distortionary costs of encouraging that worker to shirk. Moral hazard and adverse selection are inherent to this trade-off.

Identifying the welfare effects of moral hazard and adverse selection in wage contracts is challenging for several reasons. First, both forces can lead to lower observed productivity among fixed-wage workers compared to those with output-based pay, making them hard to distinguish without exogenous variation in wages. Even if wages are randomized, estimates could be biased by wage effects if higher pay induces greater effort among fixed-wage workers. Second, the choice sets faced by workers in competitive labor markets usually exclude

the margins of selection most relevant to detecting information asymmetries. Wage contracts threatened by adverse selection may be too unprofitable for employers to offer and thus impossible to observe—a phenomenon known as market unraveling (Akerlof, 1970). Relatedly, wage contracts that *are* profitable are likely offered by multiple existing employers; estimates that rely on contract decisions from workers facing these competing outside options will likely understate the insurance value of fixed wages and overstate the elasticity of fixed-wage labor supply (Dube et al., 2020). Finally, because the welfare consequences of asymmetric information require market-wide estimates of treatment and selection, studies of workers under existing employment contracts are likely to understate the effects of information asymmetries. For example, a sample of fixed-wage employees at one or more firms would exclude high-productivity workers who avoided hourly jobs in favor of self-employment or freelance work—the very workers needed to identify adverse selection.

In this paper, I experimentally estimate the equilibrium and welfare effects of moral hazard and adverse selection in fixed-wage contracts. To identify these forces, I conduct an online field experiment with two stages of randomization: First, I offer workers a choice between a randomized fixed 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 the highest offered wage. Using the initial wage offer as an instrument for accepting an hourly contract allows me to identify the moral hazard effect of fixed-wage compensation. Meanwhile, comparing output across workers on the same contract who faced different ex ante offers identifies adverse selection. Importantly, the randomized wage top-ups in the second stage of the experiment ensure that these estimates are independent of any wage effects on worker effort.

Results from my experiment provide evidence of both moral hazard and adverse selection into fixed-wage contracts. Two-stage least-squares estimates of treatment effects imply that working under hourly pay reduces workers' output value by 6.32 percent relative to the mean. At the same time, comparisons between offered wages provide 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. Meanwhile, I find no evidence of wage effects—among workers who accepted hourly contracts, those who worked under their advertised wage perform statistically the same as those whose effective wage had been randomly increased prior to working on the task.

To investigate the welfare implications of these findings, I develop a model of labor markets in which workers can sort on both potential productivity and propensity to shirk, allowing for alternative forces like monitoring costs to influence compensation structure. Much like canonical models of insurance markets (Einav et al., 2010a; Akerlof, 1970), my framework shows how the provision of fixed-wage employment contracts is determined by two curves: a worker's hourly reservation wage—the minimum payment they will accept for an hour of labor—and the average value of output among workers with lower reservation wages than their own. An hourly worker cannot be profitably hired if their reservation wage exceeds the average output value of lower-reservation-wage workers. 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 estimate this welfare loss from asymmetric information, I show how equilibrium and efficient allocations of hourly work 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. In a marginal treatment effects (MTE) framework where the hourly supply share corresponds to the propensity score of the wage-offer instrument, these marginal values are equivalent to potential outcomes in treated and untreated states. This equivalence allows me to flexibly estimate the components of my model using semi-parametric methods from the MTE literature (Björklund and Moffitt, 1987; Heckman and Vytlacil, 1999, 2005, 2007). Employing a local polynomial regression approach (Carneiro et al., 2011), I find that 61

percent of workers in my sample would pay a premium for fixed-wage contracts over piece-rate pay. This share reflects the efficient allocation that would exist if employers were fully informed of workers' potential output. By contrast, only 54 percent of workers would find hourly positions in a competitive equilibrium with adverse selection and moral hazard. The resulting welfare loss from this attenuation in hourly work is between \$0.03 and \$0.05 per hour of labor.

If adverse selection results in a suboptimal provision of fixed-wage positions, the government might consider subsidizing hourly wages or taxing piece rates to promote more insurance in labor contracts. To measure the welfare impact of such policies, I calculate their marginal values of public funds (MVPFs) (Hendren and Sprung-Keyser, 2020). I find that hourly wage subsidies can achieve MVPFs between 0.95 and 1.15, implying a modest social return on each dollar of government expenditure. Conversely, taxes on piece-rate earnings yield an MVPF between 0.87 and 1.1, meaning each dollar of tax revenue carries a net social cost as low as \$0.87 and no higher than \$1.10. My estimates imply a socially optimal piece-rate tax of 14 percent or more, depending on the MVPFs of policies to which its funds are directed. While these point estimates are specific to the data-entry workers in my experimental setting, they nonetheless provide suggestive evidence that additional taxes on commissions, bonuses, or tips in other labor markets might efficiently raise government revenue by mitigating adverse selection into fixed wages.

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 labor supply or wage setting (Mirrlees, 1971; Miyazaki, 1977; 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; Stantcheva, 2014).[1] Relatedly, several papers build upon Spence (1973) to investigate how signaling mechanisms like education (Hungerford and

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

Solon, 1987; Tyler et al., 2000; Bedard, 2001; Arcidiacono et al., 2010; Weiss, 1995), work experience (Farber and Gibbons, 1996; Gibbons and Katz, 1991), number of hours worked (Landers et al., 1996), or performance reviews (Pallais, 2014; Pallais and Sands, 2016) might narrow the informational gap between firms and workers.

This study also relates to the literature 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), rideshare drivers (Angrist et al., 2021), miners (Shearer, 1996), and physicians (Kantarevic and Kralj, 2016; Gaynor et al., 2004). More recently, Emanuel and Harrington (2024) estimate treatment and selection into another aspect of labor contracts—remote work. They find both negative productivity effects and negative selection into remote work among call-center workers following the COVID-19 pandemic.

This paper also contributes to an extensive literature on markets for insurance and insurance-like contracts. While my emphasis on the insurance value of wage contracts complements several papers studying the role of risk-sharing in employment relationships (Knight, 1921; Baily, 1974; Azariadis, 1975; Guiso et al., 2005), much of my theoretical framework builds upon existing work concerning other types of insurance contracts. 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. I advance this framework by using marginal treatment effects to directly quantify welfare loss from adverse selection and moral hazard.

While many studies use observational data to estimate selection and incentive effects

in various contract markets, comparatively few have used experimental methods. A few exceptions are DellaVigna and Pope (2018), who use an online experiment to investigate the effects of monetary and non-monetary incentives on worker performance; Shearer (2004), who estimates the productivity differences between piece-rate and fixed-wage tree-planters in British Columbia; and Nagin et al. (2002), who find heterogeneous shirking responses to randomized monitoring of call-center employees. Another notable example is Karlan and Zinman (2009), who randomize contract offerings on microfinance loans in South Africa. Using an experimental design similar to the second stage of my experiment, they isolate selection on unobservables by comparing borrowers who received different initial offers but ultimately faced the same contract terms. They find strong evidence of moral hazard and weaker evidence of adverse selection. In a related experiment, Bryan et al. (2015) estimate how referral bonuses induce selection into consumer loans. Like my study, they identify selection on potential outcomes (repayment propensity) with and without treatment (peer enforcement bonuses). But unlike my marginal treatment effects approach, which relies on observed outcomes among those who opt out of treatment, their design randomly removes the treatment condition for a subset of those who select into it. They estimate large treatment effects of social pressure on repayment, but find little evidence of selection on potential repayment or resistance to social pressure.

This study makes three contributions to the existing literature. First, I provide new evidence on how moral hazard and adverse selection can lead to an underprovision of fixed-wage jobs. While previous work has documented the presence of these forces in various labor markets, I develop an insurance-based model of wage contracts to demonstrate their effects on equilibrium and worker welfare. My experiment serves to both quantify these effects in a specific work setting and validate my model more generally, highlighting the potential for suboptimal wage contracts in the broader labor market. Thus, my findings reveal an important and unexplored channel through which many labor policies could improve workers' well-being.

Second, this paper investigates the public costs and benefits of policies aimed at reducing

workers' earning risk. Specifically, I estimate the MVPFs for a range of taxes and subsidies on wages paid to data-entry workers. The components of these MVPFs map directly to my experimental estimands, allowing me to flexibly compare each policy's insurance benefit against its fiscal costs from worker shirking. Aside from its direct relevance to the regulation of online labor platforms, this analysis can help inform related policies like the optimal tax rate for base wages versus tipped earnings.

Finally, methodologically, this paper provides an experimental framework to flexibly estimate welfare loss from information asymmetries in markets for insurance or insurance-like contracts. Building on methods from Karlan and Zinman (2009) and Bryan et al. (2015), my approach separately identifies treatment and selection over a range of experimental contract offers. Importantly, these offers include contracts that may not be profitable to a real-world firm, avoiding the "under-the-lamppost" problem inherent to many empirical studies of information asymmetries (Einav et al., 2010b). Moreover, because I observe outcomes for both accepters and decliners of these contracts, I can use MTE methods to identify marginal selection on potential outcomes in both insured and uninsured states. The resulting potential-outcome distributions map directly to the components of a "cost-curve" insurance model (Einav et al., 2010a; Herbst and Hendren, 2024), allowing me to semi-parametrically identify welfare loss from asymmetric information. Applying this flexible estimation approach to a wide range of experimental contract offers improves upon traditional methods that rely on local price changes and linear extrapolation.

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 baseline 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 experimental estimates of marginal-outcome distributions to calculate MVPFs for fixed-wage subsidies and piece-rate taxes. In Section 7, I discuss my findings and 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 twofold: First, I want 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 workers ($D_i = 1$) and piece-rate workers ($D_i = 0$) would yield the

following:

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

This difference is the sum of two components. The first is an 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 not observed.

Now suppose that, rather than facing the same menu of compensation options, workers are randomly assigned to one of 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^* 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 $D_i = W_i D_i^*$.

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):

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

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:

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

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 (the untreated state, Y_0) and hourly wages (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 now the remaining workers are randomly separated into two groups—workers assigned to $W_i = L$ are offered the choice between the piece rate and low

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

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 decliners of a given wage offer with control workers identifies average selection on Y_0 into that offer among all workers. But now I can also compare outcomes between decliners of high- and low-offer treatment offers to identify selection on Y_0 into offer H among those who would reject the less generous offer (L):

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

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):

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

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.[3]

Graphical Illustration Figure 2 illustrates my experimental design with three offer conditions and second-stage wage randomization. The top row of boxes represents individuals in each of the three experimental groups who remain on the piece rate. Because all three of these groups face the same ex-post payment terms but different ex-ante wage offers, comparisons between them isolate 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).

2.3 Experimental 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 allows

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

clients to hire online workers for short-term tasks.[4] The experimental job posting offered workers 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, often for the purpose of training artificial intelligence (AI) algorithms. The posting also informed workers 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 ten or more previous tasks, and (4) earned an approval rate above 98 percent on previous tasks.[5] These screening criteria allow me to remove the small number of casual users who may take the tasks less seriously than "professional" online workers who regularly perform tasks to earn income. In doing so, they make the sample more representative of the online hiring pool faced by profit-conscious employers.

Workers who accept the job posting are provided with a URL link to the experimental task. Upon clicking this link, workers are shown a screen with a brief task description and example entry.[6] After clicking past the description page, workers are randomized into one of eighteen experimental groups. Each group is offered a different menu of compensation options in exchange for completing the five-minute data-entry task. In the first treatment group, workers are offered a choice between a fixed $0.10 payment ($1.20 per hour) or a piece rate of $0.03 per correctly typed sentence.[7] In the second treatment group, workers are offered a choice between a fixed $0.15 payment ($1.80 per hour) or the same $0.03 piece rate. Additional treatment groups follow the same structure, with each condition offering the $0.03 piece rate but increasing the flat wage offer by multiples of $0.05, up to a maximum of $1.75 ($21.00 per hour). A control group is offered the $0.03 piece rate for

[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]More than 95 percent of Prolific workers meet the 98-percent approval threshold.

[6]The task is hosted on the Qualtrics platform. Readers can view and perform a replication of the task here. Screenshots are provided in Appendix Figure A1.

[7]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).

each correctly typed sentence, with no alternative option. Each of these options is offered as an addition to the $1.00 reward advertised in the job posting, which all workers receive for agreeing to the task. Experimental conditions are summarized in Table 1.

After receiving detailed instructions for the data-entry task, treated workers are presented with their group's payment options in randomized order, as shown in Appendix Figure A1, Panel A. Once workers choose their compensation scheme, they are brought to a new page that states, "For performing this task, you will receive $1.00, plus your chosen bonus of [*payment choice*]." A random 50 percent of workers who choose lower-valued payment 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 payment are told "you will receive $2.50, plus your chosen bonus of $0.25."

Once workers are notified of their 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 total 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.[8] 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. 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

[8]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 workers 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.

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

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

Data on task performance was collected at the conclusion of each wave. The primary outcome of interest is hourly output value, defined as

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

Output value is linked to self-reported background information from workers' 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 Baseline Experimental Results

This section describes baseline reduced-form results from the experiment. Sample sizes for each experimental group are provided in the third column of Table 1, and balance tests are reported in Appendix Table A1.[9] Table 2 reports summary statistics for the experimental

[9]One worker exited the task before observing their experimental wage offer and was dropped from the experimental sample. All other workers remained in the sample, even if they failed to enter sentences or click the submit button after the five-minute timer expired. If a worker failed to click the submit button within

sample. Across all experimental groups, 44 percent of workers accepted hourly wage offers. On average, workers completed 21.98 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 workers 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 21 percent of wage offers below $3.00 were accepted, while wage offers of $10.80 and above were accepted at a rate of 74 percent. Moving from group-specific means to a continuous supply curve, Table 3 reports estimated coefficients from a logistic regression of a binary indicator for hourly acceptance against log wage offer, 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.

Treatment Effect of Hourly Wages In Figure 5, I examine how output value varies between piece-rate and hourly workers across four aggregated 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. Blue circles measure average output values among all individuals in each of these groups. Orange bars measure average output values among workers on the piece rate. Dark green bars measure average output values 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. Light green bars measure average output values among those who chose the hourly wage offer and did not receive a top-up.

thirty minutes of accepting the task, the Prolific task scheduler automatically re-assigned their treatment condition to a new worker, even while the unsubmitted task remained in my sample. These re-assigned treatments result in an observation count ($N = 3,030$) that exceeds my pre-registered sample size of 3,000.

In the absence of wage effects, comparing means across each aggregated group in Figure 5 identifies the intent-to-treat effect of hourly wages. The blue circles decline with the generosity of the wage offer, suggesting hourly wages reduce worker output. Those in the control group, who received no hourly wage offer, produce \$8.12 (SE=\$0.17) of output value. Those receiving offers below \$3.00 produce \$7.99 (SE=\$0.10) of output value, those receiving offers between \$3.60 and \$9.60 produce \$7.92 (SE=\$0.09) of output value, and those receiving offers of \$10.80 and above produce \$7.77 (SE=\$0.10) of output value.

To estimate the treatment effect of hourly wages, I disaggregate the groups from Figure 5 into a continuous measure of wage offers to serve as an instrumental variable for hourly contract take-up. To remove the potential influence of wage effects, I first regress output value against log effective hourly wages and a full set of experimental group dummies for the sample of hourly workers who were eligible to receive random top-ups. I then residualize hourly workers' output values by subtracting the demeaned wage effect implied by the coefficient on log effective hourly wages. I use this residualized measure of output value as the dependent variable in a two-stage least-squares (2SLS) regression where I instrument for hourly wage take-up with log wage offers and an indicator variable for being in the no-offer control group.[10]

Table 4 reports 2SLS estimates of the treatment effects of hourly wages on output value. As in Table 3, Column 1 reports estimates from a univariate specification, while Columns 2 through 4 successively add controls for task timing, employment, and demographics. Across all four 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 it to \$0.49 (SE=0.20) and \$0.37 (SE=0.19), respectively. These negative and significant estimates of the treatment effect of hourly wages are consistent with moral hazard—on average, workers' output is lower under fixed wages, when they do not bear

[10] Appendix Table A2 reports estimates from 2SLS regressions using unresidualized output values. Results from these specifications are nearly identical to baseline results that adjust for potential wage effects.

the financial cost of decreased effort, than under piece rates, when their earnings are more closely tied to output.

Selection into Hourly Wages While differences in experimental-group-level means identifies treatment effects, cross-group comparisons of self-selected piece-rate or hourly workers identifies selection on potential output under counterfactual contracts. In Figure 5, the orange bars rise with the wage offer, meaning those who decline the most generous offers in favor of the piece rate have relatively high output. Those declining offers below \$3.00 produce \$8.53 (SE=\$0.11) of output value, those declining offers between \$3.60 and \$9.60 produce \$8.81 (SE=\$0.13) of output value, and those declining offers of \$10.80 and above produce \$8.86 (SE=\$0.22) of output value. All three of these averages exceed the \$8.12 (SE=\$0.17) of average output value produced by exclusively piece-rate workers in the no-offer control group. These patterns are consistent with adverse selection on Y_0, potential output under the piece rate.

The green bars also rise with the wage offer, meaning those who accept the lowest offers over the piece rate have relatively low output. Restricting attention to top-up workers who were paid the same effective rate of \$21.00 per hour (dark green bars), 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. These patterns are consistent with adverse selection on Y_1, potential output under the hourly wage. Note that the average output values among hourly workers who did not receive wage top-ups (light green bars) exhibit a similar pattern to top-up workers' averages, suggesting that wage effects are not important in this setting.

Disaggregating the groups from Figure 5 into respective experimental wage offers, I use ordinary-least squares (OLS) estimation to fit the selection patterns seen in Figure 5 to the following linear model:

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

where W_i is worker i's log hourly wage offer, D_i is a binary indicator for 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.[11]

Table 5 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 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 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 captured by these observable characteristics.

Figure 6 plots OLS estimates from a modified version of Equation (8) that replaces the linear wage-offer term, W_i, with a full set of dummy variables for each experimental wage offer. Covariates include log effective wages among hourly workers and task timing. Orange dots represent coefficients on hourly wage offers interacted with an indicator for remaining on the piece rate. Green 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.

To summarize, experimental results provide evidence of both adverse selection and moral hazard in hourly wage contracts—workers who decline more generous wage offers have higher piece-rate productivity, workers who accept less generous wage offers have lower

[11] 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 $D_i = 0$.

fixed-wage productivity, and the pooled average output of accepters and decliners rises with the wage offer they receive.[12] In the following section, I develop a model to investigate how these forces might affect labor-market equilibrium and worker welfare. I then extend the identification strategy above to semi-parametrically estimate that model using MTE methods.

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 a 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 fixed population of workers. Assume this population has already been pre-screened, so that workers are observably equivalent from the perspective of firms.[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). Assume firms know the data generating process, so they form unbiased beliefs about the distribution of q_i but cannot observe the ex-ante productivity of any individual worker.

Facing this population of observably identical workers with unknown productivity, firms have two options to purchase workers' labor product. One option is to buy worker output at a constant market price of p per unit, either through freelance hiring or more formal piece-rate employment.[14] Alternatively, they can offer a flat, up-front wage, w, in exchange

[12] In Appendix Table A3, I report multiplicity-adjusted p-values for tests of these three hypotheses using the multiple hypothesis testing procedure from List et al. (2019).

[13] In my empirical analysis, I allow employers to set wages using public information, X_i, like individual work history and approval rating. Omitting these "X_i" terms from the model simulates a market for the subpopulation of workers with observables matching a particular value, $X_i = x$.

[14] This model is also equivalent to one in which workers sell their labor product directly to consumers (e.g.,

for a claim on a worker's hourly output, q_i.[15]

For an individual worker, i, I define the reservation wage, $\overline{w}_i$, as the minimum w at which they would accept an hourly contract over selling their labor product at the piece rate. 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

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

To determine the profit-maximizing wage, firms consider the value of hourly output produced across worker types. I define the *marginal value* of type θ as

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

where $Y_i = pq_i$, the incremental value of output q_i produced by worker i under an hourly contract.[16] $MV(\theta)$ equals the expected amount type θ's hourly output would have earned them under the market piece rate, p. However, if type θ is risk averse, their reservation wages may fall below this "actuarially fair" wage (i.e., $\overline{w}\left(\theta\right) < MV\left(\theta\right)$) .

If $\overline{w}\left(\theta\right) < MV\left(\theta\right)$, a fully informed employer could profit from offering an hourly wage of

barbers, craftsmen, street performers) at price p, and firms serve as potential insurers of their earnings.

[15] While a worker's output, q_i, can differ under hourly versus piece-rate contracts, I assume it does not vary with the level of the hourly 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.

[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 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 (see Appendix Figure A2).

$w = \overline{w}(\theta)$ exclusively to workers of type θ. However, if employers cannot observe types, they cannot prevent workers with $\theta_i \neq \theta$ from opting into a contract offered at wage $w = \overline{w}(\theta)$. 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 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 some wage w are given by

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

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 $\underline{\theta} > 0$). 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 zero-profit condition implies that the equilibrium 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 hourly employees' output, $AV(\theta^{EQ})$. The efficient allocation of hourly contracts, on the other hand, is given by

$$\overline{w}(\theta^{EF}) = MV(\theta^{EF}). \tag{15}$$

Graphical Illustration 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 ($\overline{w}(\theta) \leq MV(\theta)$). However, 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

$$DWL = \int_{\theta^{EQ}}^{\theta^{EF}} \left(MV(\theta) - \overline{w}(\theta)\right) d\theta. \tag{16}$$

In summary, my model shows how worker selection on unobserved productivity can create a gap between the marginal and average values of labor, preventing Pareto-improving exchanges of fixed-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.

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 worker i's output value under the hourly wage, currently represented as Y_i, instead be denoted by Y_{1i}. Now let Y_{0i} denote the counterfactual output value that worker i's would produce if they worked under the piece rate. The moral hazard effect for worker i is given by the "individual treatment effect" of the hourly wage,

$MH_i \equiv Y_{1i} - Y_{0i}$.[17] This difference in counterfactual outcomes is not explicitly shown in the model because the distinction is not relevant to firms' hiring decisions. Since piece-rate workers sell their output at a constant price per unit, their hourly productivity has no affect on profits. So while firms care about a worker's output under the hourly contract (Y_{1i}), they do not 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 (16) are therefore inclusive of any moral hazard effects.[18]

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 or piece-rate taxes, as the public cost of these policies 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 compared to a pure piece rate.[19] To identify the model under these counterfactuals, I must explicitly separate selection from the moral hazard effects of "pure" hourly wage offers in my experiment.

To determine how market equilibrium (Equation 14) changes with and without moral hazard effects, 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})

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

[18] One could make the presence of moral hazard more explicit by rewriting Equations (11) and (12) in terms of piece-rate productivity plus the moral hazard effect of fixed wages (e.g., $MV(\theta) \equiv E[Y_{0i} + MH_i|\theta_i = \theta]$).

[19] 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.

and without (Y_{0i}) the hourly wage:

$$MV_1(\theta) \equiv E[Y_{1i}|\theta_i = \theta] \tag{17}$$

$$MV_0(\theta) \equiv E[Y_{0i}|\theta_i = \theta]. \tag{18}$$

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.[20] The difference between these two marginal value curves identifies the moral hazard effect for a given type:

$$MH(\theta) \equiv MV_1(\theta) - MV_0(\theta). \tag{19}$$

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

$$AV_1(\theta) \equiv E[Y_{1i}|\theta_i \leq \theta] \tag{20}$$

$$AV_0(\theta) \equiv E[Y_{0i}|\theta_i \leq \theta]. \tag{21}$$

$AV_1(\theta)$ 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 θ. $AV_0(\theta)$, on the other hand, equals the average value that would be produced by those same workers if they had instead worked under the piece rate.

Introducing dual marginal and average value curves means my model now has two counterfactual equilibria. The equilibrium condition that incorporates workers' labor-supply response to hourly pay is given by $\overline{w}(\theta_1^{EQ}) = AV_1(\theta_1^{EQ})$. By contrast, if hourly contracts have no such effects on labor supply—perhaps because employers implement increased

[20] In a loose sense, these two curves can be thought of as bounds on output value under mixed compensation with both fixed and piece-rate components. If the piece-rate component partially mitigates moral hazard effects, the true marginal value curve would lie somewhere between $MV_0(\theta)$ and $MV_1(\theta)$.

monitoring or partial piece rates—the equilibrium allocation would instead be given by $\overline{w}(\theta_0^{EQ}) = AV_0(\theta_0^{EQ})$. Meanwhile, efficient allocations with and without moral hazard effects are given by $\overline{w}(\theta_1^{EQ}) = MV_1(\theta_1^{EQ})$ and $\overline{w}(\theta_0^{EQ}) = MV_0(\theta_0^{EQ})$, respectively. In the next section, I estimate all five curves: $\overline{w}(\theta)$, $MV_1(\theta)$, $AV_1(\theta)$, $MV_0(\theta)$, and $AV_0(\theta)$. These estimates allow me not only to calculate counterfactual equilibria, but also to quantify the type-specific moral hazard effect, $MH(\theta)$, in Equation (19). As I show in Section 6, this labor-supply response is an important component of MVPFs for hourly wage subsidies and piece-rate taxes.

4.2 Model Extensions

The model above is designed so that objects of interest can be mapped to semi-parametric estimands from my experiment. For this reason, it omits features like monitoring costs and dynamic wage-setting, which are absent from my experimental setting and many other short-term labor markets. Here I discuss how one might extend the model to incorporate these features more commonly found in more traditional employment settings.

Monitoring Costs Existing research shows how relative costs of monitoring worker inputs and outputs can influence worker productivity and equilibrium wage structure in a variety of occupations (Lazear, 1986, 2000; Goldin, 1986; Nagin et al., 2002). 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, make fixed wage contracts more likely than payment schemes that require precise measurement of individual worker productivity.[21] Likewise, I could allow firms to face an input-monitoring cost of observing workers' time spent on the job, which would make fixed wages less likely than output-based

[21] Note that fixed wages still require some degree of output or effort monitoring so that firms can credibly threaten low-performing workers with dismissal, rejection, or damaged reputation.

pay. Appendix Figure A2 shows modified versions of my model that incorporate monitoring costs for inputs and outputs, respectively.

Dynamic Contracts In dynamic labor markets, workers tend to reveal information about their productivity over time. In long-term employment relationships, employers might use repeated observations of worker output to inform promotions, wage cuts, or dismissals, effectively updating wage contracts to better align each worker's compensation with their latent productivity and effort (Farber and Gibbons, 1996). In short-term gig markets, like the one in my experiment, this dynamic screening process operates primarily through work histories, ratings, and reviews.[22]

Rather than explicitly incorporate this dynamic evolution of wage contracts, my model considers contracts for a single realization of labor output. Recall, however, that workers in the model are assumed to be pre-screened on observable characteristics. Contracts can be placed in a dynamic context by simply defining this screenable information set to include prior realizations of output or observable measures of reputation. Indeed, my empirical analysis conditions on all information available to firms in my experimental setting, including prior work history (see Footnote 13).

5 Estimating the Model using Marginal Treatment Effects

The model above shows how the welfare effects of asymmetric information depend on counterfactual distributions of workers' marginal values across a range of reservation wages. In this section, I show how I can semi-parametrically identify these marginal values using a marginal treatment effects (MTE) framework.

As in Section 2, consider a potential outcomes framework in which treatment corresponds to working under an hourly contract. Let experimental wage offers, w, serve as a continuous

[22] While informative to firms, these measures of worker experience and reputation are likely less predictive than the repeated instances of past worker performance observed in long-term employment relationships. As I discuss in Section 7.1, these relatively limited information sets make short-term employers more vulnerable to adverse selection and moral hazard, perhaps explaining the predominance of output-based pay observed among gig workers.

instrument for taking up that treatment condition. Adopting the parlance of the causal inference literature, a worker's quantile reservation wage, $\theta_i \equiv S(\overline{w}_i)$, is their "resistance to treatment" (Björklund and Moffitt, 1987; Heckman and Vytlacil, 1999, 2005, 2007). Under this framing, the marginal values defined in Equations (17) and (18) are equivalent to marginal potential outcomes, and the moral hazard effect in Equation (19) 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, $\theta = S(w)$).

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 (i.e., propensity scores) in Equation (9) can be straightforwardly identified as the share of accepters across wage offers:

$$S(w) \equiv \Pr\left(\overline{w}_i \leq w\right) = \Pr(D_i = 1|w_i = w). \tag{22}$$

Next, at each propensity score, $\theta = S(w)$, average value under both hourly and piece-rate contracts can be identified from the conditional means of output value among respective accepters and decliners of the corresponding wage offer, w. So the 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:

$$AV_1\left(\theta\right) \equiv E\left[Y_{1i}|\theta_i \leq \theta\right] = E\left[Y_i|S(w_i) = \theta, D_i = 1\right]. \tag{23}$$

Likewise, the average value curve under the piece rate equals the average output value among those who *decline* the hourly wage offer that is accepted by θ-share of workers:

$$AV_0\left(\theta\right) \equiv E\left[Y_{0i}|\theta_i \leq \theta\right] = \frac{E\left[Y_i|S(w_i) = 0\right] - E[Y_i|S(w_i) = \theta, D_i = 0](1-\theta)}{\theta}, \tag{24}$$

where $E\left[Y_i|S(w_i)=0\right]$ is the average output value of workers in the control group, who all work under the piece rate.[23]

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

$$MV_1(\theta) = \frac{\partial\left(E\left[Y_{1i}|\theta_i \leq \theta\right]\theta\right)}{\partial\theta} = \frac{\partial\left(E\left[Y_{1i}|S(w_i)=\theta, D_i=1\right]\theta\right)}{\partial\theta} \quad (25)$$

$$MV_0(\theta) = -\frac{\partial\left(E\left[Y_{0i}|\theta_i > \theta\right](1-\theta)\right)}{\partial\theta} = -\frac{\partial\left(E\left[Y_i|S(w_i)=\theta, D_i=0\right](1-\theta)\right)}{\partial\theta}. \quad (26)$$

Intuitively, Equations (25) and (26) identify marginal values by differentiating total value ($TV(\theta) \equiv AV(\theta) * \theta$) with respect to θ under hourly and piece-rate counterfactuals, similar to the marginal cost calculation in Einav et al. (2010a).

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.

Next, I use the local polynomial regression approach from Carneiro et al. (2011) to estimate average and marginal values. First, I residualize covariates from Y_i separately for hourly and piece-rate workers using double-residual regression methods (Robinson, 1988), assuming these covariates are additively separable from $MV_1(\theta)$ and $MV_0(\theta)$.[24] To simulate potential screening or (legal) wage discrimination by hypothetical employers, these covariates include controls for number of previous tasks, task start time, and employment status.[25] For hourly workers, I also include the effective wage paid after any randomized

[23] By offering no alternative to the piece rate, the control condition effectively allows for "identification at infinity"—the average piece-rate output among workers of all reservation wages (Heckman, 1990; Chamberlain, 1986).

[24] 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.

[25] Race, gender, and age were excluded because employers cannot legally use these characteristics in employment or wage-setting decisions. Estimates of linear selection effects from Table 5 suggest including

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 residualized Y_i on $S(w_i)$ with a bandwidth of 0.2. Standard errors are calculated using five-hundred bootstrap replications.

With semi-parametric estimates of $\overline{w}(\theta)$, $MV_1(\theta)$, $AV_1(\theta)$, $MV_0(\theta)$, and $AV_0(\theta)$ curves in hand, it is straightforward to calculate the welfare loss from Equation (16). First, I calculate equilibrium (θ^{EQ}) and efficient (θ^{EF}) shares of hourly wages using the intersection of $\overline{w}(\theta)$ with $AV_1(\theta)$ and $MV_1(\theta)$, respectively. Then, I calculate the cumulative difference in $\overline{w}(\theta)$ and $MV_1(\theta)$ over the region $\theta \in \left(\theta^{EQ}, \theta^{EF}\right)$. This calculation measures lost welfare as the expected excess output value that piece-rate workers would be willing to forfeit to their employers under the hourly wage contract (see Figure 7).

Because $MV_1(\theta)$ and $AV_1(\theta)$ are derived from potential outcomes under the hourly wage, Y_1, the corresponding welfare calculation includes moral hazard effects. To estimate potential welfare loss without moral hazard effects, I repeat this calculation using piece-rate value curves, $MV_0(\theta)$ and $AV_0(\theta)$.

5.2 Results

Figure 9 plots semi-parametric estimates of supply and value curves under both hourly wage and piece-rate counterfactuals. On the horizontal axis, the type parameter θ corresponds to quantiles of workers' hourly reservation wages. The red line plots hourly reservation wage at each quantile, $\overline{w}(\theta)$, 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 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 $MV_1(\theta) \equiv E[Y_{1i}|\theta_i = \theta]$, respectively. In Panel B, green 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 $MV_0(\theta) \equiv E[Y_{0i}|\theta_i = \theta]$, respectively.

In both panels, the majority of workers produce labor at marginal values, $MV(\theta)$, that

these demographic controls would have minimal effect on the slopes of value curves.

exceed their hourly reservation wages, $\overline{w}(\theta)$. I find that 59 percent (SE=0.08) of workers have $\overline{w}(\theta) < MV_1(\theta)$. Because a worker's marginal value is equivalent to their expected output times the piece rate, these workers must be either risk averse or systematically undervalue their productive potential; a risk-neutral worker would not accept any hourly wage offer below the value of what they expect to produce because they could earn more (in expectation) by applying the same effort under the piece rate.[26] By comparison, I find that 61 percent (SE=0.08) of workers have $\overline{w}(\theta) < MV_0(\theta)$. Unlike the previous case, these workers need not be risk averse or form biased beliefs. For example, $MV_1(\theta) < \overline{w}(\theta) < MV_0(\theta)$ 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 most workers' willingness to sacrifice expected earnings in exchange for hourly wages, the implied premium they are willing to pay 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' potential effort response to hourly contracts as given, this efficient allocation would imply that 59 percent (SE=0.08) of workers would work under hourly contracts. With adverse selection, however, only 54 percent (SE=0.06) 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 percent (SE=0.08), which lowers to 55 percent (SE=0.08) 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

[26] While the small-stakes nature of my experiment may imply implausibly high coefficients of relative risk aversion for some workers with $\overline{w}(\theta) < MV_1(\theta)$ (Rabin, 2000), my findings are nonetheless consistent with a large body of existing evidence documenting persistent risk aversion over repeated, low-stakes gambles (Falk et al., 2018; Andersen et al., 2008; Harrison et al., 2007; Samuelson, 1963). Note that, because my semi-parametric approach relies entirely on revealed preferences over contracts, I can remain agnostic about the functional form of workers' utility.

hazard effects.[27]

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 how the (marginal) moral hazard effect of an hourly wage contract changes with workers' quantile reservation wage. Its shape suggests selection on moral hazard is non-linear: At low reservation wages, those with a marginally stronger preference for piece rates (higher reservation wage) have a slightly lower propensity to shirk (moral hazard effect closer to zero). This pattern is consistent with classic explanations of selection on moral hazard, whereby those with stronger preferences for insurance are more susceptible to its disincentive effects (Einav et al., 2013). At higher reservation wages, however, selection on moral hazard moves in the opposite direction—those more prone to shirking have relatively higher hourly reservation wages, indicating a preference for *less* insurance. This pattern might be explained by heterogenous risk preferences. If one's tolerance for earnings risk from piece rates correlates with their tolerance for the reputational risk of excessively low output, 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.

[27]Note that estimates of welfare loss assume that a worker's willingness to accept fixed wages, $\overline{w}(\theta)$, below their actuarially fair, break-even value, $MV(\theta)$, corresponds to a revealed preference for fixed wages rather than systematic, ex-ante "mistakes" like overly pessimistic beliefs. If workers' choices are driven by these systematic prediction errors or similar behavioral phenomena, estimates of market and full-information equilibria and would not change, but the welfare implications of those estimates could be quite different.

6 Policy Implications: MVPFs of Hourly-Wage Subsidies and Piece-Rate Taxes

If adverse selection results in a suboptimal provision of fixed-wage positions, the government could consider policies designed to induce workers and firms into these contracts. In particular, it might pay firms for each hour of fixed-wage labor (hourly-wage subsidy) or tax them for each dollar of performance-based pay (piece-rate tax). In this section, I measure the welfare impacts of such policies 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 is defined as

$$MVPF = \frac{WTP}{NC}, \tag{27}$$

where WTP is the aggregate willingness-to-pay for the policy, and NC is the policy's net cost to taxpayers. Importantly, NC includes both the direct costs of the policy and any long-term fiscal externalities it imposes on government tax revenue.

6.1 Subsidizing Hourly Employment

Consider an hourly-wage subsidy of $\$\delta$ per hour worked. In my model, the effect of such a subsidy would be to lower nominal reservation wages by $\$\delta$. This downward shift in reservation wages results in a new equilibrium share of hourly workers, θ^δ, such that $\overline{w}(\theta^\delta) = AV_1(\theta^\delta) + \delta$. The policy's 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 implied premium these workers place on hourly wages. The aggregate willingness-to-pay is therefore given by

$$WTP(\delta) = \underbrace{\delta\theta^\delta}_{\text{Transfer}} + \underbrace{\int_{\theta^{EQ}}^{\theta^\delta} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}_{\text{Insurance Benefit}}, \tag{28}$$

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 subsidy's direct cost is given by the government's transfer to all hourly workers hired under the subsidized wage, $\delta\theta^{\delta}$. 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.[28] I capture this fiscal externality using estimates of moral hazard (marginal treatment effects) for types $\theta \in \left(\theta^{EQ}, \theta^{\delta}\right)$ from Section 5.2, so that the government's net cost of the subsidy, $NC(\delta)$, is given by

$$NC(\delta) = \underbrace{\delta\theta^{\delta}}_{\text{Direct Cost of Transfer}} + \underbrace{\int_{\theta^{EQ}}^{\theta^{\delta}} -\tau MH(\theta)d\theta}_{\text{Fiscal Externality from Moral Hazard}}. \tag{29}$$

With Equations (28) and (29) in hand, I can write $MVPF_{\text{Sub}}(\delta)$—the MVPF of a $\$\delta$ subsidy—as

$$MVPF_{\text{Sub}}(\delta) \equiv \frac{WTP(\delta)}{NC(\delta)} = \frac{\delta\theta^{\delta} + \int_{\theta^{EQ}}^{\theta^{\delta}} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}{\delta\theta^{\delta} - \int_{\theta^{EQ}}^{\theta^{\delta}} \tau MH(\theta)d\theta}. \tag{30}$$

Equation (30) 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 of $MVPF_{\text{Sub}}(\delta)$. Estimated MVPFs decline with the size of the subsidy because the first worker induced into hourly pay has the highest hourly-wage

[28] 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.

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).

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. In general, 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.

To determine the optimal subsidy, I use Equations (28) and (29) above to find the value, δ^*, that maximizes aggregate net welfare:

$$\delta^* \equiv \underset{\delta}{\text{argmax}} \left\{ WTP(\delta) - \lambda NC(\delta) \right\}, \tag{31}$$

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 (31) imply

$$MVPF_{d\text{Sub}}(\delta^*) \equiv \frac{WTP'(\delta^*)}{NC'(\delta^*)} \quad = \quad \lambda \tag{32}$$

$MVPF_{d\text{Sub}}(\delta)$ is the MVPF for a *marginal increase* in hourly-wage subsidy.[29] Equation (32) 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

[29] Appendix C provides details on the derivation of $MVPF_{d\text{Sub}}(\delta)$.

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 $MVPF_{d\text{Sub}}(\delta) = \lambda$. For values of λ above 1.15, the optimal subsidy would be zero. Comparing these values to MVPFs for other policies suggests that hourly wage subsidies achieve only modest welfare gains for each dollar of government expenditure (Hendren and Sprung-Keyser, 2020). In the following subsection, I determine whether taxing piece rates or other types of performance pay may be a more efficient means of mitigating adverse selection into fixed wages.

6.2 Tax on Piece Rates and Self-Employment

Instead of hourly wage subsidies, policymakers might consider taxes on piece rates as an alternative means of promoting fixed-wage labor contracts. For example, the government might impose additional taxes on tips, sales commissions, or the performance-based portion of rideshare earnings to discourage risky forms of compensation.[30] The insurance value and distortionary effects of such policies are equivalent to those of fixed-wage subsidies, but fixed-wage subsidies transfer funds to low-reservation-wage workers on a per-hour basis, while a piece-rate tax transfers funds from high-reservation-wage workers in proportion to their output. This distinction means the two policies can have different fiscal implications and thus different impacts on social welfare. Moreover, while MVPF calculations for revenue-raising policies like piece-rate taxes follow the same principles as those for transfer policies like hourly wage subsidies, their benchmark for policy adoption is different. In particular, when comparing MVPFs across revenue-raising policies, a *lower* value implies a more efficient source of public funds (Boning et al., 2024). An MVPF below one implies the policy is more socially efficient than a non-distortionary tax.

[30] In the 2024 U.S. presidential election, both major candidates proposed eliminating taxes on tipped earnings (Nehamas et al., 2024). My analysis suggests that the opposite policy—additional taxes on tips and other performance-based compensation could be socially efficient. For example, eliminating or raising the threshold on payroll tax credits for employers of tipped workers might raise government revenue while reversing some of the welfare losses from adverse selection.

To evaluate the welfare impact of a piece-rate tax, consider an ad valorem tax, ρ, assessed on the value of labor product produced under the piece rate. Recall that a marginal and average values of hourly workers' labor product are defined as the amount the firm saves by not buying that labor product from piece-rate or self-employed workers (see Footnote 16). A piece-rate tax, ρ, would therefore increase marginal and average value curves by a factor of $1+\rho$. This upward shift in value curves results in a new equilibrium share of hourly workers, θ^ρ, such that $\overline{w}(\theta^\rho) = (1+\rho)AV_1(\theta^\rho)$.

While the MVPF of transfer policies like an hourly-wage subsidy captures its net social value per dollar of government expenditure, the MVPF of a revenue-raising policy like a piece-rate tax captures its net social cost per dollar of government revenue raised. For a piece-rate tax, ρ, this MVPF is given by

$$MVPF_{\text{Tax}}(\rho) \equiv \frac{WTP(\rho)}{NR(\rho)}. \tag{33}$$

In this case, the fiscal consequence of the tax would be to increase government revenue by $\rho MV_0(\theta)$, reflecting the total tax receipts from piece-rate workers in the new equilibrium, $\theta \in [\theta^\rho, 1]$. However, this increased revenue is partially offset by the indirect costs of inducing more workers into hourly pay—as with the hourly-wage subsidy, a tax on piece-rates could lead to lower earnings and decreased tax revenue. Net government revenue, $NR(\rho)$, from the piece-rate tax is therefore given by

$$NR(\rho) = \underbrace{\int_{\theta^\rho}^{1} \rho MV_0(\theta)d\theta}_{\text{Direct Revenue from Transfer}} + \underbrace{\int_{\theta^{EQ}}^{\theta^\rho} \tau MH(\theta)d\theta}_{\text{Fiscal Externality from Moral Hazard}}. \tag{34}$$

The social cost of raising revenue $NR(\rho)$ is given by aggregate amount individuals would pay to *avoid* the tax. This willingness-to-pay, $WTP(\rho)$, has two components: First, each worker $\theta \in [\theta^\rho, 1]$ would recoup $\rho MV_0(\theta)$ in direct savings in the absence of the piece-rate tax. Second, workers $\theta \in \left[\theta^{EQ}, \theta^\rho\right]$ would lose $MV_1(\theta) - \overline{w}(\theta)$ of insurance value from hourly positions supported by the tax. The total welfare cost of piece-rate tax, ρ, is therefore given

by

$$WTP(\rho) = \underbrace{\int_{\theta^\rho}^{1} \rho MV_0(\theta) d\theta}_{\text{Direct Tax Savings}} - \underbrace{\int_{\theta^{EQ}}^{\theta^\rho} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}_{\text{Lost Insurance Value}}. \tag{35}$$

Using Equations (34) and (35), I estimate $MVPF_{\text{Tax}}(\rho) \equiv \frac{WTP(\rho)}{NR(\rho)}$ across a range of tax rates, ρ. Estimated MVPFs, reported in Figure 12 increase with the size of the tax because the first worker induced into hourly pay has the highest risk premium among non-hourly workers. The vertical line denotes the tax that achieves the hourly supply share found in an full-information equilibrium. This "efficient" tax rate is equal to 15 percent (SE=0.15), and results in an MVPF equal to 0.95 (SE=0.001).

Optimal Tax Rates The optimal piece-rate tax equates the MVPF of a marginal increase in ρ to the marginal value of a one-dollar increase in government revenue—the MVPF of a tax reduction or policy to which the revenue might be directed:

$$MVPF_{d\text{Tax}}(\rho^*) \equiv \frac{WTP'(\rho^*)}{NR'(\rho^*)} = \eta, \tag{36}$$

where η represents the marginal value of government revenue.[31] Figure 12B plots estimates of $MVPF_{d\text{Tax}}(\rho)$. The MVPF of marginally higher taxes increases with the tax rate, reaching one at a piece-rate tax of 14 percent (SE=0.18). If we allow for a marginal value of government funds greater than zero ($\eta > 0$), the optimal tax would increase from 14 to the value of ρ at which $MVPF_{d\text{Tax}}(\rho) = \rho$.

Unlike hourly wage subsidies, MVPFs for piece-rate taxes dominate those for most alternative policies. By mitigating adverse selection costs, taxing output-based pay at a rate of 14 percent or less can raise government revenue at least as efficiently as a distortionless tax. At these levels, each dollar of piece-rate tax revenue carries a net social cost as low as \$0.87 and no higher than \$1.00.

[31] Appendix C provides details on the derivation of $MVPF_{d\text{Tax}}(\rho)$.

General Equilibrium Effects

The first-order effect of an hourly-wage subsidy or piece-rate tax is to increase the firm's relative value of hiring fixed-wage labor, corresponding to an upward shift in the average value curve. In equilibrium, however, we would expect both policies to lower the effective piece rate paid to self-employed workers. Because the piece rate, p, represents hourly workers' outside option, this decrease would likely result in a downward shift in hourly reservation wages, $\overline{w}(\theta)$. The result would be to further increase the equilibrium share of hourly workers, magnifying the welfare effects of the policies above.[32] In other words, omitting these second-order effects from my analysis only serves to understate the social efficiency of wage subsidies and piece-rate taxes, biasing my estimates of $MVPF(\delta)$ and $MVPF(\rho)$ towards one.

Relatedly, the above analysis assumes that aggregate demand for labor product, q, is perfectly inelastic. Relaxing this assumption would mean both hourly wage subsidies and piece-rate taxes could generate less social value by distorting the equilibrium quantity of labor product away from its efficient level. Note, however, that because these distortions move in opposite directions, one might mitigate their potential welfare impacts with a mix of taxes and subsidies.

7 Discussion and External Validity

My experimental results show how moral hazard and adverse selection can distort wage contracts among online workers performing a data-entry task. In this section, I discuss the implications these results might have for the broader labor market. I begin by complementing my experimental evidence with observations from other occupations and industries. I then elaborate on the unique benefits of my experimental setting and investigate the external validity of my results.

[32] Appendix Figure A3 provides a graphical illustration of both first- and second-order effects of hourly-wage subsidies or piece-rate taxes on hourly labor share. Incorporating the second-order effect into my welfare analysis would require estimates of firms' demand for labor product, q, and the elasticity of hourly labor supply with respect to piece-rates, p.

7.1 Information Asymmetries in other Labor Markets

This paper serves not only to quantify the effects of information asymmetries among online task workers, but also to highlight their potential to distort wage contracts in the broader labor market. Here I briefly discussing some qualitative evidence of moral hazard and adverse selection in other industries and occupations.

First, consider the broader market for self-employed freelance work. The so-called "gig economy" is characterized by short-term labor contracts that pay workers 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). Compared to traditional employment, these contracts offer workers the benefits of flexible schedules (Mas and Pallais, 2017) and liquid income (Garin et al., 2020; Koustas, 2018), but also come at a cost—a gig worker can choose their own hours, but faces more uncertainty over what they will earn during those hours. By comparison, fixed-wage employment offers less uncertainty. As one rideshare driver writes,

> "Having full-time contractual employment does come with some certainty. You know you have an income every month...When I had a relatively well-paying job I didn't have sleepless nights about what I was going to eat or how I was going to pay rent. If I was strapped for cash I knew I just had to make it to the end of the month. Now who knows?" (Ngubo, 2024).

This trade-off between flexible short-term contracts and wage certainty is likely not a coincidence—traditional employers are more likely to profitably sustain fixed-wage contracts because their repeated interactions with workers mitigate information asymmetries. Short-term employment relationships, on the other hand, offer less opportunity to reveal workers' latent productivity, making the implicit insurance of fixed wages more prone to moral hazard and adverse selection. Thus, gig work serves as an example of how output-based pay dominates in settings with large informational gaps between workers and employers.

The restaurant industry provides another case study in how information asymmetries

might lead to an over-reliance on risky compensation. In particular, the failure of many "no-tip restaurants" to maintain profitability is consistent with adverse selection into fixed wages. In fact, several of these restaurants have cited an exodus of qualified servers as one reason for their lack of success (Kadvany, 2022b; Moskin, 2020; Dunn, 2018). Meanwhile, the few restaurants that have maintained fixed wages often explicitly acknowledge their effects on worker selection. After eliminating tips, one San Francisco restaurant noted the following:

> "[Server positions] have been harder to fill. Many veteran servers weren't interested, saying they could make double elsewhere with tips...As a result, many of the people who work in the dining room started with little to no restaurant experience" (Kadvany, 2022a).

These reports provide suggestive evidence that the heavy-tipping equilibrium in the U.S. restaurant industry may be partly a consequence of adverse selection into fixed wages. In that case, shifting the tax burden towards tipped earnings would likely be socially efficient.

7.2 Why Online Workers?

The examples above suggest that the predominance of self-employment, freelance work, or piece-rate compensation seen in many occupations may be the consequence of information asymmetries. If so many labor markets are plagued by moral hazard and adverse selection, why does my experiment focus on online data-entry workers?

My experimental setting offers several advantages that make it uniquely suited for identifying moral hazard and adverse selection. First, the relatively low cost and flexibility of online tasking platforms gives me control over the complete menus of wage contracts faced by workers. As a result, I can observe worker selection between a single predetermined outside option and a wide range of experimental wage offers, including those that may be unprofitable to a real-world employer. These margins of selection are critical determinants of welfare loss but impossible to observe in most settings. For example, an experiment that

recruits participants through randomized posted wages can only measure selection relative to workers' existing outside options, which likely include competing offers from other fixed-wage employers. Estimates of selection among these workers would likely understate the insurance value of fixed wages and overstate the elasticity of fixed-wage labor supply (Dube et al., 2020).

Second, my experimental task provides a measure of worker output that directly maps to the employer's profit function. In many settings where the value of one's labor product is less tangible, worker productivity would be difficult to measure within a reasonable time frame, making it impossible to estimate welfare loss. Moreover, my measure of output value is observable for both accepters and decliners of a given wage offer, allowing me to estimate the treatment effects of fixed wages on worker productivity.

Third, my experimental design allows me to recruit a representative sample of workers in the targeted labor market, not just those opting into a particular employer or wage contract. By contrast, an experiment conducted in traditional employment settings might exclude high-productivity workers who avoided fixed-wage jobs in favor of self-employment or freelance work, eliminating the very margin of selection I seek to identify.

Finally, the task and setting for this experiment make it highly replicable. Researchers can recreate or modify my experimental intervention in comparable populations of online workers at minimal cost. By contrast, experiments conducted in proprietary settings can be difficult to validate or extend.

7.3 External Validity

My experiment was designed to leverage the advantages above to demonstrate how moral hazard and adverse selection can lead to an underprovision of fixed-wage jobs. In the parlance of List (2020), it aims to provide "WAVE1" insights validating the theory presented in Section 4. While point estimates directly speak to the importance of information asymmetries in some settings, they are not intended to measure welfare losses across the myriad of labor markets characterized by risky forms of compensation. For example, the pattern

of selection on data-entry skills, while applicable to many typing-related tasks, likely differs from how workers would sort on driving ability or salesmanship.

It is worth noting that such limits to generalizability are 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), call centers (Mas and Pallais, 2017; Nagin et al., 2002), cashiers (Mas and Moretti, 2009), or automotive glass repairers (Lazear, 2000), estimates of parameters concerning worker productivity are usually difficult to generalize beyond narrowly defined labor markets. For example, Herbst and Mas (2015) find that estimates of peer effects on worker output dramatically between study settings.

Because most settings would suffer from similar limits to external validity, it is difficult imagine a more generalizable experiment that would not sacrifice many of my design's most desirable features. Nonetheless, it is important to consider the settings to which my estimates can be directly applied. I therefore assess the external validity of my results using the SANS conditions from List (2020).

The experimental sample is drawn from the population of workers on Prolific, a widely used and well-established freelancing platform with over 100,000 workers. Among online workers, Profilic is widely considered the most desirable micro-task platform due to its ease of use and high pay. Consequently, the platform has a waitlist, and workers rarely turn down a task for which they are eligible (u/ProlificAc, 2024). This popularity helps ensure the sample is broadly representative of the labor market for online micro-taskers. Workers in my sample have already completed over 1,200 tasks, suggesting they regularly perform tasks to earn income. Importantly, my experimental job posting advertises generous compensation for a five-minute task—a \$1.00 flat fee plus the \$0.03-per-entry piece rate—ensuring the sample is not restricted to workers with low reservation wages or limited outside options. Perhaps as a result of this generous compensation, there was virtually no attrition from the sample—only one worker was dropped from the experimental sample for exiting the task.

Each aspect of the experimental intervention is designed to place participants in a

naturally-occurring setting. Contract options are presented in a simple and straightforward manner, offering workers a choice between a randomized hourly wage offer and a standardized \$0.03-per-entry piece rate. This \$0.03 piece rate was set to approximate observed rates for online text-to-text transcription services (Khan, 2024; Ahmad, 2024; GMR Transcription, 2024; GoTranscript, 2024; Ditto Transcripts, 2024; Transcription Services, 2024).[33] And because workers face a threat of job dismissal and reputational damage for unapproved tasks, they have an incentive to maintain a minimum standard of performance under either compensation scheme. The transcription task, described in Section 2.3, is commonly requested by clients on online platforms (Khan, 2024; Ahmad, 2024), and "traditional keyboarding" is a job requirement for 66 percent of American workers (Bureau of Labor Statistics, 2024). Finally, participants are not aware that they are part of an experiment until after they perform the task, so estimates are not biased by any desire to generate a particular result.

While point estimates from this study are specific to online data-entry workers, they can be more generally informative if one considers how workers' preferences, beliefs, and constraints vary between settings. My experimental task is more predictable, lower stakes, and shorter duration than many of those found in other labor markets. As a result, workers in my study might exhibit less fatigue, more inattention, and a greater tolerance for risk than those in other work settings prone to information asymmetries. In general, I would expect these attributes to attenuate my estimates towards zero: Workers facing higher stakes or more uncertainty over their labor products would pay a higher premium (lower reservation wage) for the implicit insurance offered by fixed wages.[34] This increased risk premium would shift the hourly supply curve downwards, resulting in a greater welfare loss than

[33] If my experimental piece rate, p, was lower (higher) than the true market value of a typed sentence, it would bias my estimates of reservation wages and values are upward (downward). In Appendix B.4, I show that under constant relative risk aversion, estimates of reservation wages and value curves are proportional to the per-unit price at which workers can sell their labor product, allowing one to extrapolate my estimates of welfare loss to alternative specifications of p.

[34] Workers' uncertainty over their labor product depends on their prior knowledge of the task. To be conservative, I intentionally design the task and instructions to maximize this task-related knowledge while maintaining realism. If instructions were less informative, each worker would face a higher subjective variance in earnings and a larger benefit from insurance.

the one I estimate. Likewise, less inattention would make hourly supply more elastic and more correlated with workers' latent productivity, exacerbating adverse selection problems. Finally, more fatigue would likely lead to larger moral hazard effects—if the cost of effort increases with the duration of the task, so would the benefits of shirking. In light of these potentially attenuating forces, the fact that workers in my experiment still make strategic, risk-averse decisions is noteworthy. For example, despite facing moderately predictable, short-term task with small monetary stakes, the majority of workers produce output values above their reservation wages.

In some settings, I would expect moral hazard and adverse selection effects to be smaller than those in my experiment. In particular, labor markets in which wages are determined by repeated employer-worker interactions or costly output monitoring are less prone to these distortions. My findings should not be extrapolated to such settings, where the presence and extent of information asymmetries are open questions. Nonetheless, this paper provides a framework from which future research could approach these questions—as I discuss in Section 4.2, both my model and experimental design can be adapted to incorporate different monitoring costs or dynamic employment relationships.

In sum, the unique features of my experimental setting allow me to credibly estimate welfare loss from moral hazard and adverse selection in fixed-wage contracts. While these features place some limits on the generalizability of my results, such limits are ubiquitous in applied research on worker selection and productivity. Moreover, because my model can predict how information asymmetries would change with the duration, predictability, or frequency of tasks, my estimates can be interpreted as approximate bounds on welfare loss in many other settings. Nonetheless, policies aimed at addressing information asymmetries in other occupations or tasks warrant further empirical evidence targeted to those settings.

8 Conclusion

This paper uses an experimental approach to estimate the equilibrium and welfare effects of moral hazard and adverse selection in fixed-wage contracts. My experiment offers workers 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. 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 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 lowest fixed amount they will accept in exchange for an hour of labor—and the average output of workers with comparatively lower reservation wages. I semi-parametrically identify these objects using a marginal treatment effects (MTE) framework in which experimental wage offers serve as an instrument for hourly wage take-up. My estimates imply that information asymmetries lead to an underprovision of fixed-wage contracts, resulting in a welfare loss between \$0.03 and \$0.04 per hour worked. To investigate the policy implications of this welfare loss, I calculate the marginal values of public funds (MVPFs) across a range of wage-based subsidy and tax policies. My estimates suggest that a 14-percent tax on performance-based pay can efficiently raise government revenue by correcting the market inefficiencies associated with adverse selection.

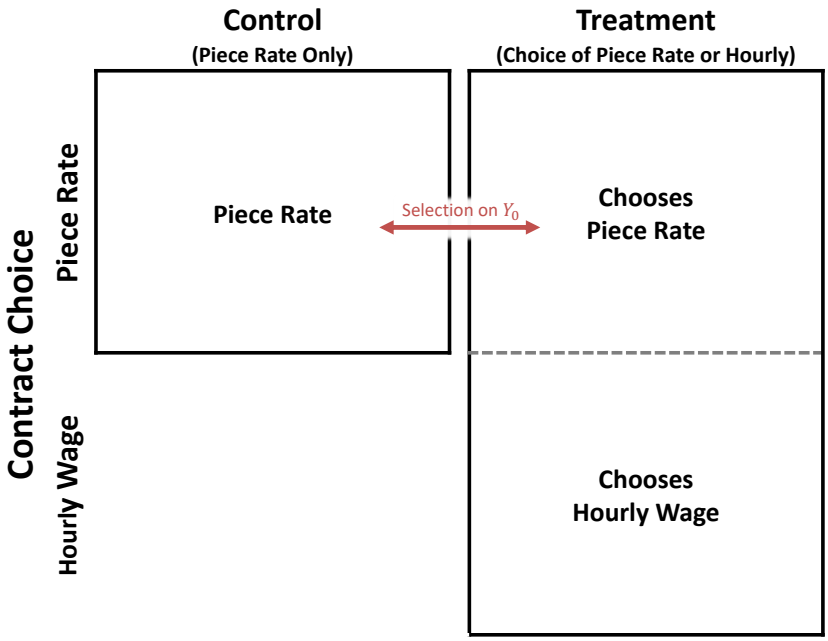
Extensions of this work might further explore how various labor-market policies influence worker welfare through these channels. For example, viewed through the lens of this paper, a binding minimum wage can act as a sort of "insurance mandate" that pools workers with different latent productivities to mitigate adverse selection. Portable benefits programs and employment classification rules offer similar opportunities to address

information asymmetry problems in labor markets.

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 their earnings from selling labor product directly to an employer or customer. In these and other settings, a better understanding of information asymmetries and the policies to address them can meaningfully improve the lives of millions of workers.

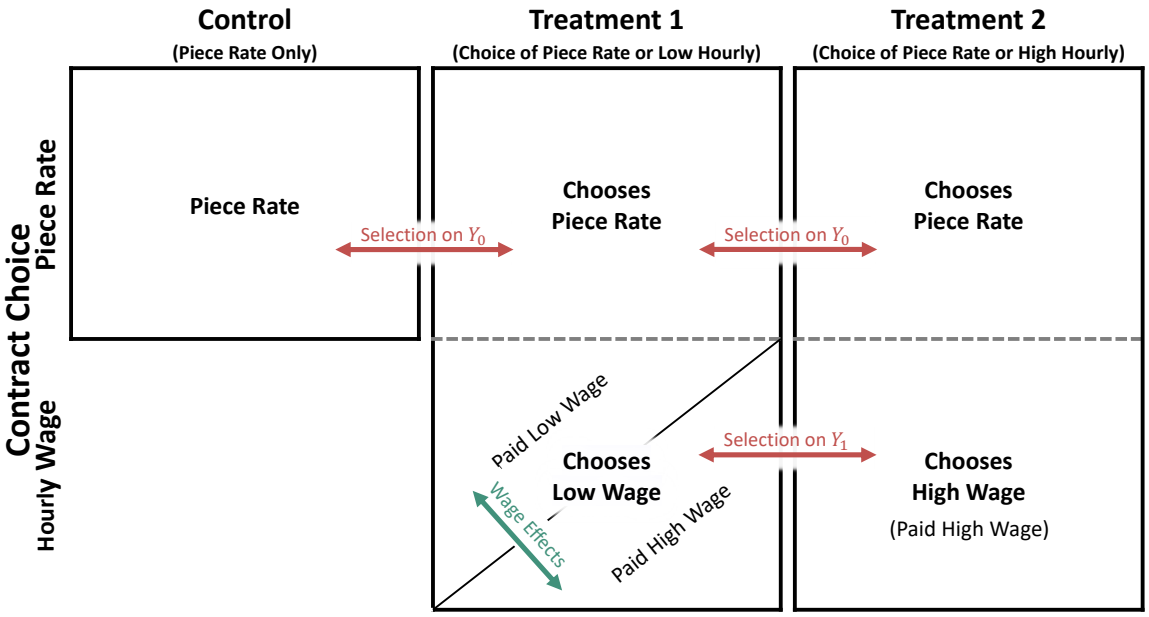
Figures and Tables

Figure 1: Experimental Design: Single Treatment



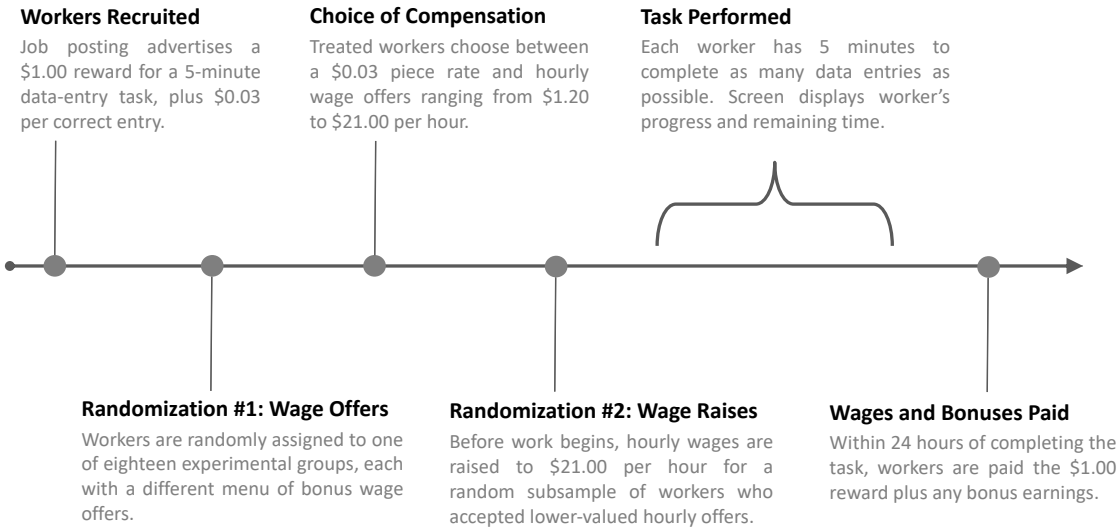
Note: This figure provides a graphical representation of a single-offer version of my experimental design. Columns denote experimental groups with different menus of wage options, and rows denote the payment contracts chosen by workers within each group. The control group, represented by the left column, 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 the comparison that identifies selection—groups that were offered different menus of contracts but ultimately face the same repayment terms. The treatment effect of hourly wages (moral hazard) is identified by instrumenting for hourly wage take-up with treatment-group assignment.

Figure 2: Experimental Design: Multiple Treatments



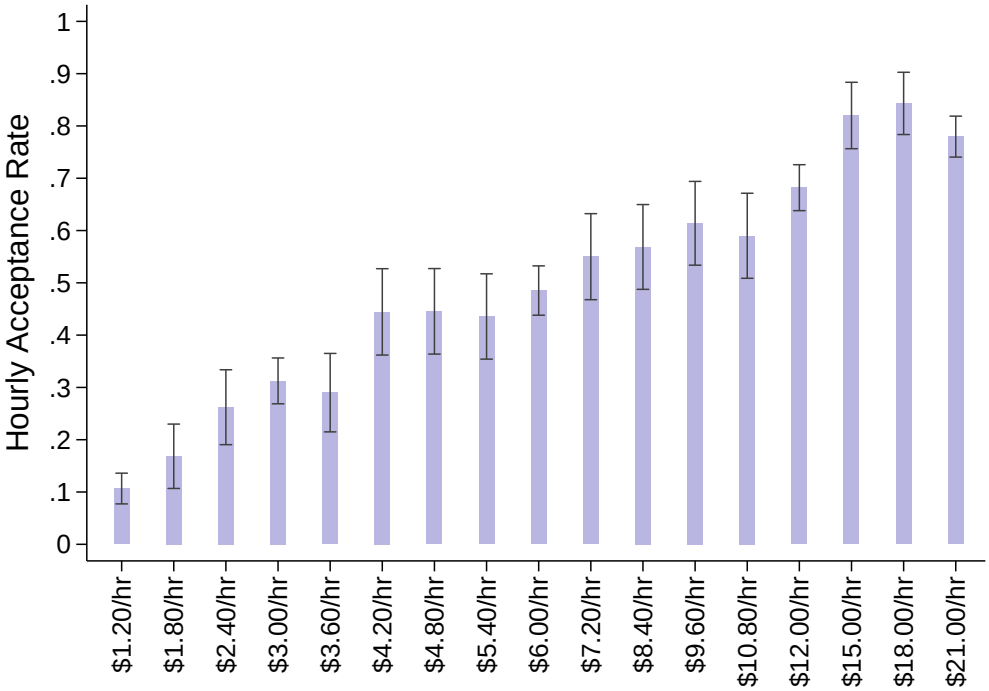
Note: This figure provides a graphical illustration of my two-stage experimental design with two treatment offers. Columns denote initial hourly wage offers, and rows denote the type of payment contract that workers choose. The diagonal split in the bottom box of Treatment 1 represents the second stage of randomization, in which some workers accepting the low hourly wage are promised the higher wage before they begin the task. Horizontal arrows denote comparisons that identify selection—groups that were offered different menus of contracts but ultimately face the same compensation terms. The diagonal arrow denotes the comparison that identifies wage effects. The treatment effect of hourly wages (moral hazard) is identified by instrumenting for hourly wage take-up with initial wage offers, controlling for wage effects (see Section 3 for details).

Figure 3: Experiment Timeline



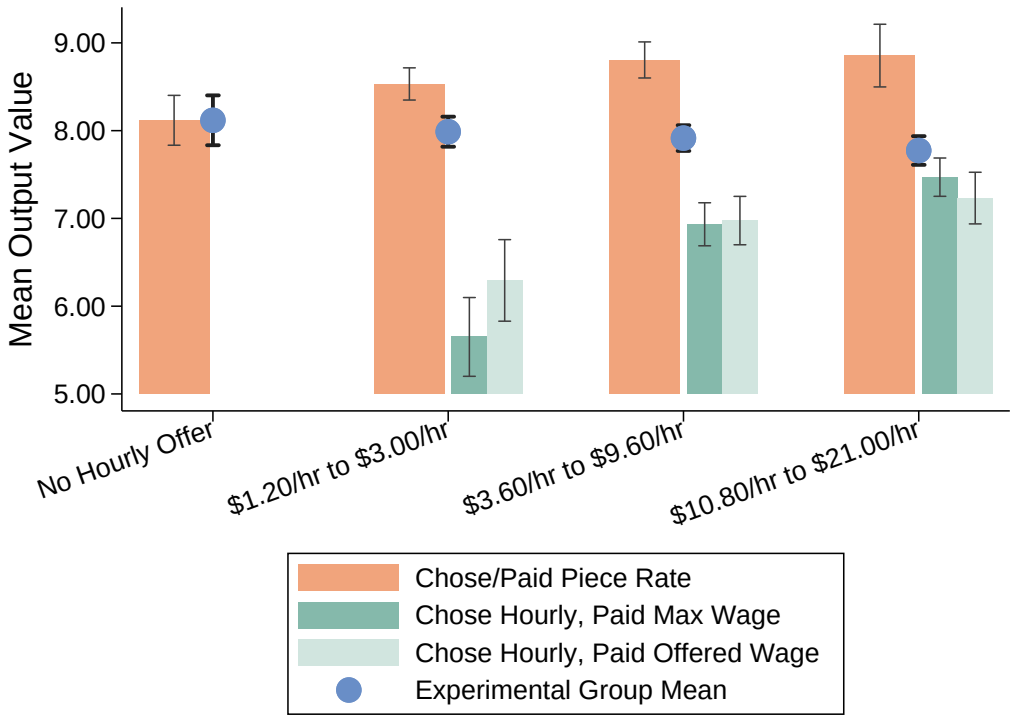
Note: This figure provides a timeline for a single wave of the experiment.

Figure 4: Hourly Wage Take-Up



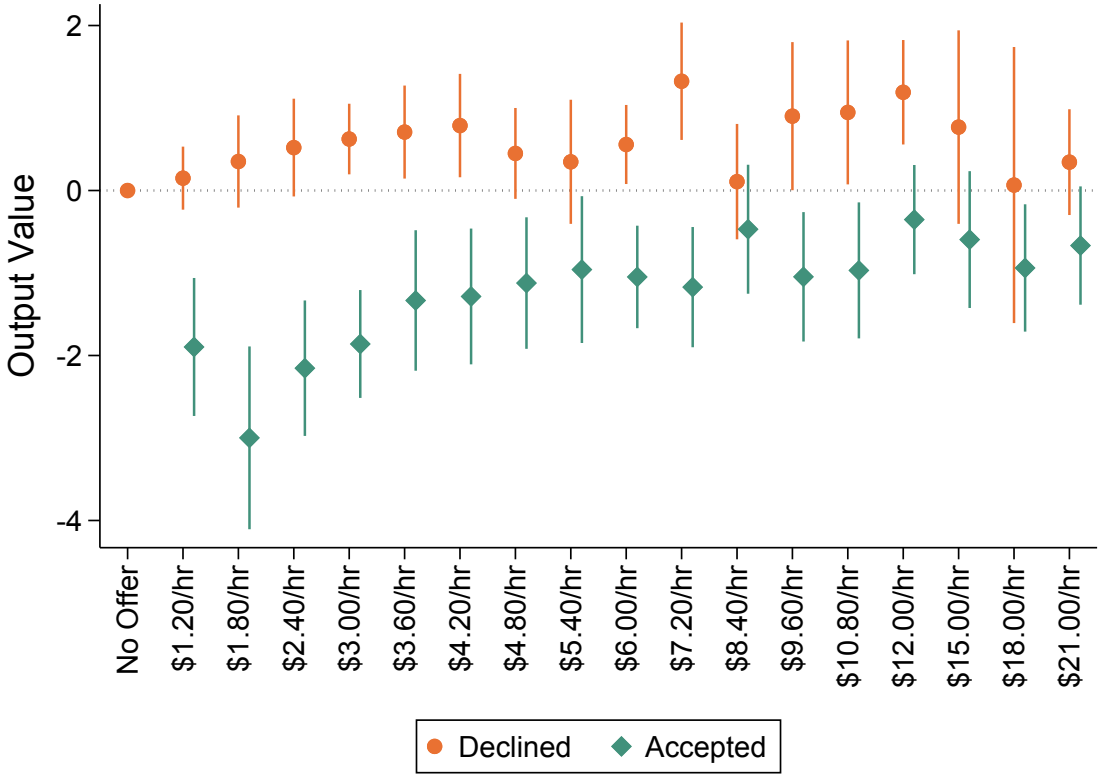
Note: This figure reports hourly-wage acceptance rates by treatment group. The y-axis measures the share of workers in each group who declined the $0.03 piece rate in favor of the hourly wage offer displayed on the x-axis. Note that both piece rate and hourly wage options are offered as supplements to a base wage of $12.00 per hour. Bands indicate 90% confidence intervals.

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



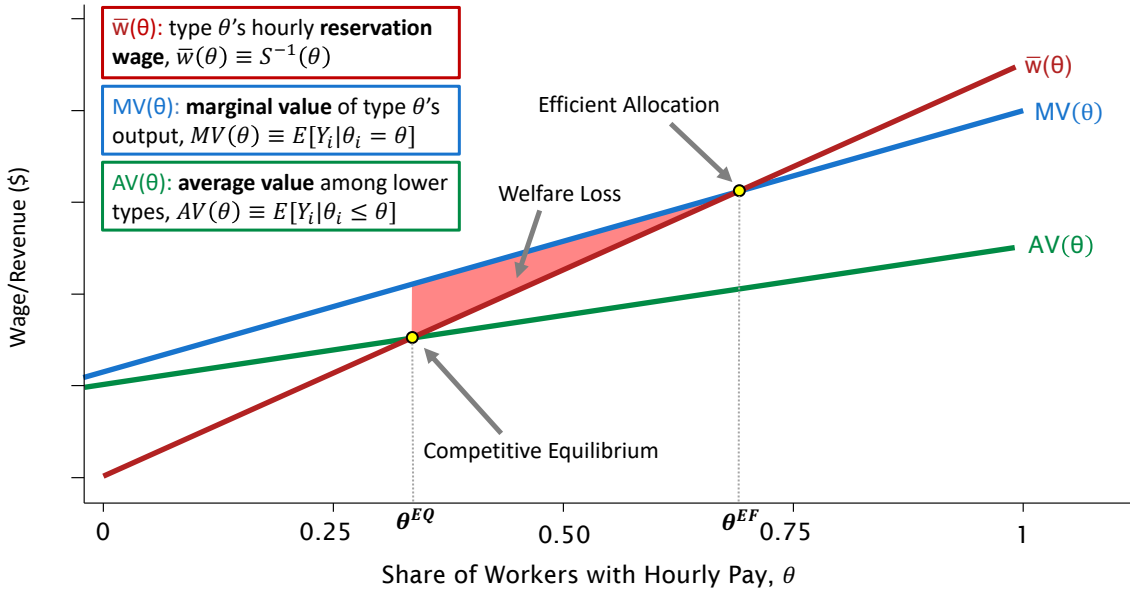
Note: This figure shows mean worker output value by wage-offer groups and compensation choice. "Output value" is defined as the number of typed sentences per hour multiplied by $0.03. Control and treatment groups are labeled on the x-axis. Blue circles measure mean output values among all individuals in each group. Orange bars measure mean output values among those who were paid the $0.03 piece rate. Dark green bars measure mean output values 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. Light green bars measure mean output values 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. Bands indicate 90% confidence intervals.

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



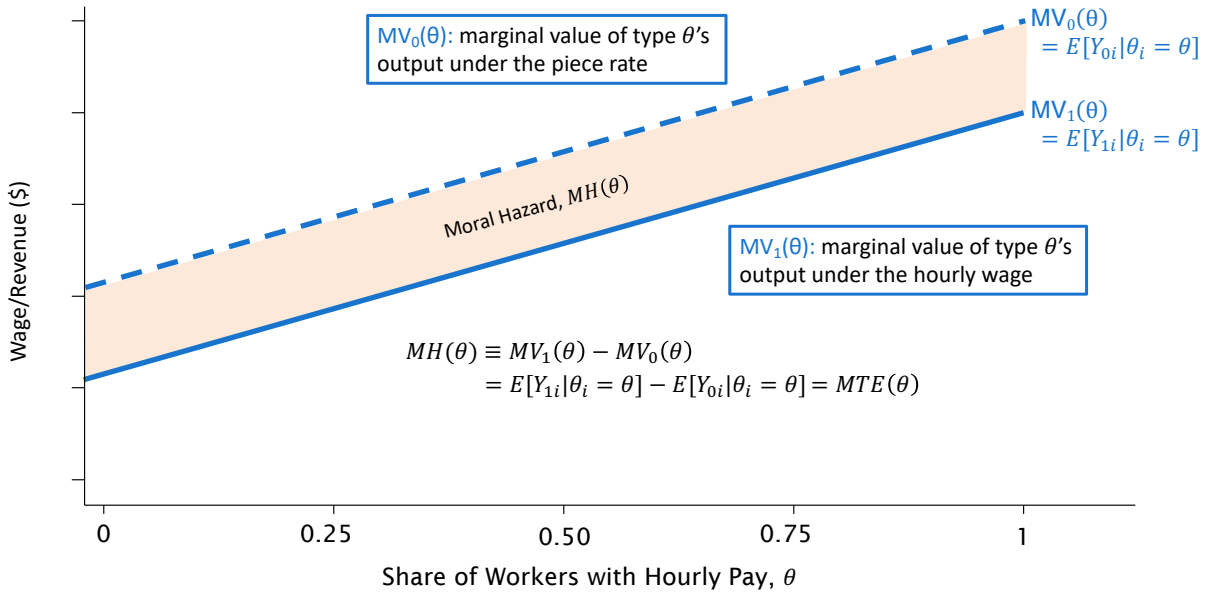
Note: This figure plots coefficients from an OLS regression of output value against the full set of dummy variables for each experimental wage offer, controlling for log effective wages among hourly workers (inclusive of top-ups) as well as task timing. Orange dots represent coefficients on hourly wage offers interacted with an indicator for remaining on the piece rate. Green diamonds represent coefficients on hourly wage offers interacted with an indicator for accepting the offer. Lines represent 90% confidence intervals.

Figure 7: Model of Asymmetric Information in Wage Contracts



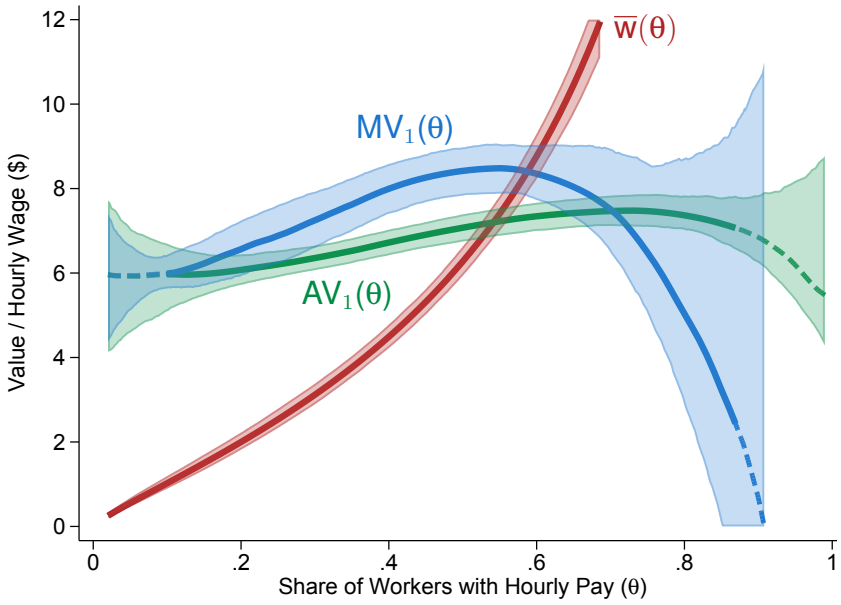
Note: This figure provides a graphical representation of adverse selection in a market for hourly wages. On the horizontal axis, types θ are enumerated in ascending order based on their hourly reservation wage, $\overline{w}_i$. The blue line plots the marginal value curve, $MV(\theta)$, which is equal 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 hourly 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, $AV(\theta) \equiv E[Y_i|\theta_i \leq \theta]$. The pink region corresponds to the welfare loss from adverse selection into hourly wages.

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

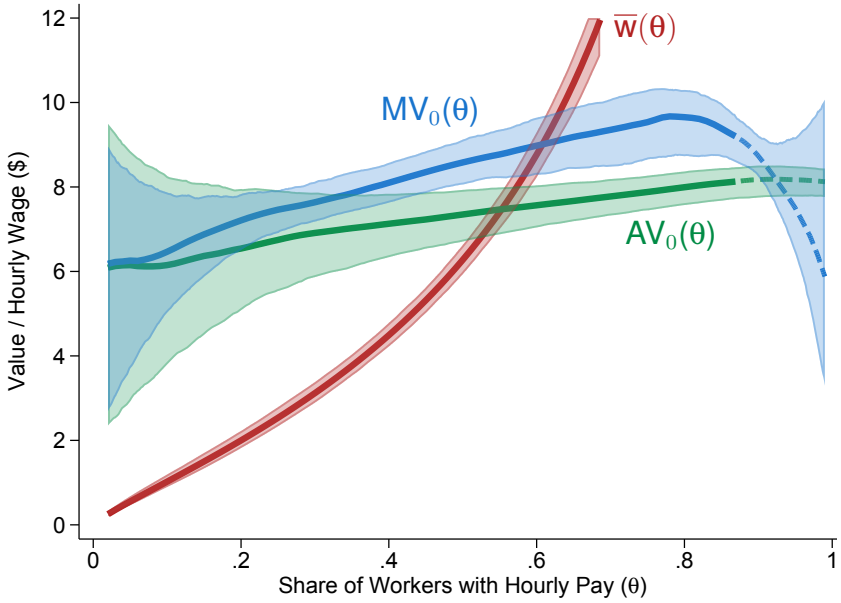


Note: This figure provides a graphical representation of moral hazard in my model. On the horizontal axis, types θ are enumerated in ascending order based on their hourly reservation wage, $\overline{w}_i$. The solid blue line plots $MV_1(\theta)$, which is equal to the expected output value among workers of type θ under the hourly wage, $MV_1(\theta) \equiv E[Y_{1i}|\theta_i = \theta]$. The dashed 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



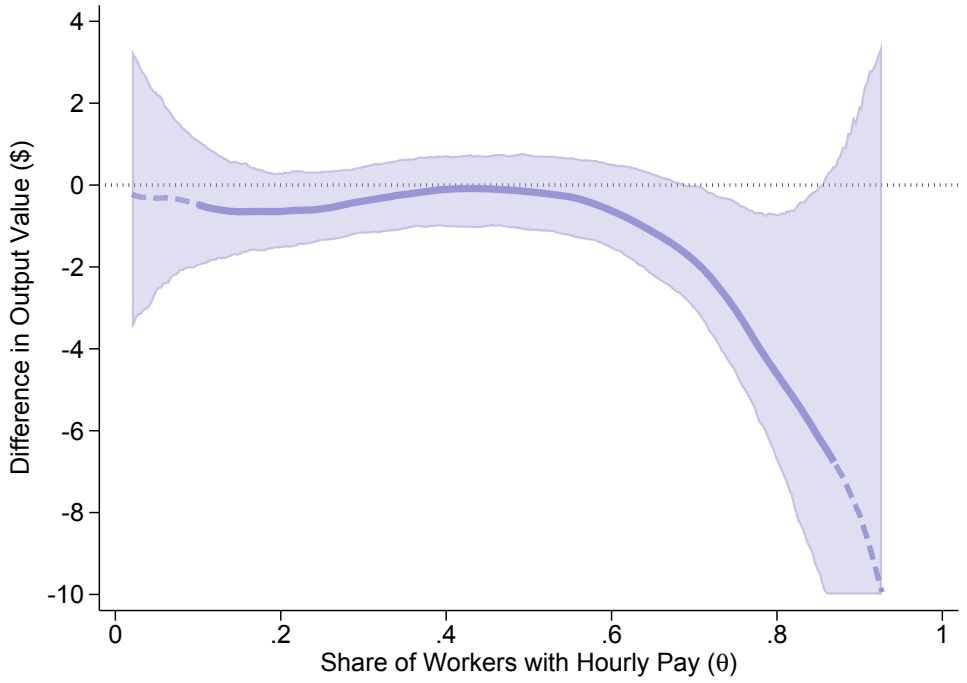
(A) Potential Value Under Hourly Wage



(B) Potential Value Under Piece Rate

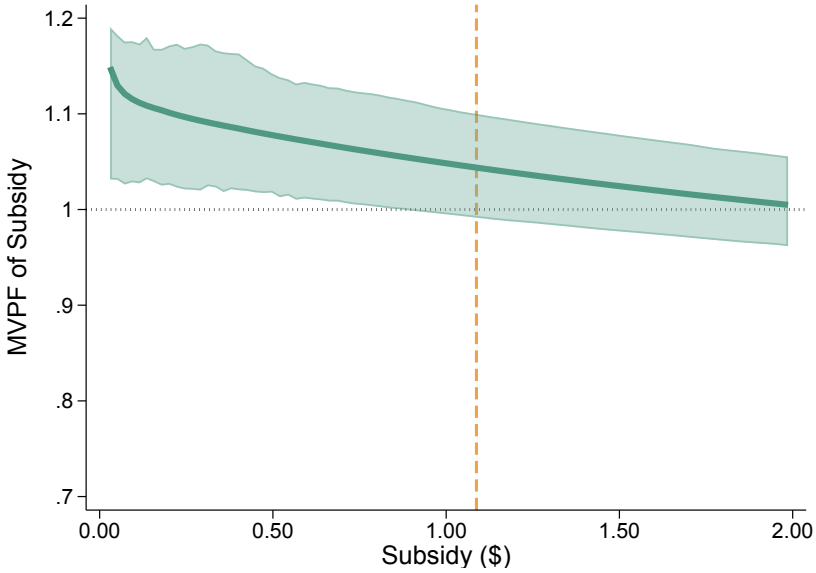
Note: This figure plots estimates supply and value curves, where output values reflect the number of typed sentences multiplied by the piece rate. In the top panel, the blue and green lines plot semi-parametric estimates of the marginal value, $MV_1(\theta)$, and average value $AV_1(\theta)$, under hourly wages, as defined in Figure 7. In the bottom 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)

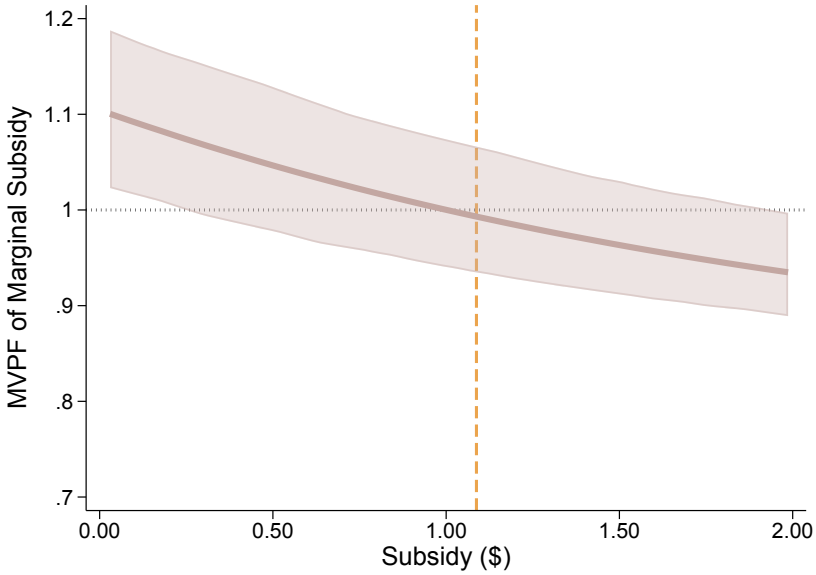


Note: This figure plots estimated marginal treatment effects of hourly wages on worker output value. Estimates are obtained using local polynomial regressions of worker output value against propensity score (i.e. hourly supply share), as described in Section 5. Solid lines denote $MH(\theta) \equiv MV_1(\theta) - MV_0(\theta)$—the difference in the marginal worker's potential output value under an hourly wage versus the piece rate. 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



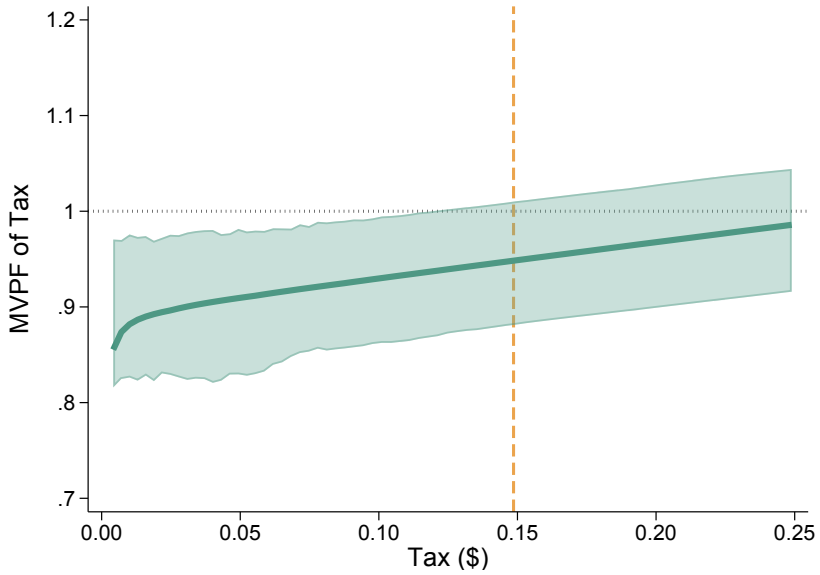
(A) MVPF of Hourly-Wage Subsidy



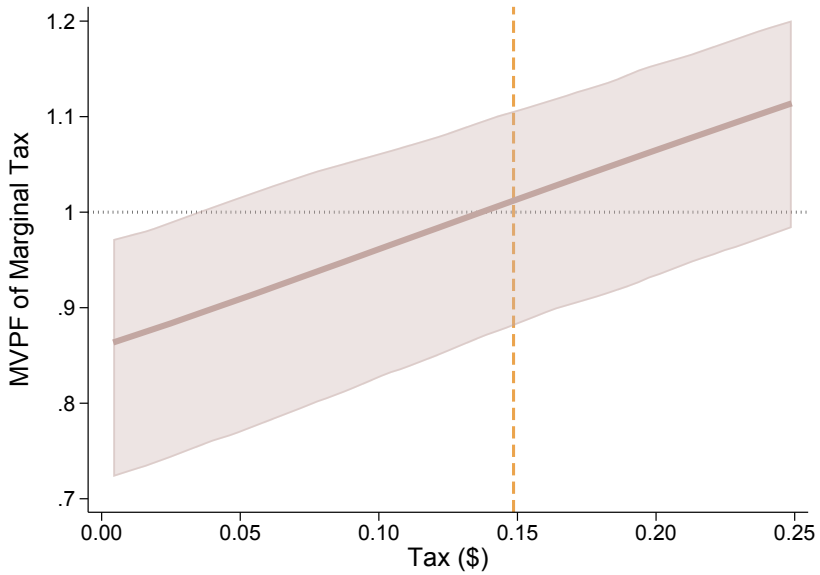
(B) MVPF of Marginal Increase in Hourly-Wage Subsidy

Note: This figure plots estimated marginal values of public funds (MVPFs) 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 (30) in the text. Shaded regions represent 90% confidence intervals.

Figure 12: Estimates of MVPF by Piece-Rate Tax



(A) MVPF of Piece-Rate Tax



(B) MVPF of Marginal Increase in Piece-Rate Tax

Note: This figure plots estimated marginal values of public funds (MVPFs) for piece-rate taxes. Tax MVPFs correspond to marginal social costs per dollar financed, so lower values imply more socially efficient revenue—a tax with an MVPF below one generates $1 of revenue at less than $1 of social cost. In Panel A, the vertical axis plots estimated MVPFs associated with hypothetical piece-rate tax rates denoted on the horizontal axis. In Panel B, the vertical axis plots estimated MVPFs associated with a marginal increase to the piece-rate tax rate on the horizontal axis. The vertical line denotes the tax rate 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 (30) 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 workers for the five-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. The total number of participating workers is 3,030.

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. Columns (2)–(4) add control variables for the categories observable characteristics listed in the bottom panel. 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: 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 log wage offer and an indicator variable for being in the no-offer control group. Columns (2)–(4) add control variables for the categories observable characteristics listed in the bottom panel. 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: 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 (see Equation (8) in the text). 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*. Columns (2)–(4) add control variables for the categories observable characteristics listed in the bottom panel. 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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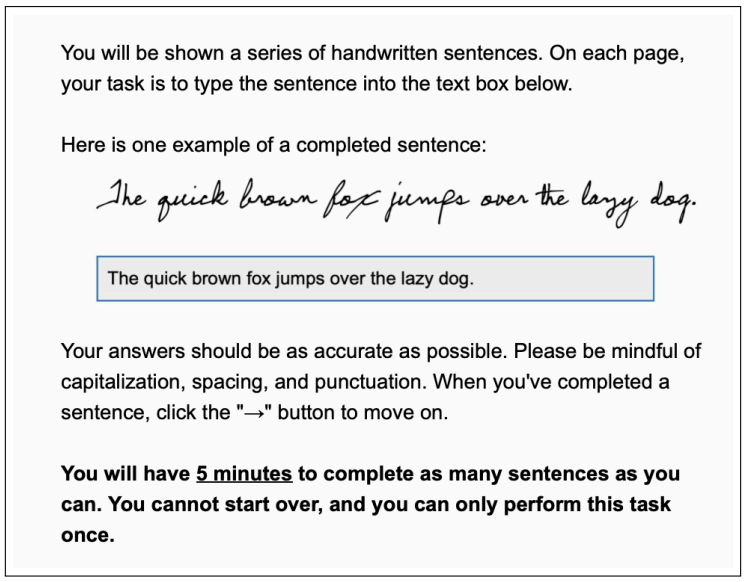
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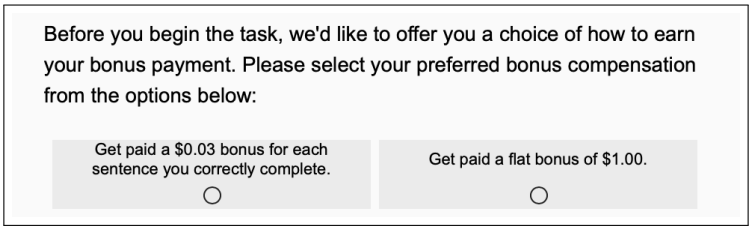
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Appendix A Additional Figures and Tables

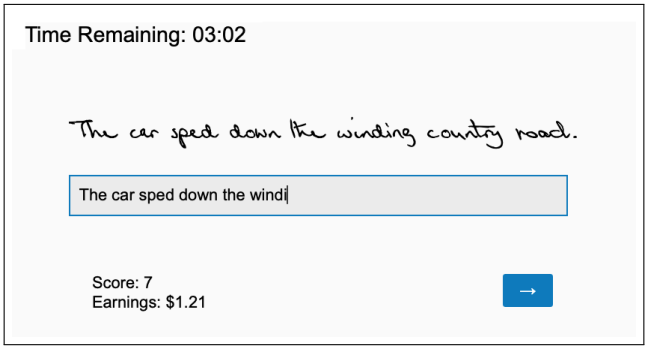
Figure A1: Example Job Posting



(A) Task Description



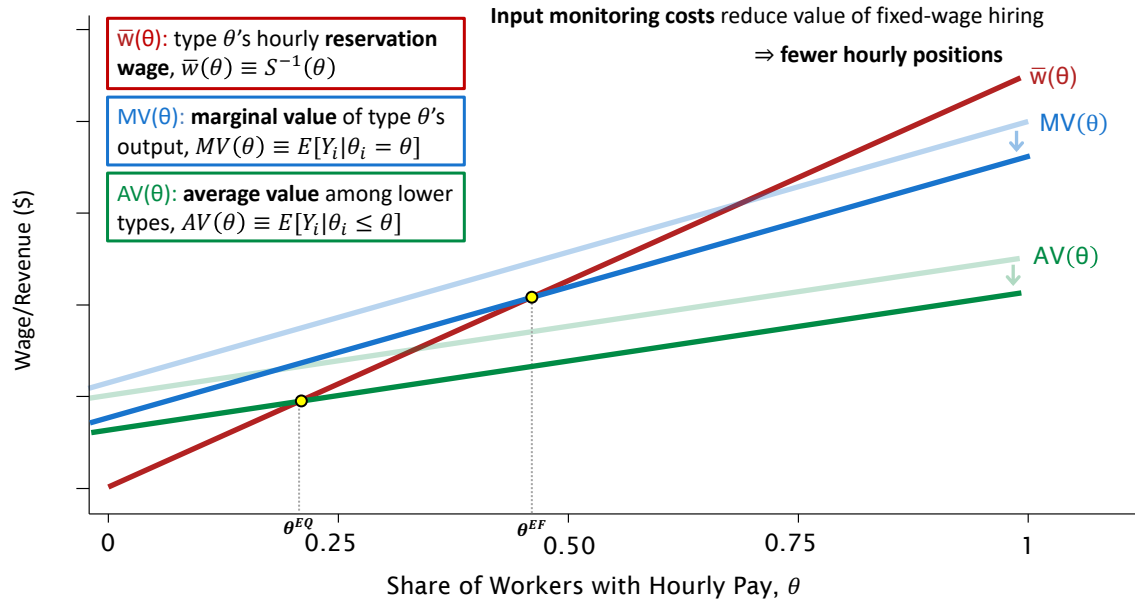
(B) Example Wage Offer



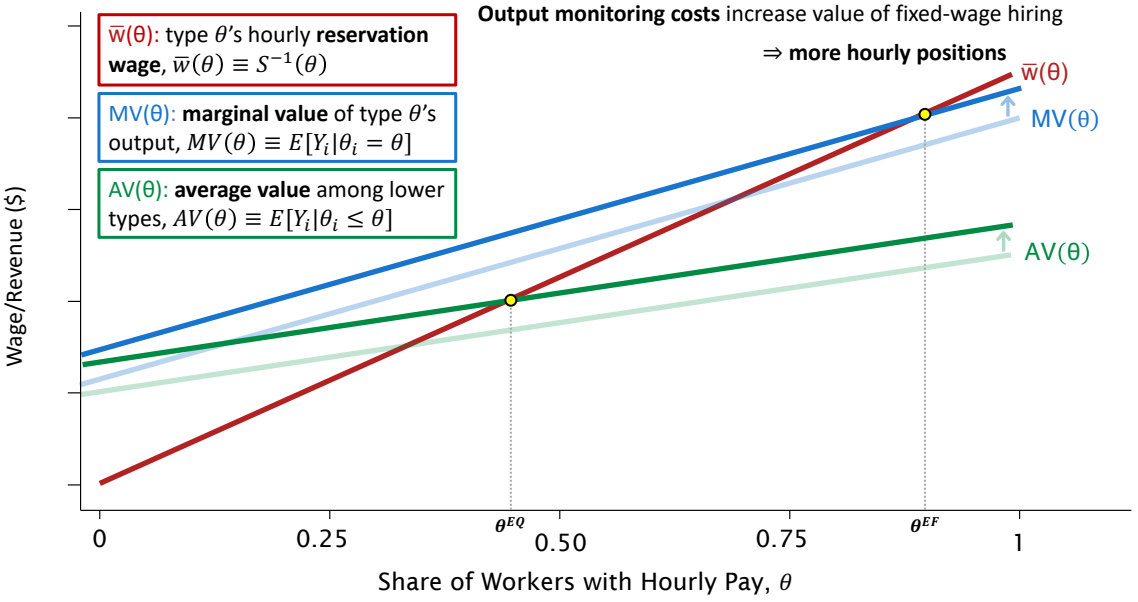
(C) Typing Task

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

Figure A2: Asymmetric Information with Input and Output Monitoring Costs



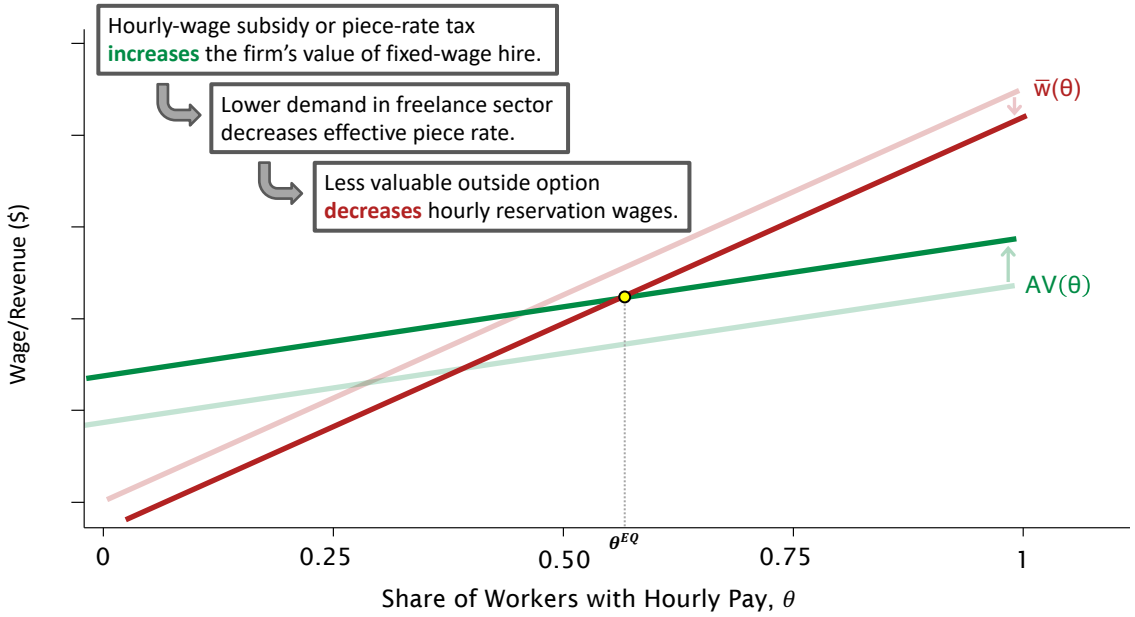
(A) Input Monitoring Costs



(B) Output Monitoring Costs

Note: This figure provides a graphical representation of a market for hourly wages under asymmetric information with input and output monitoring costs.

Figure A3: Equilibrium Effects of Hourly-Wage Subsidies or Piece-Rate Taxes



Note: This figure provides a graphical representation of of both first- and second-order effects of hourly-wage subsidies or piece-rate taxes on hourly labor share.

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: 2SLS Estimates of Treatment Effects of Hourly Wages on Output Value without Adjusting for Wage Effects

	(1) Output Value	(2) Output Value	(3) Output Value	(4) Output Value
Accepted Hourly Offer	−0.531**	−0.525***	−0.513**	−0.390**
	(0.206)	(0.200)	(0.199)	(0.185)
Number of Previous Tasks/1000			0.164***	0.174***
			(0.0338)	(0.0322)
Age				−0.0525***
				(0.00419)
Female				0.367***
				(0.108)
Task Controls	No	Yes	Yes	Yes
Employment Controls	No	No	Yes	Yes
Demographic Controls	No	No	No	Yes
R-squared	0.039	0.082	0.097	0.234
N	3030	3030	3030	3030

Note: This table reports estimated coefficients from two-stage least-squares regressions of unresidualized output value against an indicator for accepting an hourly wage offer. I instrument for hourly wage take-up with log wage offer and an indicator variable for being in the no-offer control group. Columns (2)–(4) add control variables for the categories observable characteristics listed in the bottom panel. 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 A3: Multiple Hypothesis Tests

	Multiplicity Adjusted p-values			
Selection on Y_0				
$H_0 : \beta_0 = 0$	0.0777	0.0397	0.0227	0.0157
Selection on Y_1				
$H_0 : \beta_1 = 0$	0.0003	0.0003	0.0003	0.0003
Treatment Effect				
$H_0 : \psi = 0$	0.0223	0.0137	0.0207	0.0373
Task Controls	No	Yes	Yes	Yes
Employment Controls	No	No	Yes	Yes
Demographic Controls	No	No	No	Yes

Note: This tables reports p-values adjusted for multiple hypothesis testing following Theorem 3.1 from List et al. (2019). Each cell reports the smallest family-wise error rate (the rate of at least one false rejection) across all three hypotheses that still rejects the null hypothesis listed in that row. The first row corresponds to the null hypothesis of zero selection into higher wage offers on potential output under the piece rate ($H_0 : \beta_0 = 0$ in Equation (8)). The second row corresponds to the null hypothesis of zero selection into higher wage offers on potential output under the hourly wage ($H_0 : \beta_1 = 0$ in Equation (8)). The third row corresponds to the null hypothesis of zero treatment effect of the wage offer on output ($H_0 : \psi = 0$, where $\psi = Cov(Y_i, \widetilde{W}_i)/Var(\widetilde{W}_i)$). Columns (2)–(4) add control variables for the categories observable characteristics listed in the bottom panel. 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.

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:

$$\begin{aligned} &E\left[Y_i|W_i = H, D_i = 1\right] - E\left[Y_i|W_i = L, D_i = 1\right] \\ &= \underbrace{E\left[Y_{Hi} - Y_{Li}|D_{Li} = 1\right]}_{\text{Wage Effect}} + \underbrace{E\left[Y_{Hi}|D_{Hi} = 1\right] - E\left[Y_{Hi}|D_{Li} = 1\right]}_{\text{Selection}}. \end{aligned} \tag{37}$$

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:

$$\begin{aligned} \text{Wage Effect} &= E\left[Y_i|W_i = L, D_i = 1, W_i^P = 1\right] - E\left[Y_i|W_i = L, D_i = 1, W_i^P = 0\right] \\ &= E\left[Y_{Hi} - Y_{Li}|D_{Li} = 1\right] \end{aligned} \tag{38}$$

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

high realized wages:

$$\begin{aligned}\text{Selection} &= E\left[Y_i|W_i = H, D_{Hi} = 1\right] - E\left[Y_i|W_i = L, D_{Li} = 1, W_i^P = 1\right] \\ &= E\left[Y_{Hi}|D_{Hi} = 1\right] - E\left[Y_{Hi}|D_{Li} = 1\right]. \end{aligned} \tag{39}$$

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.

$$E\left[Y_{1i}|D_i^H = 1, D_i^L = 0\right] = \frac{\pi^H E\left[Y_i|D_i = 1, W_i = H\right] - \pi^L E\left[Y_i|D_i = 1, W_i = L\right]}{\pi^H - \pi^L} \tag{40}$$

$$E\left[Y_{0i}|D_i^H = 1, D_i^L = 0\right] = \frac{\left(1-\pi^L\right) E\left[Y_i|D_i = 0, W_i = L\right] - \left(1-\pi^H\right) E\left[Y_i|D_i = 0, W_i = H\right]}{\pi^H - \pi^L} \tag{41}$$

Let $\overline{w}_i$ denote the lowest offer individual i is willing to accept. Let $H = w$ and $L = w - \tau$ in Equations (40) and (41). 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 $\tau \to 0$ can be written as

$$E\left[Y_{1i}|\overline{w}_i = w\right] = \frac{\partial\left(E\left[Y_i|D_i(w) = 1\right] S(w)\right)}{\partial S(w)} \tag{42}$$

$$E\left[Y_{0i}|\overline{w}_i = w\right] = -\frac{\partial\left(E\left[Y_i|D_i(w) = 0\right]\left(1 - S(w)\right)\right)}{\partial S(w)}. \tag{43}$$

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

$$S(w) = \alpha + \beta w \tag{44}$$

$$E[Y_i|D_i(w) = 1] = \gamma_1 + \delta_1 w \tag{45}$$

$$E[Y_i|D_i(w) = 0] = \gamma_0 + \delta_0 w. \tag{46}$$

We therefore have

$$E\left[Y_{1i}|\overline{w}_i = w\right] = \frac{(\gamma_1 + \delta_1 w)\beta + (\alpha + \beta w)\delta_1}{\beta} \tag{47}$$

$$= \frac{\alpha\delta_1}{\beta} + \gamma_1 + 2\delta_1 w. \tag{48}$$

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

$$E\left[Y_{0i}|\overline{w}_i = w\right] = \frac{-(\gamma_0 + \delta_0 w)\beta + (1 - \alpha - \beta w)\delta_0}{-\beta} \tag{49}$$

$$= \frac{(\alpha - 1)\delta_0}{\beta} + \gamma_0 + 2\delta_0 w. \tag{50}$$

We therefore have

$$\frac{\partial E\left[Y_{1i}|\overline{w}_i = w\right]}{\partial w} = 2\delta_1 \tag{51}$$

$$\frac{\partial E\left[Y_{0i}|\overline{w}_i = w\right]}{\partial w} = 2\delta_0 \tag{52}$$

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*:

$$AV_1^E(\theta) \equiv E\left[Y_{1i}(\overline{w}(\theta))|\theta_i \leq \theta\right]. \tag{53}$$

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).[35] I thus rewrite $MV_1(\theta)$ as the marginal value of type θ's output *at their profit-maximizing wage*, so

$$MV_1^E(\theta) \equiv E\left[Y_{1i}(w^*(\theta))|\theta_i = \theta\right], \tag{54}$$

where

$$w^*(\theta) \equiv \underset{w}{\operatorname{argmax}}\, E\left[Y_{1i}(w) - w|\theta_i = \theta\right]. \tag{55}$$

Note that allowing for wage effects means I can no longer interpret Equation 19 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.

[35] 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,

$$\begin{aligned}
\overline{w}(\theta;p) &= u^{-1}\left(E\left[u(pq)|\theta\right]\right) && (56)\\
&= \left((1-\rho)E\left[\frac{(pq)^{1-\rho}}{1-\rho}|\theta\right]\right)^{\frac{1}{1-\rho}} && (57)\\
&= pu^{-1}\left(E\left[u(q)|\theta\right]\right) && (58)\\
&= p\overline{w}(\theta;1), && (59)
\end{aligned}$$

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:

$$\begin{aligned}
MV\left(\theta;p\right) &\equiv E\left[pq_i|\theta_i=\theta\right] && (60)\\
&= pE\left[q_i|\theta_i=\theta\right] = pMV(\theta;1). && (61)
\end{aligned}$$

Equations (59) and (61) allow me to rewrite welfare loss from Equation (16) for a given piece-rate, p, as

$$\begin{aligned}
DWL(p) &= \int_{\theta_{EQ}}^{\theta_{EF}} \left(MV(\theta;p) - \overline{w}(\theta;p)\right) d\theta && (62)\\
&= \int_{\theta_{EQ}}^{\theta_{EF}} \left(pMV(\theta;1) - p\overline{w}(\theta;1)\right) d\theta && (63)\\
&= pDWL(1). && (64)
\end{aligned}$$

Equation (64) 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.

Appendix C Derivations of MVPFs and Optimal Policies

In this appendix, I derive optimal tax and subsidy policies from Section 6.

C.1 Subsidy

Using Equations (28), (29), and (31), the welfare-maximizing level of subsidy is given by

$$\max_{\delta} \left\{ \underbrace{\delta\theta^{\delta} + \int_{\theta^{EQ}}^{\theta^{\delta}} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}_{WTP(\delta)} - \lambda \underbrace{\left(\delta\theta^{\delta} + \int_{\theta^{EQ}}^{\theta^{\delta}} \tau MH(\theta) d\theta \right)}_{NC(\delta)} \right\}, \tag{65}$$

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 (65) imply

$$MVPF_{d\text{Sub}}(\delta^*) \equiv \frac{WTP'(\delta^*)}{NC(\delta^*)} = \lambda \tag{66}$$

$$\frac{\frac{d\delta}{d\theta^{\delta}}\theta^{\delta^*} + MV_1(\theta^{\delta^*}) - \overline{w}(\theta^{\delta^*})}{\frac{d\delta}{d\theta^{\delta}}\theta^{\delta^*} - \tau MH(\theta^{\delta^*})} = \lambda. \tag{67}$$

$MVPF_{d\text{Sub}}(\delta)$ is the MVPF for a *marginal increase* in hourly-wage subsidy.

To calculate $\frac{d\delta}{d\theta^{\delta}}$, consider the equilibrium condition from Equation (14) in the presence of an hourly-wage subsidy, δ:

$$\overline{w}(\theta^{\delta}) = AV_1(\theta^{\delta}) + \delta. \tag{68}$$

Differentiating with respect to θ^{δ} yields

$$\frac{d\delta}{d\theta^{\delta}} = \frac{d\overline{w}}{d\theta^{\delta}} - \frac{dAV_1(\theta^{\delta})}{d\theta^{\delta}} \tag{69}$$

$$= \left(\frac{dS}{d\overline{w}}\right)^{-1} - \frac{MV_1(\theta^{\delta}) - AV_1(\theta^{\delta})}{\theta^{\delta}} \tag{70}$$

$$= \frac{\overline{w}}{\beta\theta^{\delta}(1-\theta^{\delta})} - \frac{MV_1(\theta^{\delta}) - AV_1(\theta^{\delta})}{\theta^{\delta}} \tag{71}$$

$$\tag{72}$$

where β is the coefficient on a $\ln \overline{w}$ in a logistic model of hourly labor supply.

C.2 Tax

The welfare-maximizing level of tax is given by

$$\max_{\rho} \left\{ \eta NR(\rho) - WTP(\rho) \right\}, \tag{73}$$

where $NR(\rho)$ is the government's revenue from the piece-rate tax net of any fiscal externalities, and $WTP(\rho)$ is individuals' aggregate willingness-to-pay to *avoid* the tax. η reflects the highest-MVPF policy for which revenue might be used. Under a balanced budget, η would represent the MVPF of the least efficient revenue source one could replace with the piece-rate tax.

$$\max_{\rho} \left\{ \eta \underbrace{\left(\int_{\theta^{\rho}}^{1} \rho MV_0(\theta) d\theta + \int_{\theta^{EQ}}^{\theta^{\rho}} \tau MH(\theta) d\theta \right)}_{NR(\rho)} - \underbrace{\left(\int_{\theta^{\rho}}^{1} \rho MV_0(\theta) d\theta - \int_{\theta^{EQ}}^{\theta^{\rho}} \left(MV_1(\theta) - \overline{w}(\theta) \right) d\theta \right)}_{WTP(\rho)} \right\}, \tag{74}$$

The first order conditions for (74) imply

$$MVPF_{d\text{Tax}}(\rho^*) \equiv \frac{WTP'(\rho^*)}{NR'(\rho^*)} = \eta \tag{75}$$

$$\frac{\frac{d\rho}{d\theta^{\rho}} \int_{\theta^{\rho^*}}^{1} MV_0(\theta) d\theta - \rho^* MV_0(\theta^{\rho^*}) - \left(MV_1(\theta^{\rho^*}) - \overline{w}(\theta^{\rho^*}) \right)}{\frac{d\rho}{d\theta^{\rho}} \int_{\theta^{\rho^*}}^{1} MV_0(\theta) d\theta - \rho^* MV_0(\theta^{\rho^*} + \tau MH(\theta^{\rho^*})} = \eta. \tag{76}$$

$MVPF_{d\text{Tax}}(\rho)$ is the MVPF for a *marginal increase* in piece-rate tax.

To calculate $\frac{d\rho}{d\theta^{\rho}}$, consider the equilibrium condition from Equation (14) in the presence of piece-rate tax, ρ:

$$\overline{w}(\theta^{\rho}) = (1 + \rho) AV_1(\theta^{\rho}). \tag{77}$$

Differentiating with respect to θ^ρ yields

$$\frac{d\rho}{d\theta^\rho} = \frac{\frac{d\overline{w}}{d\theta^\rho}}{AV_1(\theta^\rho)} - \frac{\overline{w}(\theta^\rho)}{2AV_1(\theta^\rho)}\frac{dAV_1(\theta^\rho)}{d\theta^\rho} \tag{78}$$

$$= \left(\frac{dS}{d\overline{w}}\right)^{-1}\frac{1}{AV_1(\theta^\rho)} - \frac{\overline{w}(\theta^\rho)}{2AV_1(\theta^\rho)}\frac{MV_1(\theta^\rho) - AV_1(\theta^\rho)}{\theta^\rho} \tag{79}$$

$$= \frac{\overline{w}(\theta^\rho)}{\beta\theta^\rho(1-\theta^\rho)AV_1(\theta^\rho)} - \frac{\overline{w}(\theta^\rho)\left(MV_1(\theta^\rho) - AV_1(\theta^\rho)\right)}{2\theta^\rho AV_1(\theta^\rho)} \tag{80}$$

where β is the coefficient on a $\ln \overline{w}$ in a logistic model of hourly labor supply.