Asymmetric Information in Wage Contracts: Evidence from an Online Experiment

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Abstract

Compared to self-employment or performance-based pay, fixed wages offer workers a guaranteed return on each hour of work, even when their labor product is unpredictable. But like many insurance products, 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 choose between a randomized fixed wage and a piece rate. I find evidence of both moral hazard and adverse selection. Fixed wages reduce worker productivity by an estimated 6.4 percent relative to the mean. Meanwhile, a 10 percent increase in the fixed wage offer attracts a marginal worker whose productivity is higher by 1.6 percent of the mean. Using semi-parametric MTE estimation, I calculate the welfare loss associated with adverse selection and the marginal values of public funds (MVPFs) for corrective subsidy and tax policies. My estimates suggest that a 14-percent tax on piece-rate earnings 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 wages offer workers a guaranteed return on each hour of work, even when output is unpredictable. In financial terms, they operate like equity contracts in which the employer buys a claim on the worker's next hour of labor product. But these contracts are also vulnerable to moral hazard and adverse selection—a fixed wage might induce less effort or attract less productive workers than freelance hiring or piece-rate pay. Such information asymmetry problems can distort equilibrium wages, leaving workers over-reliant on output-based compensation like piece rates, tips, or commissions. They may, for example, explain why millions of short-term "gig" workers are compensated by the number of miles driven, pages written, or tasks completed. While these workers may benefit from choosing their own hours (Mas and Pallais, 2017; Garin et al., 2020; Koustas, 2018), they also face uncertainty over what they will earn during those hours.[1] Could asymmetric information be to blame?

The potential for market failures surrounding output-based compensation holds important policy implications. Fixed-wage subsidies, taxes on piece rates or tips, employment classification rules, and even the minimum wage can mitigate the welfare costs of asymmetric information in markets dominated by output-based pay. However, designing these policies requires knowledge of both moral hazard and adverse selection, not just on average, but with respect to marginal wage changes. For example, an optimal fixed-wage subsidy must balance the welfare 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, but identifying their effects on 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. Second, estimates that rely on labor supply decisions in the presence of competitive outside options will likely understate the value of fixed wages and overstate supply elasticities relative to their market-level values (Dube et al., 2020; Caldwell and Oehlsen, 2023). Third, detecting information asymmetries requires a representative sample of both existing and *potential* fixed-wage workers—a sample

[1] As one gig worker 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).

of employees at an existing firm would exclude workers who turned down prevailing fixed wages in favor of self-employment or freelance work. Finally, adversely selected wage contracts may be too unprofitable for employers to offer and thus impossible to observe in existing markets, forcing researchers to rely on wage variation that excludes the margins most relevant to measuring welfare loss (Einav et al., 2010b).

In this paper, I experimentally estimate the equilibrium and welfare effects of moral hazard and adverse selection in a large online labor market. To identify these forces, I conduct a field experiment with two stages of randomization: First, I offer workers a choice between a randomized fixed hourly wage and a standardized piece rate. Then, after workers choose a payment option but before they begin their assigned 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 moral hazard as the treatment effect of fixed-wage compensation on worker output. Meanwhile, comparing output across workers on the same contract who faced different ex-ante offers identifies adverse selection into fixed wages.

Results from my experiment provide evidence of both moral hazard and adverse selection into fixed-wage contracts. Estimated treatment effects imply that working under hourly pay reduces workers' output value by 6.39 percent relative to the mean. At the same time, a ten-percent increase in the hourly wage offer attracts a marginal worker with 1.57-percent higher productivity compared to the mean. This finding appears driven by selection on *unobserved* determinants of productivity; results persist after conditioning on demographics and work experience, suggesting that pre-employment screening cannot fully resolve asymmetric information problems in this labor market.

What do these findings imply for equilibrium wages and social welfare? The answer depends on how estimates of treatment and selection evolve with marginal changes to the fixed wage. In the second half of the paper, I show how both moral hazard and adverse selection can be expressed using marginal potential outcomes under fixed-wage and piece-rate counterfactuals—the principal estimands of marginal treatment effects (MTE) analysis. Embedding these MTE estimands into a model of labor markets under asymmetric information allows me to characterize equilibrium and efficient allocations of fixed-wage labor without parametric assumptions. Much like canonical models of insurance markets (Einav et al., 2010a; Akerlof, 1970), my model 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. A worker cannot be profitably hired for a fixed-wage job if their reservation wage exceeds the average output value of lower-reservation-wage workers. Relative to a full-information equilibrium, this profit condition leads to an underprovision of hourly work—some piece-rate workers would like to forfeit a portion of their expected earnings in exchange for a fixed-wage contract, but the threat of adverse selection prevents employers from offering such contracts at those workers' reservation wages.

To quantify this welfare loss from asymmetric information, I 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 reduction in hourly work is between \$0.03 and \$0.04 per hour of labor. These two equilibria reflect a non-linear pattern of selection on moral hazard: At low reservation wages, those with marginally stronger preferences for fixed wages have a slightly higher propensity to shirk, consistent with patterns of selection in insurance markets (Einav et al., 2013). At higher reservation wages, however, shirkers are more likely to prefer piece rates, a pattern that could be explained by heterogeneous risk preferences—those who prefer the variability of piece-rate pay may also be more likely to shirk under fixed wages because they are less fearful of poor performance reviews.

If adverse selection results in suboptimal fixed-wage contracts, the government might consider subsidies or taxes aimed at promoting these contracts. However, such policies come with a trade-off: a fixed wage benefits the marginal worker but also encourages them to shirk, reducing their earnings and tax payments. To quantify this trade-off, I calculate the marginal values of public funds (MVPFs) for subsidizing hourly wages or taxing piece rates (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. On the other hand, taxes on piece-rate earnings yield a marginal *cost* of public funds (MCPF) as low as 0.87, meaning each dollar of tax revenue carries a net social cost of just \$0.87. 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. Conversely, these findings suggest that eliminating taxes on output-based earnings like tips may amplify the welfare costs of adverse selection into fixed wages.

While my 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 might efficiently raise government revenue in other labor markets, especially those for short-term gig work. In fact, the social benefits of such policies would likely be larger in higher-stakes environments than my experimental setting. To illustrate how my framework might be applied to other settings, I calibrate my model to the market for rideshare driver using experimental estimates from Angrist et al. (2021). In this setting, adverse selection manifests as the sorting of more productive drivers into taxi-style contracts that require fixed weekly lease payments in exchange for higher commissions on ride fares. Using estimates of driver supply and calibrated value curves from Angrist et al. (2021), I find that inefficiencies associated with this selection pattern results in an approximate welfare loss of \$0.09 per hour worked, comparable to my estimates of welfare loss in the market for online data-entry.

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).[2] Empirically, several papers document 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

[2]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).

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; Caldwell and Oehlsen, 2023), stylists (Butschek et al., 2022), miners (Shearer, 1996), and physicians (Kantarevic and Kralj, 2016; Gaynor et al., 2004). More recently, Emanuel and Harrington (2024) estimate negative productivity effects and negative selection into remote work among call-center workers following the COVID-19 pandemic. Experimental studies of compensation and productivity include DellaVigna and Pope (2018), who use an online experiment to investigate the effects of monetary and non-monetary incentives on worker performance and Shearer (2004), who estimates the productivity differences between piece-rate and fixed-wage tree-planters in British Columbia.

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, and my estimation 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 in fixed-wage labor contracts.

Methodologically, my experimental design builds upon 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 online gig workers. The components of these MVPFs map directly to my experimental estimands, allowing me to flexibly compare each policy's welfare benefits 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 the broader implications of my findings and calibrate my model to the market for rideshare drivers. 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 fixed 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 fixed hourly wage and a standardized piece rate.[3] 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. I first illustrate the intuition behind this design with a stylized two-contract setting before extrapolating to settings with multiple wage offers.

[3]My design holds piece rates constant because employers face no costs of adverse selection or moral hazard from varying the piece rate—they simply want to pay the lowest possible price per unit of labor product. In other words, the experimental piece rate represents the “no-insurance” outside option to potential fixed-wage contracts. See footnote 18.

2.1 Example using a Single Wage Offer

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 $Y_i = D_i Y_{1i} + (1 - D_i)Y_{0i}$, 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 sum of two components—average treatment-on-the-treated and average selection on untreated outcomes:

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

The treatment-on-the-treated component corresponds to the average effect of hourly pay ($Y_{1i} - Y_{0i}$) among those who accept the hourly wage offer ($D_i = 1$), while the selection component corresponds to the average difference in potential piece-rate outcomes (Y_{0i}) 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.

To separate these forces of treatment and selection, my experimental design randomizes the menu of compensation options faced by workers. In the simple two-contract setting presented above, that means randomly assigning each worker to one of two 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):

$$\underbrace{E\left[Y_{1i}-Y_{0i}|D_i^*=1\right]}_{\text{Average Treatment on the Treated}} = \frac{E\left[Y_i|W_i=1\right]-E\left[Y_i|W_i=0\right]}{\pi}, \tag{2}$$

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 (1) is equally as important as treatment effects. I can identify this component by simply comparing output between piece-rate workers in the control group ($W_i=0$) and piece-rate workers in the hourly-offer group ($W_i=1$), who declined the hourly wage offer:

$$\underbrace{\left(E\left[Y_{0i}|D_i^*=1\right]-E\left[Y_{0i}|D_i^*=0\right]\right)}_{\text{Average Selection on } Y_0} = \frac{E\left[Y_i|W_i=0\right]-E\left[Y_i|D_i=0,W_i=1\right]}{\pi}, \tag{3}$$

where equality follows from randomized assignment.[4]

Figure 1, Panel A illustrates the intuition from Equation (3). 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 (top left box) to those in the treatment group who chose to remain on the piece rate (top right box). 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 provides a simplified illustration 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

[4]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 (3) can also be derived by subtracting the Wald estimator (2) from the difference in hourly versus piece-rate outcomes in the treatment-offer group, $E\left[Y_i|D_i=1,W_i=1\right]-E\left[Y_i|D_i=0,W_i=1\right]$.

treated state, Y_1) across multiple margins.[5] 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 hourly wage, while workers assigned to $W_i = H$ are offered the choice between the piece rate and a high hourly wage.

As before, I can identify selection on Y_0 by comparing outcomes between piece-rate workers who faced different ex-ante hourly offers—none ($W_i = 0$), low ($W_i = L$), or high ($W_i = H$). 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 potential output under the piece rate, Y_0. But now I can also identify selection on Y_1, potential output under hourly pay, by comparing between hourly workers who *accepted* their respective wage offers.

Importantly, however, my identifying assumption requires wage offers to only affect workers' output through their choice of hourly versus piece-rate contract, $W_i \perp\!\!\!\perp (Y_{1i}, Y_{0i})$. If both accepters both high- and low-offer groups work under the wages they were offered, this exclusion restriction could be violated through wage effects—higher pay might induce greater effort through increased motivation or satisfaction, biasing my estimates. To separate these wage effects from the incentive effects of hourly contract structure, the second stage of my experiment increases wages for a random subset of workers accepting the low hourly wage offer, equalizing their pay with the high hourly wage offer just before the task begins. This surprise top-up creates random variation in *effective* wages among those accepting a given *offered* wage, allowing me to separate potential wage effects from moral hazard and adverse selection.[6]

The intuition behind the multiple wage-offer experimental design is illustrated in Figure 1, Panel B. The top row of boxes represents individuals in each of the three experimental groups, $W_i \in \{0, L, H\}$, who remain on the piece rate. Because all

[5] Details are provided in Appendix B.1.

[6] Because variation between offered and effective wages is generated through unexpected top-ups, estimated wage effects also include potential behavioral responses to receiving a "surprise" pay raise. As I discuss in Section 3, the wide range of wage offers in my design allows separate such responses from true wage effects—a response to surprises should persist for very small wage top-ups, whereas wage effects should reduce to zero as the effective wage approaches the offered wage.

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 accepted low ($W_i = L$) and high ($W_i = H$) hourly wage offers, 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 (Herbst, 2024). Appendix C provides complete details on the experimental protocol.

Participants in my experiment were recruited on Prolific, an online platform that allows clients to hire online workers for short-term tasks.[7] The experimental job posting offered workers a $1.00 reward plus a $0.03 per-entry bonus 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 market for such data-labeling tasks is already worth billions of U.S. dollars and growing rapidly as companies deploy AI models that require large volumes of annotated data (Grand View Research, 2024; Mordor Intelligence, 2025). Participants were not informed that they were part of an experiment until after they performed the task.

Upon accepting the experimental job, workers were randomized into one of eighteen experimental groups. Each group was offered a different menu of compensation options in exchange for completing the five-minute data-entry task. In the first treatment group, workers were offered a choice between a fixed $0.10 payment ($1.20 per hour) or a piece rate of $0.03 per correctly typed sentence.[8] In the second treatment group, workers were offered a choice between a fixed $0.15 payment ($1.80 per hour)

[7]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.

[8]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).

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 was offered the \$0.03 piece rate for each correctly typed sentence, with no alternative option. Each of these options was offered as an addition to the \$1.00 reward advertised in the job posting, which all workers received for agreeing to the task. Experimental conditions are listed in Table 1.

The experiment took place in ten waves of three-hundred job postings. Waves were launched at a broad range of days and times to ensure the sample was not restricted to workers with a particular schedule. Data on task performance was collected at the conclusion of each wave. The primary outcome of interest is hourly output value, defined as

$$\text{Output Value} \equiv \frac{\text{Completed Sentences} \times \$0.03}{{}^{1}\!/_{12}\ \text{Hours}}. \tag{4}$$

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 is important to simulate a sample of workers who would be observably equivalent to a hypothetical employer.

Importantly, clients on the Prolific platform have the ability to reject or approve a given worker's assignment. Rejected assignments do not earn rewards and lower workers' approval ratings. The reputational damage from rejected assignments is a salient concern among workers on Prolific and similar platforms (u/ProlificAc, 2024). As in most labor markets, this threat of rejection creates an incentive for online workers to maintain a minimum standard of performance, even if they are paid a fixed wage.

3 Baseline Experimental Results

This section describes baseline reduced-form results from the experiment. Sample sizes are listed alongside wage offers for each experimental group in Table 1, and balance tests are reported in Appendix Table A1.[9] Table 2 reports summary statistics for the experimental 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 2 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, wage offers of $3 or lower were accepted at a rate of 21 percent, while wage offers above $10 were accepted at a rate of 74 percent. To fit these results 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.

3.1 Evidence of Moral Hazard and Adverse Selection

Figure 2 illustrates how gradual increases in experimental wage offers result in incrementally higher rates of take-up, creating different groups of accepters (hourly workers) and decliners (piece-rate workers) for each hourly offer. In Figure 3, I examine how output value for these groups varies with the generosity of the wage offer. For readability, experimental conditions are aggregated into four categories—those in the control group who received no hourly offers, those receiving wage offers between $1.20 and $3.00, those receiving wage offers between $3.60 and $9.60, and those receiving wage offers of $10.80 or higher. Blue circles measure average output values among all individuals in each of these categories. Orange bars measure average output values

[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 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.

among workers on the piece rate. Dark green bars measure average output values among workers who accepted their hourly wage offers and received randomized top-ups, bringing their effective hourly wages to the $21.00 per hour maximum. Light green bars measure average output values among those who accepted their hourly wage offers and did not receive top-ups. Following Section 2, I compare these different groups across wage-offer categories to identify treatment and selection into hourly pay, providing evidence for both moral hazard and adverse selection.

Treatment Effect of Hourly Wages In the absence of wage effects, comparing means across each aggregated group in Figure 3 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, consistent with moral hazard. Those in the control group, who received no hourly wage offer, produce $8.12 (SE=$0.17) of output value. Those receiving wage offers between $1.20 and $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 obtain point estimates for the treatment effect of hourly wages on workers' output value, I disaggregate the groups from Figure 3 into a continuous measure of wage offers, which I use 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 (i.e., inclusive of top-ups) 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 statis-

[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.

tically significant reduction in worker productivity. Absent controls, accepting an hourly contract reduces a worker's output value by \$0.51 (SE=0.21) or 6.39 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 treatment effect estimates are consistent with moral hazard—on average, workers' output is lower under hourly wages, when they do not bear the financial cost of decreased effort, than under piece rates, when their earnings are more closely tied to output.

Selection into Hourly Wages While comparisons of pooled means across wage-offer groups identifies treatment effects, comparisons of means for accepters and decliners across wage-offer groups identifies selection on potential output under hourly wages and piece rates, respectively. In Figure 3, the orange bars increase with the wage offer, meaning those who decline the most generous hourly wages in favor of the piece rate have relatively high output. Those declining offers between \$1.20 and \$3.00 produce \$8.53 (SE=\$0.11) of average output value, those declining offers between \$3.60 and \$9.60 produce \$8.81 (SE=\$0.13) of average output value, and those declining offers of \$10.80 and above produce \$8.86 (SE=\$0.22) of average 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 hourly 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 between \$1.20 and \$3.00 produce \$5.65 of average output value, those accepting offers between \$3.60 and \$9.60 produce \$6.93 of average output value, and those accepting offers of \$10.80 and above produce \$7.47 of average 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 topped-up workers' averages, suggesting that wage effects are not important in this setting.

Disaggregating the groups from Figure 3 into respective experimental wage offers, I use ordinary-least squares (OLS) estimation to fit the selection patterns seen in Figure 3 to the following linear model:

$$Y_i = \alpha D_i + \beta_0(1 - D_i) \times W_i + \beta_1 D_i \times W_i + \gamma D_i \times W_i^P + \boldsymbol{\xi X_i} + \epsilon_i, \qquad (5)$$

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, a constant term, and a dummy variable for being in the control group.[11]

Table 5 reports OLS estimates of coefficients from Equation (5). In Column 1, 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" is small and statistically insignificant, once again implying that 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 4 plots OLS estimates from a modified version of Equation (5) 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

[11] Rather than include a common W_i term and only one interaction term, Equation (5) 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, the parameterization of 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 $D_i = 0$ (piece-rate workers are ineligible for top-ups).

workers.

Instrument Validity In the description above, I interpret my experimental estimates as treatment and selection effects of fixed-wage contracts. In theory, this interpretation could be threatened by behavioral responses to the experimental intervention. For example, workers' effort might exhibit reference dependence after being "primed" with a wage offer before the task begins.[12] If workers place a premium on earning at least as much as they were offered, their potential piece-rate output, Y_0, might increase with the generosity of their experimental wage offer, W_i, violating the exclusion restriction. In this case, however, we would expect piece-rate workers' output to discontinuously decline when their earnings meets the wage-offer reference point, $Y_i \geq W_i$ (McCrary, 2008).[13] Appendix Figure A1 reports results from a partial test of this hypothesis and finds no evidence of such discontinuity. Using methods from Cattaneo et al. (2020), I estimate piece-rate earnings densities on either side of the wage-offer threshold and find no significant difference (p-value=0.835), suggesting minimal influence from reference points.

A related concern is the potential presence of menu or framing effects (Simonson and Tversky, 1992). If workers' productivity was influenced not only by their compensation scheme, but also by their ability to *choose* that compensation scheme, it would bias comparisons between treatment and control. If this were the case, however, we would expect a discontinuous jump in Figure 4 between piece-rate workers in the "No Offer" control group (leftmost orange dot) who have no ability to choose and piece rate workers in the lowest offer group (second-to-leftmost orange dot) who had the ability to choose but primarily opted for the piece rate. Instead, we see a gradual rise in piece-rate output, consistent with continuous selection into more generous hourly wage contracts.

One might also be concerned about framing effects biasing estimates of wage effects. Because variation between offered and effective wages is generated through unexpected top-ups, estimated wage effects also include potential behavioral responses

[12] A large literature shows how "loss aversion"—a form of reference dependence—can explain the sensitivity of short-term labor supply decisions to benchmark earnings levels (Crawford and Meng, 2011; Farber, 2015; Thakral and Tô, 2021; Angrist et al., 2021; Andersen et al., 2025). While experimental offers are deliberately not framed as potential losses, workers may still feel regret if they earn less than their initial wage offer.

[13] Recall that the "counter" function in my experiment allows workers to observe piece-rate earnings in real time, making output highly manipulable.

to receiving a "surprise" pay raise. However, the wide range of wage offers in my design allows separate such responses from true wage effects—a response to surprises should persist for very small wage top-ups, whereas wage effects should reduce to zero as the effective wage approaches the offered wage. In Table 5, the null estimate on "Accepted × Log Effective Hourly Wage" is inconsistent with a behavioral response in effort from receiving an unexpected pay raise above one's chosen hourly wage.[14]

Summary of Results 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 fixed-wage productivity, and the pooled average output of accepters and decliners rises with generosity of the wage they were offered.[15] In the following sections, I develop a model to investigate how these forces affect labor-market equilibrium and worker welfare. I then show how the components of this model correspond to marginal potential outcomes under fixed-wage and piece-rate counterfactuals—objects which I estimate in the subsequent MTE analysis.

4 Model of Asymmetric Information in Wage Contracts

In this section, I present a 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.[16]

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.[17] Each worker,

[14]Adding an indicator variable for receiving *any* hourly raise (i.e., $R_i \equiv \mathbf{1}\{\text{Effective Hourly Wage} = \text{Offered Hourly Wage}\}$) in Equation (5) yields further null estimates.

[15]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).

[16]In Appendix D, I discuss how the model can be extended to incorporate monitoring costs, partially fixed compensation, wage effects, and dynamic contracts.

[17]In my empirical analysis, I allow employers to set wages using public information, X_i, like individual work history and approval rating, which can act as signals of future productivity (Spence, 1973; Farber and Gibbons, 1996; Gibbons and Katz, 1991; Pallais and Sands, 2016). For simplicity,

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.[18] Alternatively, they can offer a flat, up-front wage, w, in exchange for a claim on a worker's hourly output, q_i.[19]

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

$$S(w) \equiv \Pr(\overline{w}_i \leq w). \tag{6}$$

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

$$\overline{w}(\theta) \equiv S^{-1}(\theta). \tag{7}$$

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

$$MV(\theta) \equiv E[Y_i|\theta_i = \theta], \tag{8}$$

I omit these "X_i" terms from the model, which effectively considers a subpopulation of workers with observables matching a particular value, $X_i = x$.

[18] Note that competitive employers cannot profitably offer piece rates that deviate from this market price, p, which is exogenously fixed. Instead, they consider buying ex-ante *claims* on labor product through fixed-wage contracts. This model is isomorphic to one in which firms sell earnings insurance at some fixed premium to self-employed workers whose labor product is competitively priced at \$$p$ per unit.

[19] 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 D for completeness.

where $Y_i = pq_i$, the incremental value of output q_i produced by worker i under an hourly contract.[20] $MV(\theta)$ equals the expected amount type θ's hourly output would have earned them under the market piece rate, p. However, type θ's reservation wages may fall below this "actuarially fair" wage (i.e., $\overline{w}(\theta) < MV(\theta)$), especially if they are risk averse.

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

$$AV(\theta) \equiv E\left[Y_i | \theta_i \leq \theta\right]. \tag{9}$$

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

$$\Pi(w) = S(w)\left(AV(\theta^w) - w\right), \tag{10}$$

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

$$\overline{w}(\theta^{EQ}) = AV(\theta^{EQ}). \tag{11}$$

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'

[20] 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 and Appendix D).

output, $AV(\theta^{EQ})$. The efficient allocation of hourly contracts, on the other hand, is given by

$$\overline{w}(\theta^{EF}) = MV(\theta^{EF}). \tag{12}$$

Under this allocation, θ^{EF}, all workers with reservation wages below their marginal values are hired for fixed-wage positions. This allocation also corresponds to the share of fixed-wage workers under a full-information equilibrium, in which firms can observe workers' potential productivity and offer them type-specific contracts.

Graphical Illustration Figure 5, Panel A 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 orange, which is equal to

$$DWL = \int_{\theta^{EQ}}^{\theta^{EF}} \left(MV(\theta) - \overline{w}(\theta)\right) d\theta. \tag{13}$$

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, $MH_i \equiv Y_{1i} - Y_{0i}$.[21] This difference in counterfactual outcomes is not explicitly shown in the model because $AV(\theta)$ and $MV(\theta)$ are defined conditional on accepting the hourly contract, and thus depend only on Y_{1i}. The profit condition (10) and welfare calculation (13) are therefore inclusive of any moral hazard effects because $MV(\theta) \equiv E[Y_{1i}|\theta_i = \theta] = E[Y_{0i} + MH_i|\theta_i = \theta]$.

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 needed 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 allows me to consider scenarios in which firms can mitigate the shirking response to fixed wages. For example, combining hourly wages with a partial piece-rate or commission might attenuate the disincentive effects of hourly pay, but such strategies would do little to prevent adverse selection.[22] 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 11) changes with and without moral hazard effects, I split Equations (8) and (9) into two pairs of curves. First, I define marginal values of a type θ as the conditional means of potential output value

[21] 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."

[22] In Appendix D, I incorporate this mixed-compensation scenario into my framework by recasting the model as a market for supplemental hourly wages on top of a preexisting piece rate.

with (Y_{1i}) and without (Y_{0i}) the hourly wage:

$$\begin{aligned} MV_1(\theta) &\equiv E[Y_{1i}|\theta_i = \theta] && (14)\\ MV_0(\theta) &\equiv E[Y_{0i}|\theta_i = \theta]. && (15)\end{aligned}$$

Note that $MV_1(\theta)$ is simply a relabeling of $MV(\theta)$ from Equation (8)—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.[23] The difference between these two marginal value curves identifies the moral hazard effect for a given type:

$$MH(\theta) \equiv MV_1(\theta) - MV_0(\theta). \quad (16)$$

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

$$\begin{aligned} AV_1(\theta) &\equiv E[Y_{1i}|\theta_i \leq \theta] && (17)\\ AV_0(\theta) &\equiv E[Y_{0i}|\theta_i \leq \theta]. && (18)\end{aligned}$$

$AV_1(\theta)$ is equivalent to $AV(\theta)$ from Equation (9); 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 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 use MTE methods to 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

[23]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 $MV_1(\theta)$.

calculate counterfactual equilibria, but also to quantify the type-specific moral hazard effect, $MH(\theta)$, in Equation (16). As I show in Section 6, this labor-supply response is an important component of MVPFs for hourly wage subsidies and piece-rate taxes.

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 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 (14) and (15) are equivalent to marginal potential outcomes, and the moral hazard effect in Equation (16) is equivalent to the marginal treatment effect of the hourly contract, $MTE(\theta) \equiv E[Y_{1i} - Y_{0i} | \theta_i = \theta] = MH(\theta)$. As Figure 5, Panel B illustrates, this marginal treatment effect measures the average effect of treatment (hourly contract) among those with a given resistance to treatment (quantile reservation wage, θ_i).[24]

The correspondence above means I can apply insights from the MTE literature to identify the model with minimal parametric assumptions. First, note that the propensity score of the wage-offer instrument is equivalent to the supply curve, $S(w)$, in Equation (6). It can be straightforwardly identified as the share of accepters across wage offers:

$$S(w) \equiv \Pr\left(\overline{w}_i \leq w\right) = \Pr(D_i = 1 | W_i = w). \tag{19}$$

Next, at each propensity score, $\theta = S(w)$, average value under both hourly and piece-

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

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:

$$AV_1(\theta) \equiv E\left[Y_{1i}|\theta_i \leq \theta\right] = E\left[Y_i|S(W_i) = \theta, D_i = 1\right]. \tag{20}$$

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:

$$AV_0(\theta) \equiv E\left[Y_{0i}|\theta_i \leq \theta\right] = \frac{E\left[Y_i|S(W_i) = 0\right] - E[Y_i|S(W_i) = \theta, D_i = 0](1-\theta)}{\theta}, \tag{21}$$

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

$$MV_1(\theta) = \frac{\partial\left(E\left[Y_{1i}|\theta_i \leq \theta\right]\theta\right)}{\partial\theta} = \frac{\partial\left(E\left[Y_{1i}|S(W_i) = \theta, D_i = 1\right]\theta\right)}{\partial\theta} \tag{22}$$

$$MV_0(\theta) = -\frac{\partial\left(E\left[Y_{0i}|\theta_i > \theta\right](1-\theta)\right)}{\partial\theta} = -\frac{\partial\left(E\left[Y_i|S(W_i) = \theta, D_i = 0\right](1-\theta)\right)}{\partial\theta} \tag{23}$$

Intuitively, Equations (22) and (23) 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 ensures that estimates of θ are bound between zero and one and 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,

[25]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).

1988), assuming these covariates are additively separable from $MV_1(\theta)$ and $MV_0(\theta)$.[26] 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.[27] For hourly workers, I also include the effective wage paid after any randomized top-up payments in the second round of my experiment. As in Section 3, this residualization prevents potential wage effects from violating the exclusion restriction for the wage-offer instrument. I then estimate marginal and average values using local polynomial regression of 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 (13). 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 5, Panel A).

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 6 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, $AV_1(\theta) \equiv$

[26] More formally, I assume $E[Y_{Ji}|X_i = x, \theta_i = \theta] = \xi_J \widetilde{X}_i + MV_J(\theta)$ 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.

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

$E[Y_{1i}|\theta_i \leq \theta]$ 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.

Risk Preferences and Full Information Benchmark In both panels of Figure 6, the majority of workers produce labor at marginal values, $MV(\theta)$, that exceed their hourly reservation wages, $\overline{w}(\theta)$. I find that 59 percent (SE=0.08) of workers have $\overline{w}(\theta) < MV_1(\theta)$. This share represents the equilibrium that would exist if employers were fully informed of workers' potential output and set fixed wages to incorporate their moral hazard response. These shares reflect the allocations that would exist if employers were fully informed of workers' potential output. By comparison, I find that 61 percent (SE=0.08) of workers have $\overline{w}(\theta) < MV_0(\theta)$. This share represents the same full-information equilibrium in the absence of moral hazard effects, simulating an environment in which firms can eliminate shirking through partial piece rates or other means (see Section 4.1).

Why are so many workers willing to accept fixed wages below their actuarially fair, breakeven value? This finding is consistent with existing research documenting ostensibly risk-averse behavior, even in repeated, low-stakes gambles (Falk et al., 2018; Andersen et al., 2008; Harrison et al., 2007). Under standard utility functions, however, such behavior implies implausibly high levels of risk aversion in higher-stakes environments (Rabin, 2000), leaving researchers to rely on behavioral explanations like myopia (Kahneman and Tversky, 1979; Prelec, 1998), mental accounting (Rabin and Weizsäcker, 2009; Barberis et al., 2006), and reference dependence (Kahneman and Tversky, 1991).[28] In my setting, systematically biased beliefs provide yet another potential explanation for seemingly risk-averse decisions—a risk-neutral worker might prefer $w < MV(\theta)$ if they undervalue their productive potential or $w > MV(\theta)$ if they overvalue it. Importantly, my design allows me to remain agnostic about which of these forces is driving workers' preferences for fixed wages. Because semi-parametric estimates of marginal and average value curves rely entirely on revealed preferences over contracts, I can determine both competitive equilibrium and its full-information counterfactual without imposing explicit structure on worker utility or the distribution of parameters governing it. Workers' choices could be driven by any

[28]In my experiment, partial tests for reference dependence or loss aversion yield null results. See Section 3 and Appendix Figure A1.

combination of risk aversion, myopia, or other behavioral phenomena, and the market outcomes of those choices would remain the same.[29]

Partial Unraveling from Adverse Selection Despite most workers' willingness to sacrifice expected earnings in exchange for a fixed wage contract, the most productive of these workers remain on piece rates due to adverse selection. This inefficiency can be seen in the divergence between the marginal and average value curves in both panels of Figure 6. 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=0.0015) per hour of labor excluding moral hazard effects.

Selection on Moral Hazard The two sets of equilibria shown in Figure 6 are driven by differences in selection on hourly-wage marginal values, $MV_1(\theta)$, and selection on piece-rate marginal values, $MV_0(\theta)$. Figure 7 plots these differences across the distribution of worker types, $MV_1(\theta) - MV_0(\theta)$, which is equivalent to the marginal treatment effect of hourly wages. 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 that selection on moral hazard is non-linear: Among workers with below-median reservation wages, those with marginally stronger preferences for fixed wages (lower θ) have a slightly higher propensity to shirk (more negative treatment effect), consistent with patterns of selection in

[29]Note that, even if they have no impact on equilibria, non-classical explanations of worker choice may have different welfare implications. Under many behavioral theories these implications depend upon which choices reflect "true" preferences and which reflect "mistakes" (Goldin and Reck, 2022). Rather than weigh in on this question, this paper takes a classical approach to welfare and policy analysis, assuming that that a worker's willingness to accept wage offers below their breakeven value corresponds to a revealed preference for fixed wages rather than systematic errors.

insurance markets (Einav et al., 2013). Among those with above-median reservation wages, however, shirkers tend to prefer piece rates—those most resistant to hourly wages are most likely to shirk once they have it. This pattern could be explained by heterogeneous risk preferences: If tolerance for earnings risk correlates with tolerance for reputational risk from excessively low output, those who prefer the variability of piece-rate pay may also be more likely to shirk under fixed wages because they are less fearful of poor performance reviews.

Regardless of the underlying mechanism, moral hazard estimates play an important role in policy evaluation. Hourly wage subsidies or piece rate taxes might mitigate adverse selection into fixed wages, but such policies must balance the welfare benefits it provides to the marginal fixed-wage worker with the distortionary costs of encouraging that worker to shirk. I explore this tradeoff in the following section.

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

$$MVPF = \frac{WTP}{NC}, \tag{24}$$

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 $\overline{w}(\theta^{\delta}) = AV_1(\theta^{\delta}) + \delta$.[30] 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

$$WTP(\delta) = \underbrace{\delta\theta^{\delta}}_{\text{Transfer}} + \underbrace{\int_{\theta^{EQ}}^{\theta^{\delta}} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}_{\text{Insurance Benefit}}, \tag{25}$$

which captures the subsidy's net transfer to beneficiaries as well as its insurance benefits to 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.[31] 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

$$NC(\delta) = \underbrace{\delta\theta^{\delta}}_{\text{Direct Cost of Transfer}} + \underbrace{\int_{\theta^{EQ}}^{\theta^{\delta}} -\tau MH(\theta) d\theta}_{\text{Fiscal Externality from Moral Hazard}} . \tag{26}$$

With Equations (25) and (26) in hand, I can write $MVPF_{\text{Sub}}(\delta)$—the MVPF of

[30] Note that, in equilibrium, this increased hourly labor share might exert negative pressure on equilibrium piece rates, further reducing hourly reservation wages by decreasing the value of outside options. While my analysis ignores such second-order effects, including them would only serve to magnify the welfare benefits of both hourly wage subsidies and piece-rate taxes. See Appendix Figure A3.

[31] 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.

a \$$\delta$ subsidy—as

$$MVPF_{\text{Sub}}(\delta) \equiv \frac{WTP(\delta)}{NC(\delta)} = \frac{\delta\theta^{\delta} + \int_{\theta^{EQ}}^{\theta^{\delta}} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}{\delta\theta^{\delta} - \int_{\theta^{EQ}}^{\theta^{\delta}} \tau MH(\theta) d\theta}. \tag{27}$$

Equation (27) 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.

The green line in Figure 8, Panel A 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 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 (25) and (26) above to find the value, δ^*, that maximizes aggregate net welfare:

$$\delta^* \equiv \underset{\delta}{\operatorname{argmax}} \left\{WTP(\delta) - \lambda NC(\delta)\right\}, \tag{28}$$

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 (28) imply

$$MVPF_{d\text{Sub}}(\delta^*) \equiv \frac{WTP'(\delta^*)}{NC'(\delta^*)} \quad = \quad \lambda \tag{29}$$

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

The pink line in Figure 8, Panel A 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=0.013) per hour. Note that, in the absence of the fiscal externality imposed by the moral hazard effects of hourly wages, the subsidy at which the MVPF equals one would coincide with the \$1.09 subsidy that achieves the full-information benchmark. The attenuation to \$1.00 reflects the small added cost the reduced tax revenue from lower earnings. If we allow for a non-zero marginal cost of acquiring public financing ($\lambda > 1$), the optimal subsidy would decrease from \$1.00 to the value of δ at which $MVPF_{d\text{Sub}}(\delta) = \lambda$. 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 Taxing Piece Rates and Self-Employment

Instead of hourly wage subsidies, policymakers might consider raising taxes on piece rates as an alternative means of promoting fixed-wage labor contracts. Notably, recent legislation has done the exact opposite: The One Big Beautiful Bill (OBBB) Act, signed into law July 4, 2025, grants tax-advantaged status to tips over fixed-wage compensation—an action that is likely to exacerbate welfare losses from adverse selection. The following analysis quantifies the inefficiency costs one would expect from OBBB-like tax exemptions to piece-rate earnings in my experimental setting. It calculates the marginal value of each government dollar that is lost through tax cuts to piece rates. Equivalently, it measures the marginal *cost* in social welfare per dollar of revenue raised through *increased* taxes on piece rates. For revenue-raising policies, a lower-valued MVPF implies that piece-rate taxes are more efficient source

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

of public funds, with values below one implying they are more socially efficient than a non-distortionary tax (Boning et al., 2024). For this reason, I refer to this quantity as the marginal *cost* of public funds (MCPF) associated with the tax.

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 the marginal and average values of hourly workers' labor product is defined as the amount the firm saves by not buying that labor product from piece-rate or self-employed workers (see Footnote 20). 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 $\overline{w}(\theta^{\rho}) = (1+\rho)AV_1(\theta^{\rho})$.

For a piece-rate tax, ρ, the MCPF is given by its net social cost per dollar of government revenue raised:

$$MCPF_{\text{Tax}}(\rho) \equiv \frac{WTP(\rho)}{NR(\rho)}. \tag{30}$$

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

$$NR(\rho) = \underbrace{\int_{\theta^{\rho}}^{1} \rho MV_0(\theta) d\theta}_{\text{Direct Revenue from Transfer}} + \underbrace{\int_{\theta^{EQ}}^{\theta^{\rho}} \tau MH(\theta) d\theta}_{\text{Fiscal Externality from Moral Hazard}}. \tag{31}$$

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, workers with $\theta \in [\theta^{\rho}, 1]$ would recoup $\rho MV_0(\theta)$ in direct savings in the absence of the piece-rate tax. Second, workers with $\theta \in \left[\theta^{EQ}, \theta^{\rho}\right]$ 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

$$WTP(\rho) = \underbrace{\int_{\theta^{\rho}}^{1} \rho MV_0(\theta) d\theta}_{\text{Direct Tax Savings}} - \underbrace{\int_{\theta^{EQ}}^{\theta^{\rho}} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta}_{\text{Lost Insurance Value}}. \tag{32}$$

Using Equations (31) and (32), I estimate $MCPF_{\text{Tax}}(\rho) \equiv \frac{WTP(\rho)}{NR(\rho)}$ across a range of tax rates, ρ. Estimated MCPFs, reported in Figure 8, Panel B 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=0.14) and results in an MCPF equal to 0.95 (SE=0.001).

Optimal Tax Rates The optimal piece-rate tax equates the MCPF 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:

$$MCPF_{d\text{Tax}}(\rho^*) \equiv \frac{WTP'(\rho^*)}{NR'(\rho^*)} = \eta, \tag{33}$$

where η represents the marginal value of government revenue.[33] The pink line in Figure 8, Panel B plots estimates of $MCPF_{d\text{Tax}}(\rho)$. The MCPF 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 one ($\eta > 1$), the optimal tax would increase from 14 to the value of ρ at which $MCPF_{d\text{Tax}}(\rho) = \eta$.

Unlike hourly wage subsidies, MCPFs 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.

7 Implications for Other Labor Markets

While my experiment focuses on online data-entry work, any job with an uncertain, effort-intensive labor product is susceptible to the forces of moral hazard and adverse selection. Perhaps as a consequence, many of these jobs are characterized by some degree of self-employment, freelance work, or piece-rate compensation.[34] In this sec-

[33]Appendix E provides details on the derivation of $MCPF_{d\text{Tax}}(\rho)$.

[34]Failed attempts at "no-tipping restaurants" provide one case study: After replacing tipped earnings with fixed wages, many restaurants struggled to maintain profitability and ultimately reverted

tion, I explain why my experimental setting—a large, online labor platform—offers several advantages over these alternatives. I also discuss the external validity of my results, how they might generalize to other labor markets, and conduct a calibration exercise to estimate similar distortions in the market for rideshare drivers.

7.1 Why Online Data-Entry?

The online labor platform and data-entry job used in my experiment offer several distinct advantages over alternative settings or tasks. First, online labor markets and data-transcription services represent a large and growing part of the broader gig economy. Over 160 million workers are registered on online labor platforms (Kässi and Lehdonvirta, 2018; Kässi et al., 2021), which have drawn increased attention from both policymakers and academics (Stanton and Thomas, 2025; Horton, 2025; Caplin et al., 2024; Pallais and Sands, 2016; Pallais, 2014; Horton, 2017; Horton et al., 2011). Meanwhile, the market for AI "data-labeling" tasks like the one in my experiment has been valued as high as $19 billion and is expected to grow rapidly (Grand View Research, 2024; Mordor Intelligence, 2025).

Second, the flexibility of online labor 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 (the $0.03 piece rate) 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 (Dube et al., 2020).

Third, 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

course, often citing an exodus of qualified servers as the cause (Kadvany, 2022b; Moskin, 2020; Dunn, 2018). One San Francisco restaurant noted that "[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).

wage offer, allowing me to estimate the treatment effects of fixed wages on worker productivity.

Fourth, 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 protocol for this experiment can be easily replicated: 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.

7.2 Generalizing to Other Labor Markets

While my estimates directly speak to the importance of information asymmetries in online tasking platforms, they are not intended to measure welfare losses across the myriad of labor markets characterized by risky forms of compensation. Such limits to generalizability are ubiquitous in applied research on worker incentives—whether they come from 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), specific estimates of parameters concerning worker productivity are usually difficult to generalize beyond narrowly defined labor markets.[35] Despite these limitations, my experiment has many features that help maximize external validity. For example, the experimental job posting was designed to mimic a private firm seeking "AI Taskers," and the typing task requires a dimension of effort and skill that is increasingly requested by AI-based businesses. Moreover, participants were not informed that they were part of an experiment until after they performed the task. In Appendix F, I further assess the externality validity of my design using the SANS conditions from List (2020). This assessment establishes how, at a minimum, my results speak to information asymmetries in the large and growing online labor markets for data-labeling services. However, this paper can also be informative in the broader labor market if one considers how workers' preferences,

[35]For example, Herbst and Mas (2015) find that estimates of peer effects on worker output dramatically between study settings.

beliefs, and constraints vary between settings.

Consider other labor markets characterized by short-term employment, like delivery drivers or freelance writers. Compared to these markets, the small stakes and short duration of my experimental task would likely attenuate welfare 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.[36] This increased risk premium would shift the hourly supply curve downwards, resulting in a greater welfare loss than the one I estimate. Unless risk aversion is high enough to sustain fixed wages for the entire market, higher stakes would typically result in a greater welfare loss. In other words, my analysis should *underestimate* the welfare loss we would expect from output-based compensation with higher stakes than those in my experiment. 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.[37]

While my welfare estimates are likely attenuated relative to many short-term labor markets, this relationship is unlikely to hold for every comparison. As I discuss in Appendix D, labor markets with dynamically adjusting contracts or costly output monitoring might be less prone to adverse selection or moral hazard than workers in my setting. Policies aimed at addressing information asymmetries in these markets warrant further evidence targeted to those settings. Luckily, this paper provides a flexible theoretical and empirical framework for gathering this evidence. In the following calibration exercise, I apply this framework to the market for rideshare drivers using estimates from Angrist et al. (2021).

[36] 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.

[37] 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.

7.3 Application to Rideshare Drivers: Calibration from Angrist et al. (2021)

To demonstrate how my framework might be applied to other settings, I calibrate my model to approximate welfare loss from adverse selection in the market for rideshare drivers. My calibration exercise uses estimates from Angrist et al. (2021), who conduct an experiment that offers Uber drivers the opportunity to increase their commission on ride fares in exchange for making fixed weekly payments that do not vary with earnings. Offering this "taxi-style" compensation structure effectively gives the driver an opportunity to buy back a share of the fare revenue they generate. Viewed through this lens, opting into a taxi-style lease is the same as opting *out* of a (partial) fixed wage contract—a driver who accepts a lease offer gives up some fixed weekly income in favor of a higher share of their labor product. This equivalence means I can calibrate my model using estimates of selection *out of* taxi leases from Angrist et al. (2021) to approximate welfare losses from inefficient compensation in the market for rideshare drivers.[38]

Figure A4 plots results from this exercise. The horizontal axis denotes the share of drivers declining weekly lease offers. The red curve plots the inverse supply of lease-free drivers, $\overline{w}_B(\theta) \equiv S^{-1}(\theta)$. The blue line plots the marginal value curve, $MV(\theta) \equiv E[Y_i|\theta_i = \theta]$, where Y_i denotes driver i's weekly revenue from ride fares. The green line plots the average value curve, $AV(\theta) \equiv E[Y_i|\theta_i \leq \theta]$. The equilibrium share of lease-free contracts is $\theta^{EQ} = 0.55$, while the efficient share of lease-free contracts we would expect in a full-information equilibrium is $\theta^{EF} = 0.59$. The difference of $\theta^{EF} - \theta^{EQ} = 0.05$ represents potential drivers who would generate profitable levels of fare revenue if they were charged a lower proportional fee or paid some additional fixed weekly compensation that placed a higher value on their labor product. However, the cost of adverse selection among less productive drivers would make offering this compensation unprofitable. The corresponding welfare loss, shaded in orange, is \$1.32 per week, or approximately \$0.09 per hour worked, comparable to my estimates of welfare loss in the market for online data-entry.

There are several limitations to this calibration exercise. Calibrated curves, particularly the average value curve, rely on transformations across a small number of point estimates. Linear extrapolating market-wide selection patterns from these

[38]Calibration details are provided in Appendix G.

points comes with strong functional-form assumptions, and the absence of standard errors prevents any meaningful discussion of statistical significance. Moreover, as I discuss in Section 1, a precise accounting for welfare costs of selection must consider the value of labor product "off the equilibrium path," but the experimental sample in Angrist et al. (2021) consists of *existing* Uber drivers. In this sample, observed selection into taxi-style lease offers likely excludes drivers who desire it most—the ones who are already working as taxi drivers! More generally, 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. Nonetheless, this calibration exercise provides an example of how my framework can be applied to a variety of labor markets where workers selection on potential productivity can prevent efficient contracting.

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.

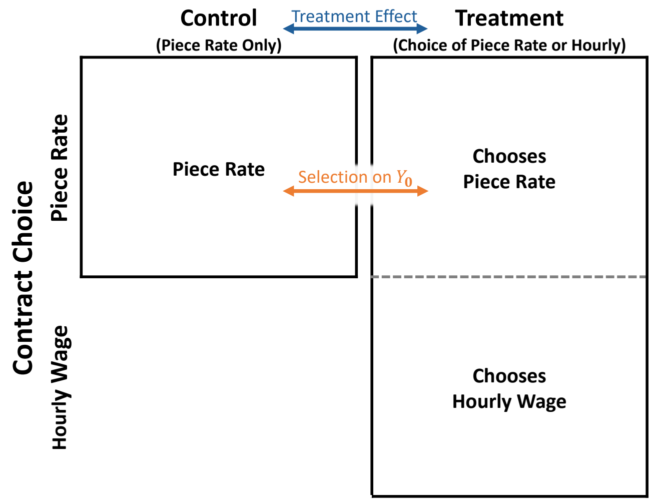
I place these experimental estimates into a theoretical framework that shows how the provision of hourly employment contracts is determined by two factors: a worker's reservation wage—the lowest fixed amount they will accept in exchange for an hour of labor—and the average output of workers with comparatively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

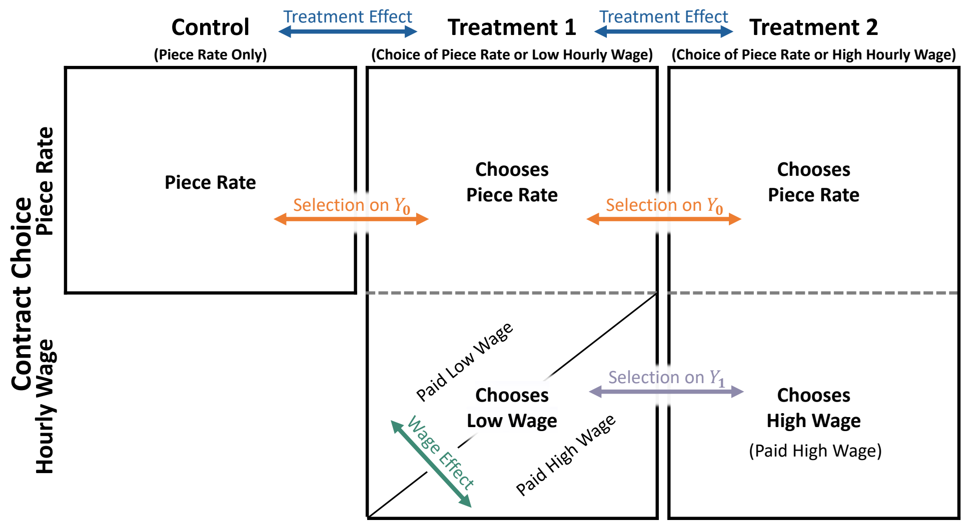
A vast number of jobs are characterized by some degree of self-employment, freelance work, or piece-rate compensation. Restaurant servers, barbers, salespeople, and delivery workers are just a few of the occupations where, rather than clocking their hours, workers derive most of their earnings from selling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



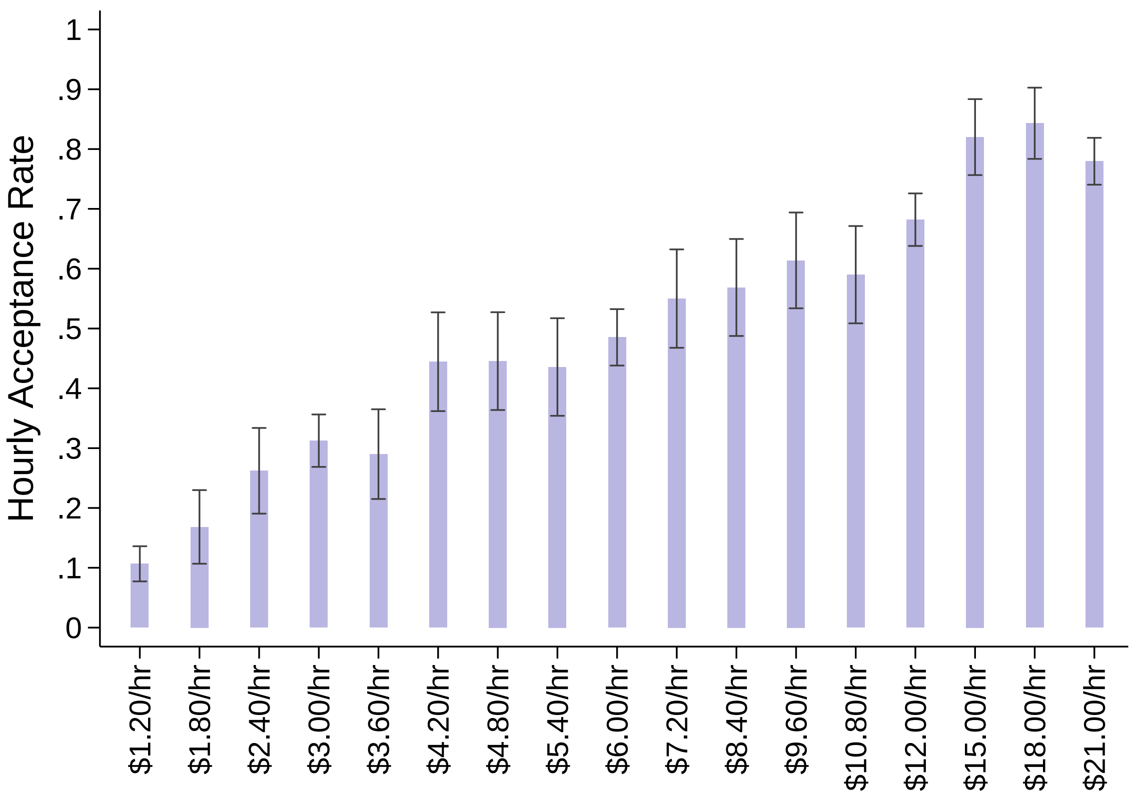
(A) Single Treatment Example



(B) Multiple Treatment Example

Note: This figure provides a graphical illustration of my experimental design, simplified to include only two (Panel A) or three (Panel B) wage-offer conditions. In each panel, columns denote experimental groups with different offer conditions. The control group is only compensated through the piece-rate contract, and treatment groups are offered a choice between the piece-rate contract and different hourly wages. Treatment groups are separated into those who accept the piece-rate contract (upper boxes) and those who accept their respective hourly wage offers (lower boxes). The diagonal split in the bottom box of Treatment 1, Panel B 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. Arrows denote comparisons that, after scaling by take-up, identify treatment effects (blue), selection on output under the piece rate, Y_0 (orange), selection on output under hourly wages, Y_1 (purple), and wage effects (teal). See Section 2 for details.

Figure 2: 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.

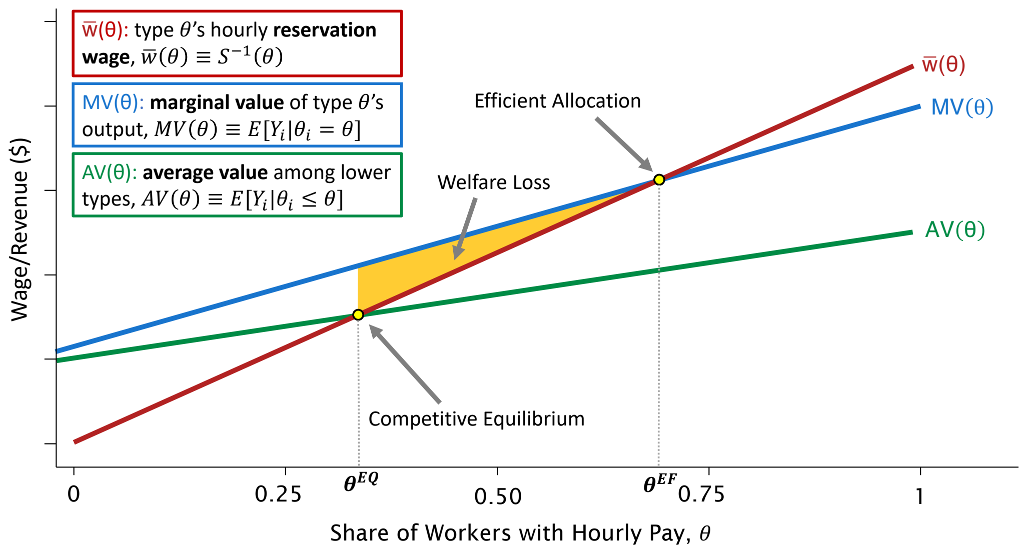
Figure 3: Worker Output Value by Treatment Offer and Acceptance Status

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.

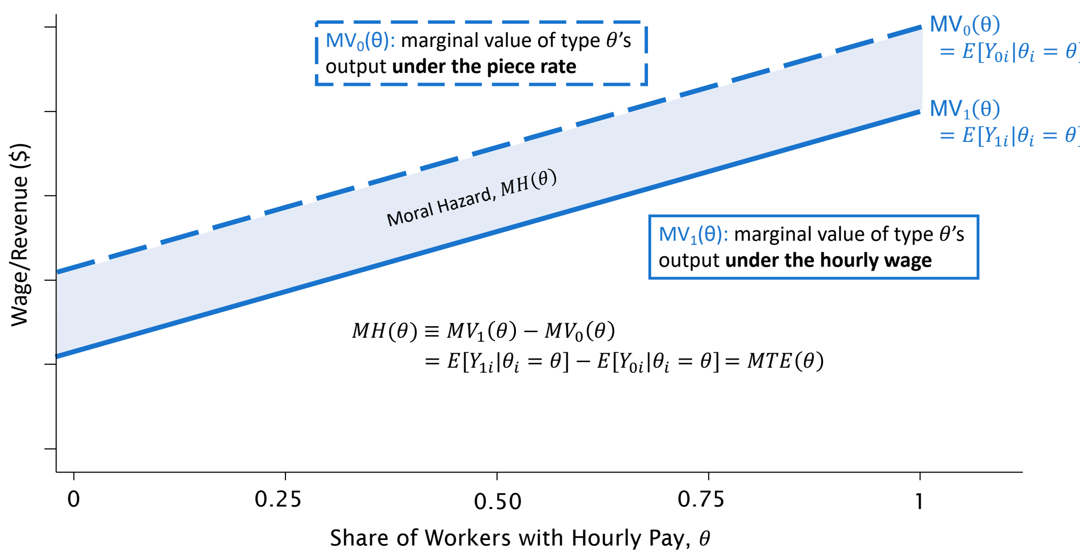
Figure 4: OLS Estimates of Selection on Output Value by Wage Offer

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 5: Model of Asymmetric Information in Wage Contracts



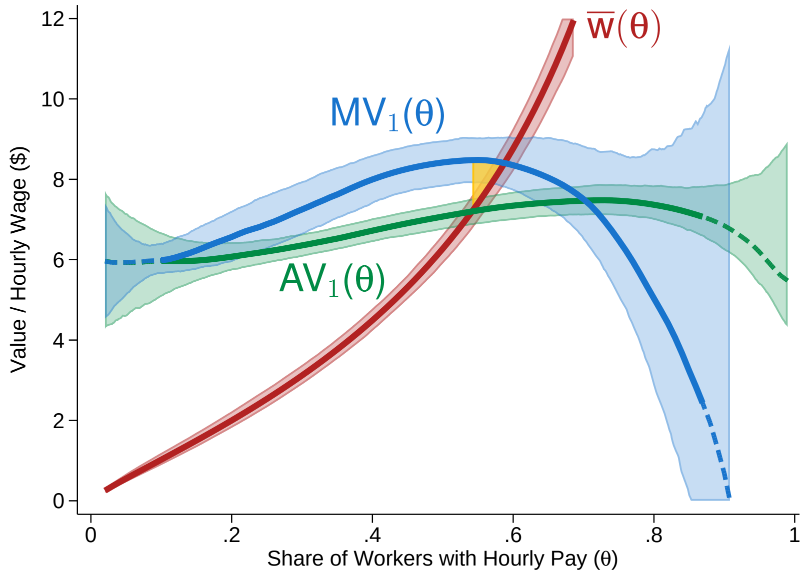
(A) Welfare Loss from Adverse Selection



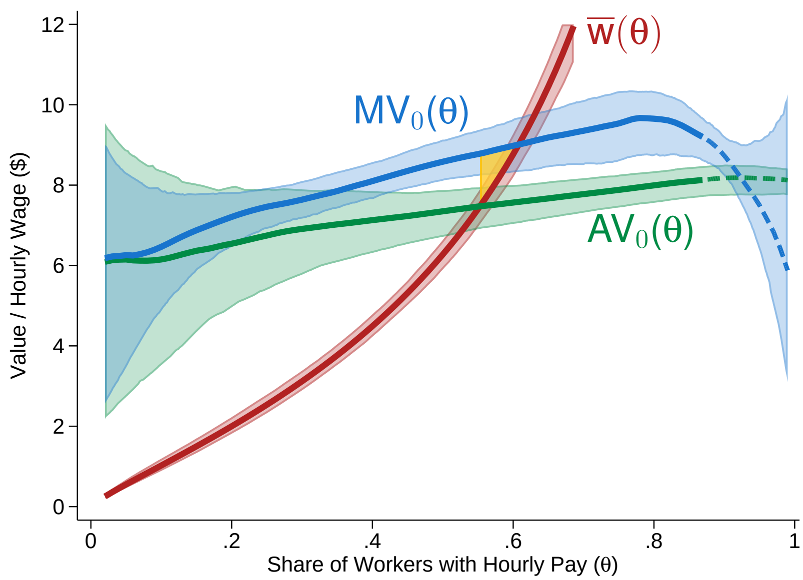
(B) Incorporating Moral Hazard

Note: This figure provides a graphical example of my model. Panel A illustrates welfare loss from adverse selection. 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, $MV(\theta) \equiv E[Y_i|\theta_i = \theta]$, where Y_i denotes output value under the hourly wage. The red line plots hourly reservation wage, $\overline{w}(\theta) \equiv S^{-1}(\theta)$. The green line plots the average value curve, $AV(\theta) \equiv E[Y_i|\theta_i \leq \theta]$. The orange region corresponds to the welfare loss from adverse selection into hourly wages. Panel B incorporates moral hazard into the model. The solid and dashed blue lines denote marginal values of potential output under hourly wages, $MV_1(\theta) \equiv E[Y_{1i}|\theta_i = \theta]$, and under piece rate, $MV_0(\theta) \equiv E[Y_{0i}|\theta_i = \theta]$, respectively. 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 6: Estimates of Marginal and Average Value Curves



(A) Potential Value Under Hourly Wage



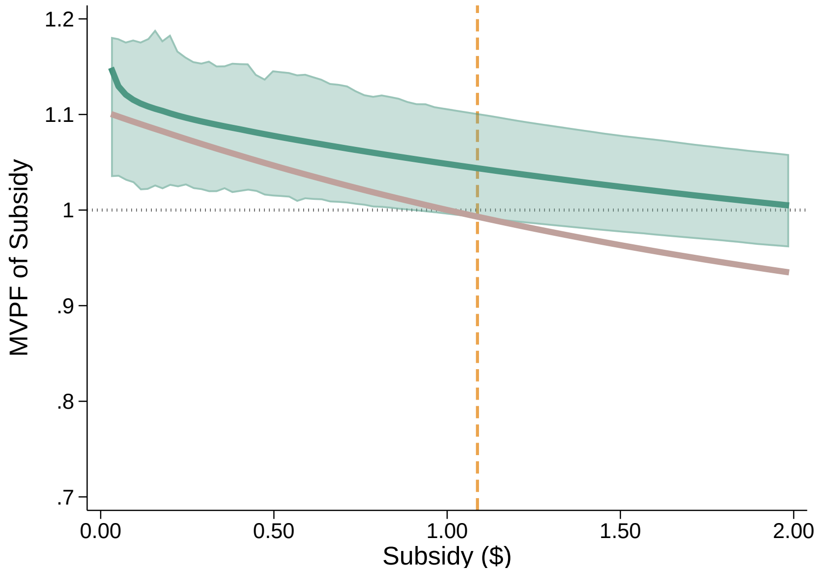
(B) Potential Value Under Piece Rate

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 5. 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 log experimental wage offers. Areas in orange denote estimated welfare loss from adverse selection into hourly wages. 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.

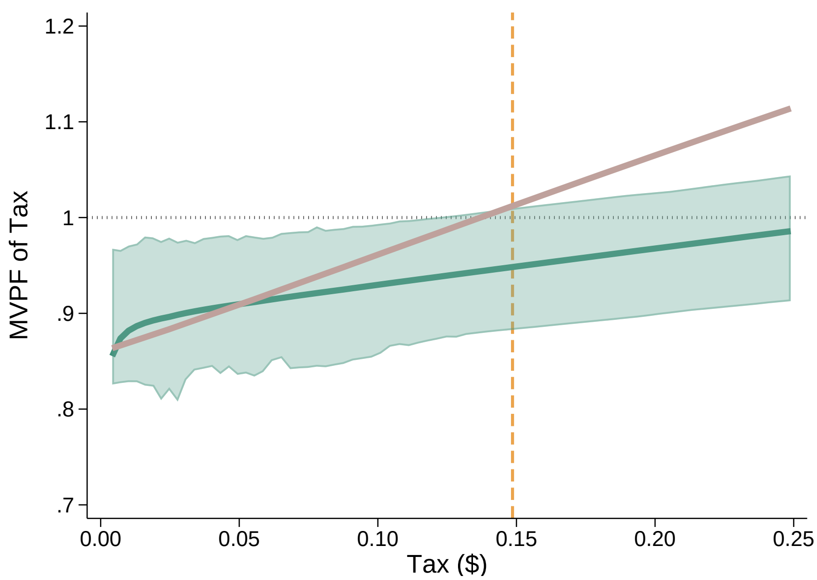
Figure 7: Estimates of Marginal Treatment Effects (Moral Hazard)

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 8: Estimated MVPFs/MCPFs for Hourly-Wage Subsidy and Piece-Rate Tax



(A) Marginal Value of Hourly-Wage Subsidy



(B) Marginal Cost of Piece-Rate Tax

Note: This figure plots estimated marginal values of public funds (MVPFs) for hourly wage subsidies and the marginal costs of public funds (MCPFs) for piece-rate taxes. In Panel A, the green lines plot estimated MVPFs associated with hypothetical hourly wage subsidies (in dollars per hour worked) denoted on the horizontal axis, and the pink line plots estimated MVPFs associated with a marginal increase to the hourly wage subsidies on the horizontal axis. In Panel B, the green line plots estimated MCPFs associated with hypothetical piece-rate tax rates denoted on the horizontal axis, and the pink line plots estimated MCPFs associated with a marginal increase to the piece-rate tax rate on the horizontal axis. In both panels, the vertical line denotes the subsidy or tax that achieves the "efficient" hourly supply share found in an full-information equilibrium. MVPFs and MCPFs are constructed using marginal value and supply curve estimates applied to Equation (27) 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	8.147
	Correct Sentences	17.79	9.360
	Output Value	7.913	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% level, ** = significant at 5% level, * = significant at 10% 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^{**}	-0.366^{**}
	(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% level, ** = significant at 5% level, * = significant at 10% 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	-2.599^{***}	-2.481^{***}	-2.439^{***}	-2.257^{***}
	(0.329)	(0.319)	(0.320)	(0.300)
Declined × Log Hourly Wage Offer	0.167^{*}	0.193^{**}	0.210^{**}	0.229^{***}
	(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	-0.000133
	(0.122)	(0.118)	(0.118)	(0.110)
Control Group (No Hourly Offer)	-0.341	-0.303	-0.250	-0.236
	(0.225)	(0.219)	(0.219)	(0.201)
Number of Previous Tasks/1000			0.166^{***}	0.173^{***}
			(0.0324)	(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 (5) 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% level, ** = significant at 5% level, * = significant at 10% level.

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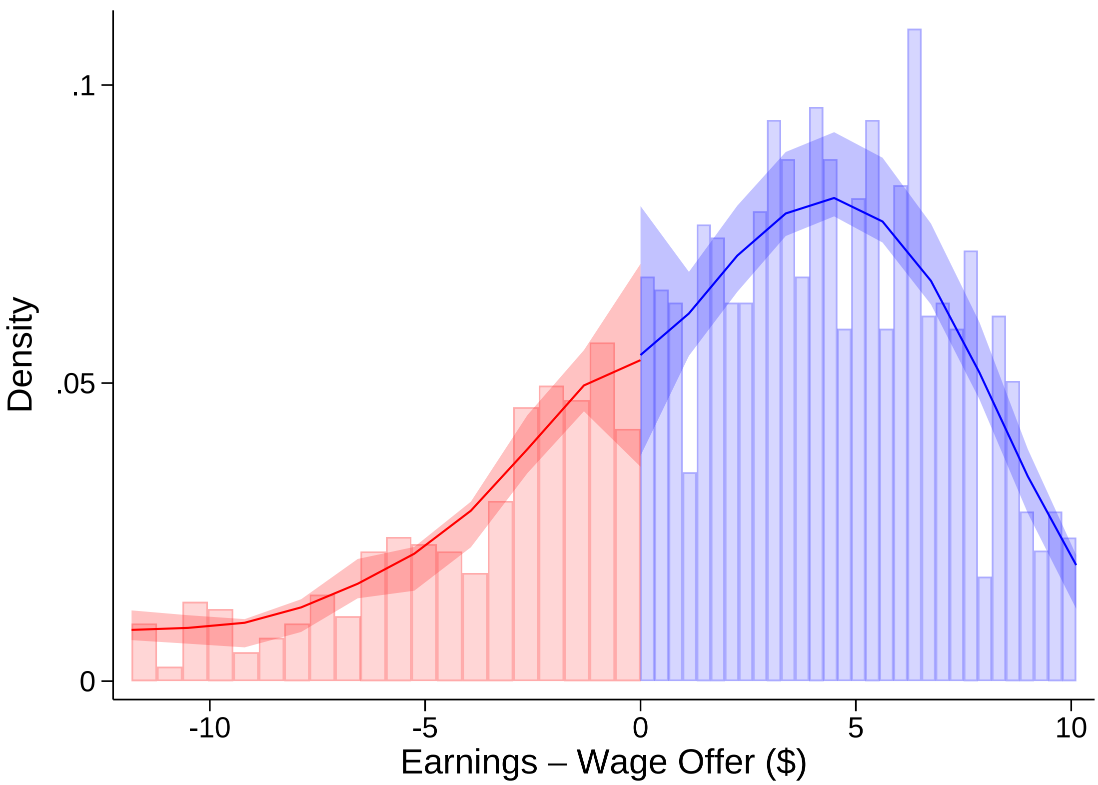
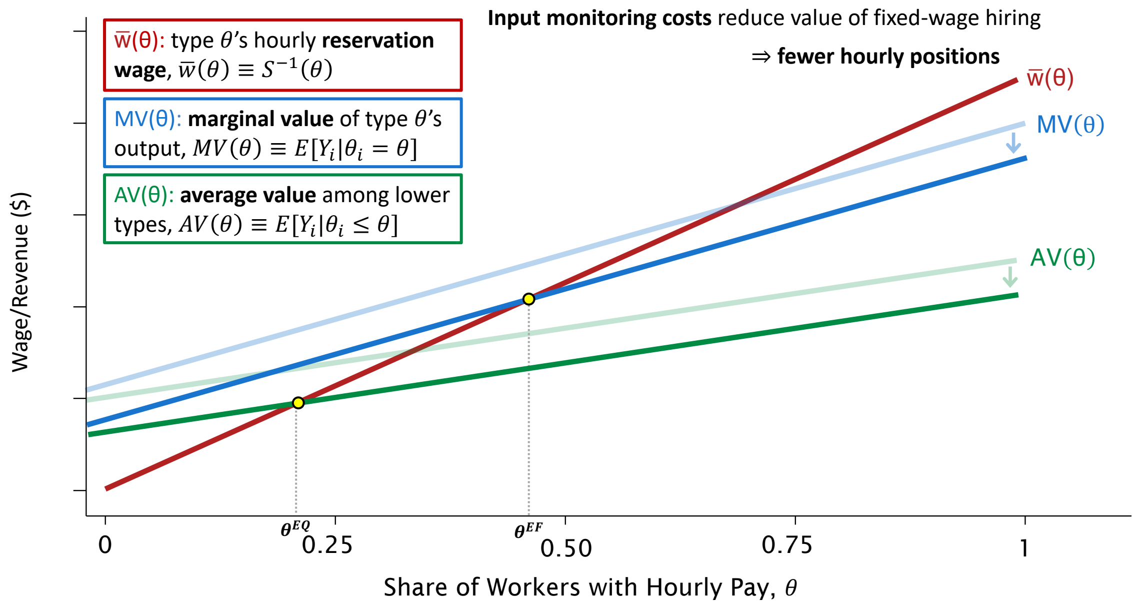
Appendix A Additional Figures and Tables

Figure A1: Test for Bunching at Wage-Offer Reference Points

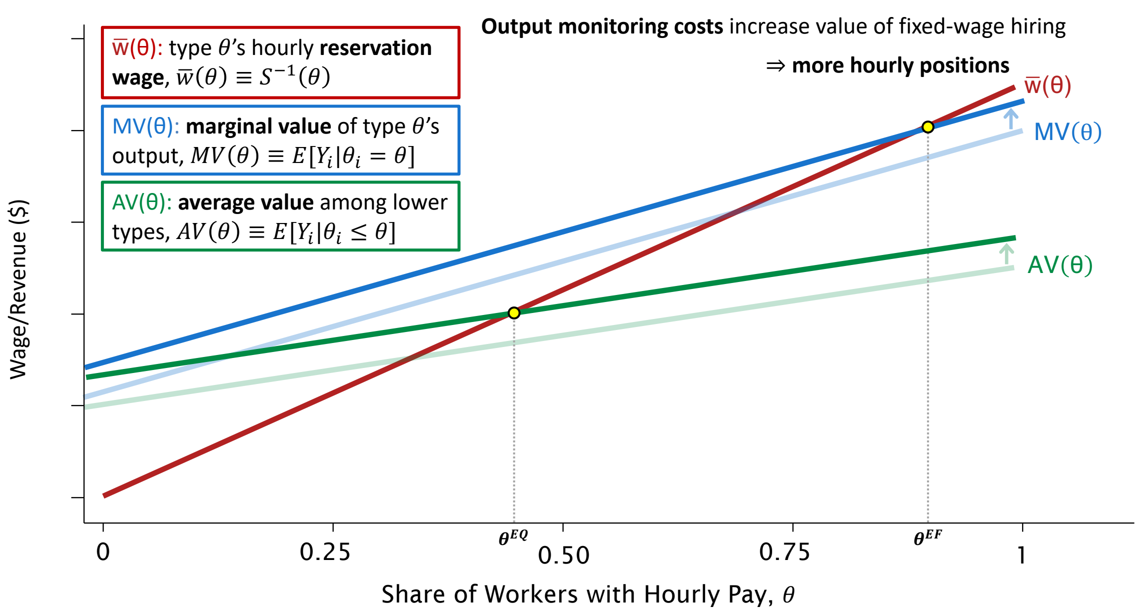


Note: This figure reports estimated densities of realized hourly earnings minus initial wage offers among workers in all treatment-offer groups who declined their wage offers in favor of the piece rate. The red and blue lines denote separate estimated densities for earnings below and above initial wage offers. Second-order local polynomial density estimates are based on a triangular kernel method from Cattaneo et al. (2020), using optimal bandwidths of 3.94 (left) and 3.37 (right) of the cutoff. The p-value for the continuity test at the cutoff is 0.835. The shaded indicate 90% confidence intervals computed from bias-corrected jackknife standard errors.

Figure A2: Asymmetric Information with Input and Output Monitoring Costs



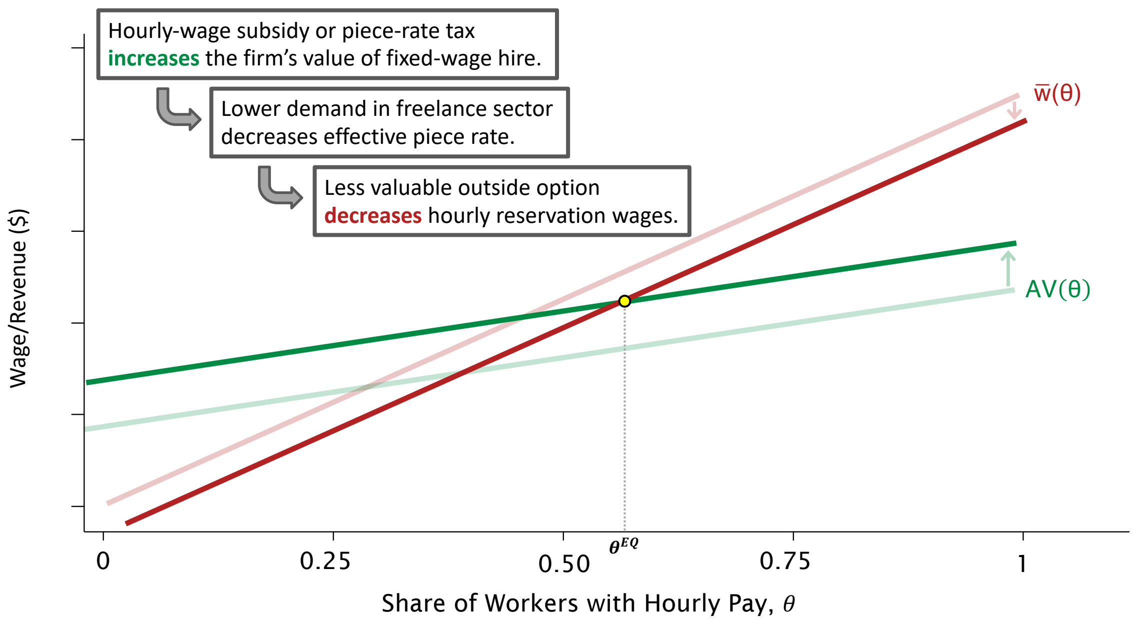
(A) Input Monitoring Costs



(B) Output Monitoring Costs

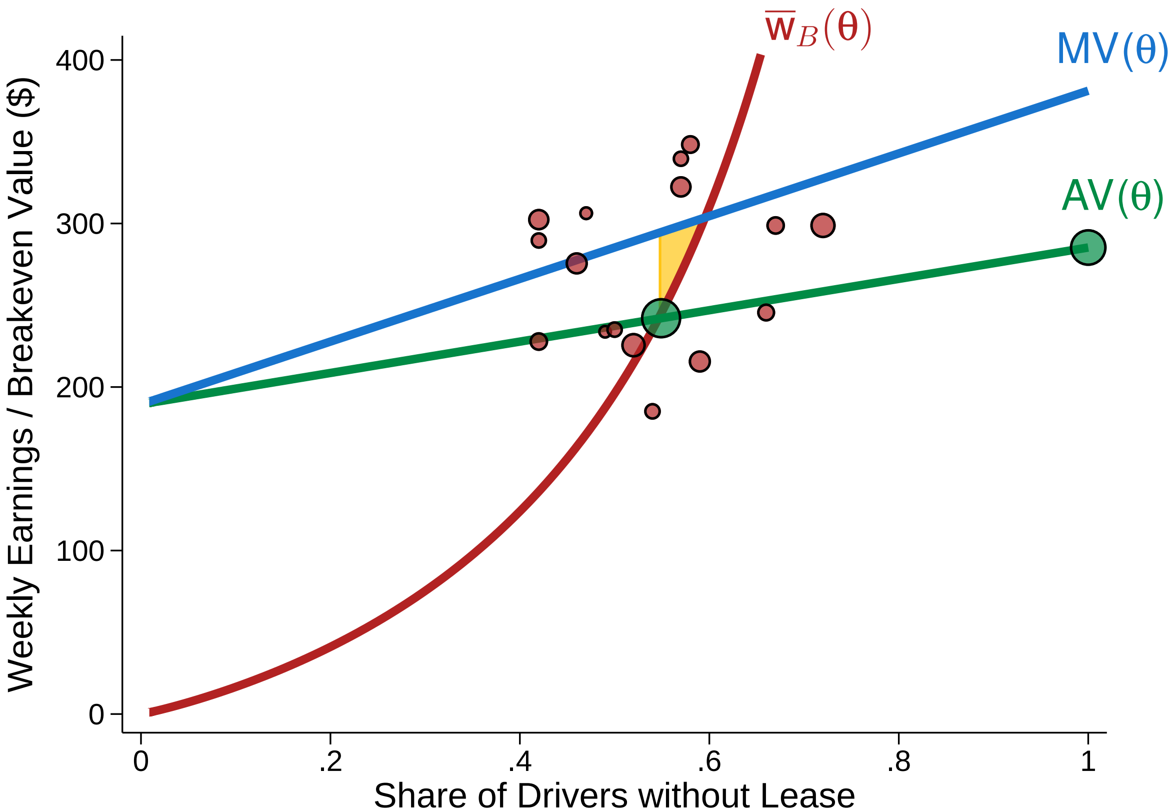
Note: This figure provides a graphical representation of a market for hourly wages under asymmetric information with input and output monitoring costs.

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.

Figure A4: Value Curves for Lease-Free Rideshare Driving, Calibrated from Angrist et al. (2021)



Note: This figure plots reservation wages and value curves for lease-free rideshare contracts, calibrated using estimates from Angrist et al. (2021).The horizontal axis denotes the share of drivers declining weekly lease offers. The red curve plots the inverse supply of lease-free drivers, $\overline{w}_B(\theta)\,(\theta) \equiv S^{-1}(\theta)$—the breakeven value, w_B, at which a $1-\theta$ share of drivers will accept taxi leases. The blue line plots the marginal value curve, $MV\,(\theta) \equiv E[Y_i|\theta_i = \theta]$, where Y_i denotes driver i's weekly revenue from ride fares. The green line plots the average value curve, $AV\,(\theta) \equiv E[Y_i|\theta_i \leq \theta]$. Red circles denote average lease opt-out rates by experimental breakeven offers, residualized by strata- and week-fixed effects. Green circles denote estimates of average fare revenues earned by decliners of lease offers and all drivers, respectively. Circle sizes reflect frequency weights based on reported observation counts. The orange region corresponds to the welfare loss from adverse selection into lease-free ride share contracts. See Appendix G for details.

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	36.446
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^{**}	-0.391^{**}
	(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% level, ** = significant at 5% level, * = significant at 10% level.

Table A3: Multiple Hypothesis Tests

	Multiplicity-Adjusted p-values			
Selection on Y_0				
$H_0 : \beta_0 = 0$	0.0770	0.0377	0.0250	0.0160
Selection on Y_1				
$H_0 : \beta_1 = 0$	0.0003	0.0003	0.0003	0.0003
Treatment Effect				
$H_0 : \psi = 0$	0.0213	0.0160	0.0170	0.0360
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 (5)). 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 (5)). 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 Identification of Experimental Estimands

This appendix provides additional details and proofs behind the target estimands in my experimental design.

B.1 Identifying Average Selection in Multiple-Offer Experiment

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 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 (3), 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):

$$\underbrace{E\left[Y_{0i}|D_i^H = 1, D_i^L = 0\right] - E\left[Y_{0i}|D_i^H = 0\right]}_{\text{Average Selection on } Y_0} \\ = \frac{1-\pi^L}{\pi^H - \pi^L}(E[Y_i|D_i = 0, W_i = L] - E\left[Y_i|D_i = 0, W_i = H\right]). \tag{34}$$

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):

$$\underbrace{E\left[Y_{1i}|D_i^L=1\right]-E\left[Y_{1i}|D_i^H=1,D_i^L=0\right]}_{\text{Average Selection on } Y_1}$$
$$=\frac{\pi^H}{\pi^H-\pi^L}(E[Y_i|D_i=1,W_i=L]-E\left[Y_i|D_i=1,W_i=H\right]), \tag{35}$$

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).

B.2 Identification of 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.

To see how randomized wage top-ups separately identifies wage effects and selection on Y_1, 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:

$$\begin{aligned}
&E\left[Y_i|W_i=H,D_i=1\right]-E\left[Y_i|W_i=L,D_i=1\right] \\
&=\underbrace{E\left[Y_{Hi}-Y_{Li}|D_{Li}=1\right]}_{\text{Wage Effect}}+\underbrace{E\left[Y_{Hi}|D_{Hi}=1\right]-E\left[Y_{Hi}|D_{Li}=1\right]}_{\text{Selection}}.
\end{aligned} \tag{36}$$

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:

$$\begin{aligned}
\text{Wage Effect} &= E\left[Y_i|W_i=L,D_i=1,W_i^P=1\right]-E\left[Y_i|W_i=L,D_i=1,W_i^P=0\right] \\
&= E\left[Y_{Hi}-Y_{Li}|D_{Li}=1\right]
\end{aligned} \tag{37}$$

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

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

B.3 Identifying Marginal Value in a Linear Model

Drawing from Equations (34) and (35), consider the average potential outcomes among workers who reject over L but accept offer H.

$$E\left[Y_{1i}|D_i^H=1,D_i^L=0\right] = \frac{\pi^H E\left[Y_i|D_i=1,W_i=H\right]-\pi^L E\left[Y_i|D_i=1,W_i=L\right]}{\pi^H-\pi^L} \tag{39}$$

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

Let $\overline{w}_i$ denote the lowest offer individual i is willing to accept. Let $H=w$ and $L=w-\tau$ in Equations (39) and (40). 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 $\tau\rightarrow 0$ can be written as

$$E\left[Y_{1i}|\overline{w}_i=w\right] = \frac{\partial\left(E\left[Y_i|D_i(w)=1\right]S(w)\right)}{\partial S(w)} \tag{41}$$

$$E\left[Y_{0i}|\overline{w}_i=w\right] = -\frac{\partial\left(E\left[Y_i|D_i(w)=0\right](1-S(w))\right)}{\partial S(w)}. \tag{42}$$

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:

$$S(w) = \alpha+\beta w \tag{43}$$

$$E[Y_i|D_i(w)=1] = \gamma_1+\delta_1 w \tag{44}$$

$$E[Y_i|D_i(w)=0] = \gamma_0+\delta_0 w. \tag{45}$$

We therefore have

$$E\left[Y_{1i}|\overline{w}_i=w\right] = \frac{(\gamma_1+\delta_1 w)\beta+(\alpha+\beta w)\delta_1}{\beta} \tag{46}$$

$$= \frac{\alpha\delta_1}{\beta}+\gamma_1+2\delta_1 w. \tag{47}$$

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

$$E\left[Y_{0i}|\overline{w}_i=w\right] = \frac{-(\gamma_0+\delta_0 w)\beta+(1-\alpha-\beta w)\delta_0}{-\beta} \tag{48}$$

$$= \frac{(\alpha-1)\delta_0}{\beta}+\gamma_0+2\delta_0 w. \tag{49}$$

We therefore have

$$\frac{\partial E\left[Y_{1i}|\overline{w}_i=w\right]}{\partial w} = 2\delta_1 \tag{50}$$

$$\frac{\partial E\left[Y_{0i}|\overline{w}_i=w\right]}{\partial w} = 2\delta_0 \tag{51}$$

Appendix C Experimental Protocol

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). The experiment took place in ten waves of three-hundred job postings launched over the course of two weeks beginning August 31, 2024. Figure C1 provides a timeline of the experimental protocol.

Participants in my experiment were recruited on Prolific, an online platform that allows clients to hire online workers for short-term tasks.[39] 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.[40] 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.[41] 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 sen-

[39] 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.

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

[41] The task is hosted on the Qualtrics platform. Readers can view and perform a replication of the task here. Screenshots are provided in Figure C2.

tence.[42] 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 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.

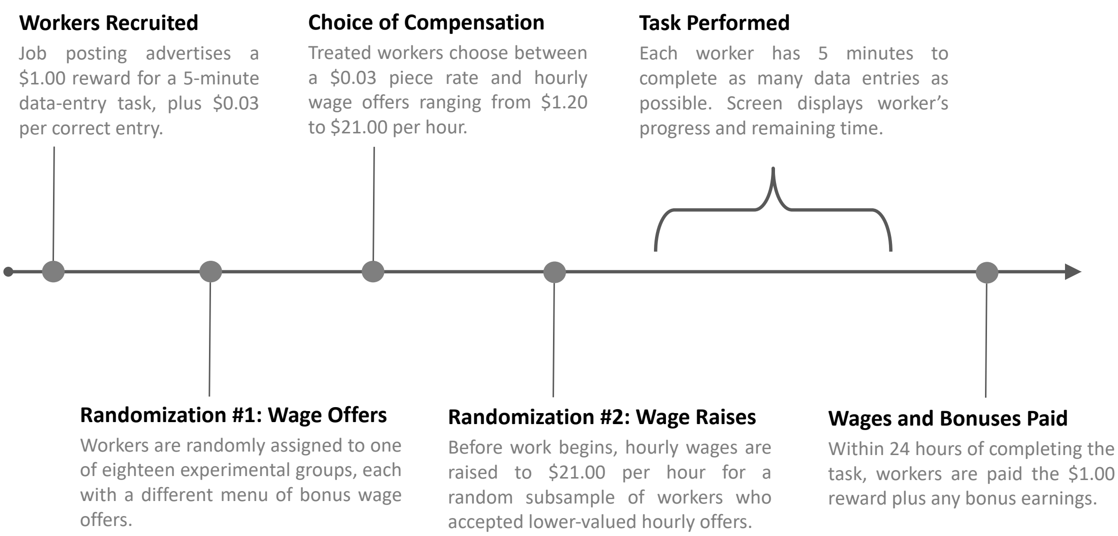
After receiving detailed instructions for the data-entry task, treated workers are presented with their group's payment options in randomized order, as shown in Figure C2, Panel B. Once workers choose their compensation scheme, they are brought to a new page that states, "For performing this task, you 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.[43] 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.

[42] 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).

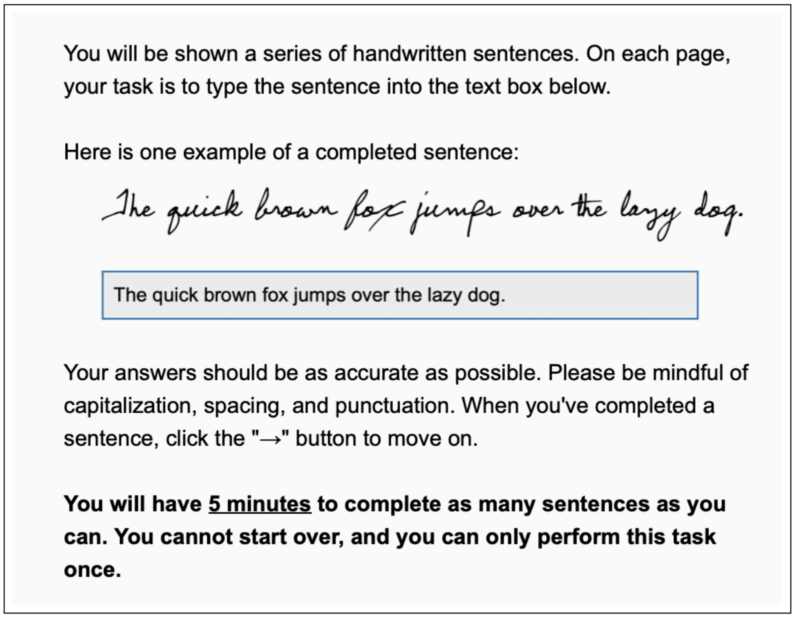
[43] Figure C2, Panel C provides a screenshot of the task. The display and submission methods for this task designed to prevent workers from cheating through automation software or bots. While it is possible that some workers may have tried to make use of such software, performance statistics suggest any such attempts were unsuccessful at increasing output—the maximum score achieved was 52.

Figure C1: Experiment Timeline

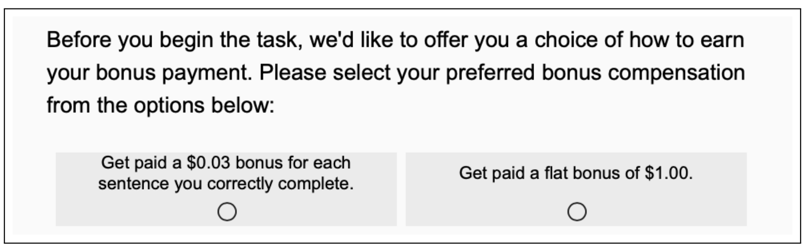


Note: This figure provides a timeline for a single wave of the experiment.

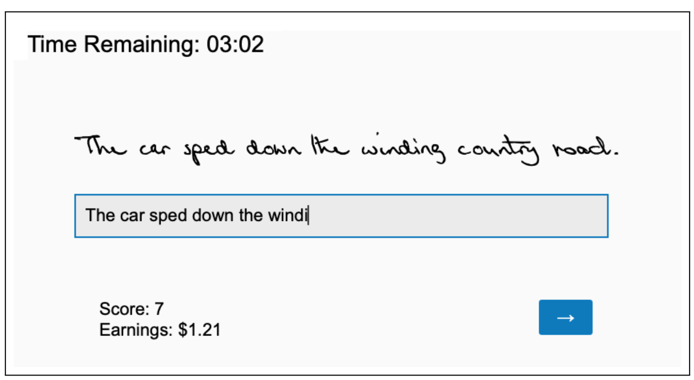
Figure C2: Example Job Posting



(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.

Appendix D Model Extensions

My model 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. It also omits wage effects, which are statistically insignificant in my setting (see Section 3). In this appendix, I discuss how one might extend the model to incorporate these features.

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

Mixed Compensation In my baseline model, fixed-wage contracts transfer the entirety of a worker's labor product, Y_i, to the employer. In reality, a firm could offer partial contracts that transfer some share of that labor product. 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.

My model can easily be recast to consider such partial contracts. Imagine firms offer a fixed hourly payment, w^p, in exchange for some *portion*, $\eta \leq 1$, of workers' output value, $Y_i^p \equiv \eta Y_i$. Contracted workers would receive this fixed hourly payment or "base wage," w^p, in addition to a variable piece-rate component, $(1-\eta)Y_i$, corre-

[44] 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.

sponding to the portion of their labor product not covered by the contract. It is not difficult to see how, much like an insurance co-payment, this piece-rate component would attenuate moral hazard effects from the (partial) fixed wage—as η decreases, the worker bears more of the cost of decreased effort, lowering their incentive to shirk.

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 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*:

$$AV_1^E(\theta) \equiv E\left[Y_{1i}(\overline{w}(\theta))|\theta_i \leq \theta\right]. \tag{52}$$

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

$$MV_1^E(\theta) \equiv E\left[Y_{1i}(w^*(\theta))|\theta_i = \theta\right], \tag{53}$$

[45] 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).

where

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

Note that allowing for wage effects means I can no longer interpret Equation 16 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.

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 my experimental setting, this dynamic screening process operates primarily through work histories, ratings, and reviews, which have been shown to narrow the informational gap between workers and firms (Pallais, 2014; Pallais and Sands, 2016).[46] 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 17).

[46] 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. 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.

Appendix E Derivations of MVPFs and Optimal Policies

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

Subsidy

Using Equations (25), (26), and (28), the welfare-maximizing level of subsidy is given by

$$\max_{\delta}\left\{\underbrace{\delta\theta^{\delta}+\int_{\theta^{EQ}}^{\theta^{\delta}}\left(MV_1(\theta)-\overline{w}(\theta)\right)d\theta}_{WTP(\delta)}-\lambda\underbrace{\left(\delta\theta^{\delta}+\int_{\theta^{EQ}}^{\theta^{\delta}}\tau MH(\theta)d\theta\right)}_{NC(\delta)}\right\}, \tag{55}$$

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 (55) imply

$$MVPF_{d\text{Sub}}(\delta^*)\equiv\frac{WTP'(\delta^*)}{NC(\delta^*)} = \lambda \tag{56}$$

$$\frac{\frac{d\delta}{d\theta^{\delta}}\theta^{\delta^*}+MV_1(\theta^{\delta^*})-\overline{w}(\theta^{\delta^*})}{\frac{d\delta}{d\theta^{\delta}}\theta^{\delta^*}-\tau MH(\theta^{\delta^*})} = \lambda. \tag{57}$$

$MVPF_{d\text{Sub}}(\delta)$ 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 (11) in the presence of an hourly-wage subsidy, δ:

$$\overline{w}(\theta^{\delta})=AV_1(\theta^{\delta})+\delta. \tag{58}$$

Differentiating with respect to θ^δ yields

$$\begin{aligned}
\frac{d\delta}{d\theta^\delta} &= \frac{d\overline{w}}{d\theta^\delta} - \frac{dAV_1(\theta^\delta)}{d\theta^\delta} && (59)\\
&= \left(\frac{dS}{d\overline{w}}\right)^{-1} - \frac{MV_1(\theta^\delta) - AV_1(\theta^\delta)}{\theta^\delta} && (60)\\
&= \frac{\overline{w}}{\beta\theta^\delta(1-\theta^\delta)} - \frac{MV_1(\theta^\delta) - AV_1(\theta^\delta)}{\theta^\delta} && (61)\\
& && (62)
\end{aligned}$$

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

Tax

The welfare-maximizing level of tax is given by

$$\max_{\rho} \left\{ \eta NR(\rho) - WTP(\rho) \right\}, \tag{63}$$

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 MCPF of the least efficient revenue source one could replace with the piece-rate tax.

$$\max_{\rho} \left\{ \eta \underbrace{\left(\int_{\theta^\rho}^{1} \rho MV_0(\theta) d\theta + \int_{\theta^{EQ}}^{\theta^\rho} \tau MH(\theta) d\theta \right)}_{NR(\rho)} - \underbrace{\left(\int_{\theta^\rho}^{1} \rho MV_0(\theta) d\theta - \int_{\theta^{EQ}}^{\theta^\rho} \left(MV_1(\theta) - \overline{w}(\theta)\right) d\theta \right)}_{WTP(\rho)} \right\}, \tag{64}$$

The first order conditions for (64) imply

$$\begin{aligned}
MCPF_{d\text{Tax}}(\rho^*) \equiv \frac{WTP'(\rho^*)}{NR'(\rho^*)} &= \eta && (65)\\
\frac{\frac{d\rho}{d\theta^\rho}\int_{\theta^{\rho^*}}^{1} MV_0(\theta)d\theta - \rho^* MV_0(\theta^{\rho^*}) - \left(MV_1(\theta^{\rho^*}) - \overline{w}(\theta^{\rho^*})\right)}{\frac{d\rho}{d\theta^\rho}\int_{\theta^{\rho^*}}^{1} MV_0(\theta)d\theta - \rho^* MV_0(\theta^{\rho^*} + \tau MH(\theta^{\rho^*})} &= \eta. && (66)
\end{aligned}$$

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

To calculate $\frac{d\rho}{d\theta^{\rho}}$, consider the equilibrium condition from Equation (11) in the presence of piece-rate tax, ρ:

$$\overline{w}(\theta^{\rho}) = (1+\rho)AV_1(\theta^{\rho}). \tag{67}$$

Differentiating with respect to θ^{ρ} yields

$$\begin{aligned}
\frac{d\rho}{d\theta^{\rho}} &= \frac{\frac{d\overline{w}}{d\theta^{\rho}}}{AV_1(\theta^{\rho})} - \frac{\overline{w}(\theta^{\rho})}{2AV_1(\theta^{\rho})}\frac{dAV_1(\theta^{\rho})}{d\theta^{\rho}} && (68)\\
&= \left(\frac{dS}{d\overline{w}}\right)^{-1}\frac{1}{AV_1(\theta^{\rho})} - \frac{\overline{w}(\theta^{\rho})}{2AV_1(\theta^{\rho})}\frac{MV_1(\theta^{\rho}) - AV_1(\theta^{\rho})}{\theta^{\rho}} && (69)\\
&= \frac{\overline{w}(\theta^{\rho})}{\beta\theta^{\rho}(1-\theta^{\rho})AV_1(\theta^{\rho})} - \frac{\overline{w}(\theta^{\rho})\left(MV_1(\theta^{\rho}) - AV_1(\theta^{\rho})\right)}{2\theta^{\rho}AV_1(\theta^{\rho})} && (70)
\end{aligned}$$

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

Appendix F External Validity

My experiment was designed too 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. 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).

Selection The experimental sample was 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). Workers in this population were eligible for my experimental job posting if they met four 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. More than 95 percent of Prolific workers meet the 98-percent approval threshold. Importantly, my experimental job posting advertised a generous compensation for a five-minute task—a $1.00 flat fee in addition to the $0.03-per-entry piece rate—ensuring the sample is not restricted to workers with low reservation wages or limited outside options. Experimental jobs were posted across a broad range of days and times to ensure the sample was not restricted to workers with a particular schedule.

Attrition There was virtually no attrition from the sample—only one worker was dropped from the experimental sample for exiting the task. 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.

Naturalness Each aspect of the experimental intervention was 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). Like most online employment, hired workers faced a threat of job dismissal and reputational damage for unapproved tasks, so they had an incentive to maintain a minimum standard of performance under either compensation scheme. The transcription task, described in Appendix C, 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 were not aware that they were part of an experiment until after performing the task, so estimates are not biased by any desire to generate a particular result.

Scaling My experimental task is more predictable, lower stakes, and shorter duration than many of those found in other labor markets. As a result, workers might exhibit less fatigue, more inattention, and a greater tolerance for risk than those in other work settings. 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.[47] This increased risk premium would shift the hourly supply curve downwards, resulting in a greater welfare loss than the one I estimate. Unless risk aversion is high enough sustain fixed wages for the entire market, higher stakes (i.e., more risk aversion) would typically result in a greater welfare loss. In other words, my analysis should *underestimate* the welfare loss we would expect from output-based compensation with higher stakes than those in my experiment. 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.[48]

[47]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.

[48]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

While the small stakes and short duration of my experimental task are likely to attenuate welfare estimates, other characteristics of the experiment might have the opposite effect. For example, as I discuss in Section D, labor markets with dynamically adjusting contracts or costly output monitoring might be less prone to adverse selection or moral hazard than workers in my setting. Policies aimed at addressing information asymmetries in these markets warrant further evidence targeted to those settings.

with small monetary stakes, the majority of workers produce output values above their reservation wages.

Appendix G Selection into Lease-Free Rideshare Driving: Calibrations from Angrist et al. (2021)

In Angrist et al. (2021), experimental "taxi" offers consist of a reduced proportional fee on fares charged to drivers, t_1, and a weekly lease payment, L. For a driver who earns Y_i per week in ride fares, accepting an offer would increase their take-home pay from $(1 - t_0)Y_i$ to $(1 - t_1)Y_i$, where t_0 is the pre-existing Uber fee of 20 or 25 percent, in exchange for paying Uber \$$L$ each week. For a given lease offer (t_1, L), the "breakeven value," w_B, is defined as the weekly fare revenue required for a driver's increase in take-home earnings, $(t_0 - t_1)Y_i$ to cover the cost of their weeekly lease payment, L:

$$w_B \equiv \frac{L}{\Delta_t}, \tag{71}$$

where $\Delta_t \equiv t_0 - t_1$. So, a lease offer (L, t_1), effectively gives the driver an opportunity to buy back a Δ_t-share of their own earnings at a valuation or "share price" of w_B. Viewed through this lens, opting into a taxi-style lease is the same as opting *out* of a (partial) fixed wage contract—a driver who accepts a lease offer gives up \$$L$ in fixed weekly income in favor of a Δ_t-higher share of their labor product. This equivalence means I can calibrate my model using estimates of selection *out of* taxi leases from Angrist et al. (2021) to approximate welfare losses from inefficient compensation in the market for rideshare drivers.

To calibrate my model to this setting, I estimate a supply curve for lease-free driving by fitting a logit model to the aggregated statistics from Table 4 of Angrist et al. (2021), which reports lease take-up rates and observation counts by week, experimental strata, and treatment condition. Specifically, I derive $S(w_B) \equiv \Pr[1 - Lease_i | w_{Bi} = w_B]$ by estimating the following:

$$\log\left(\frac{1 - \text{Lease}_i}{\text{Lease}_i}\right) = \alpha + \beta \ln w_{Bi} + \boldsymbol{\gamma} \boldsymbol{X_i}, \tag{72}$$

where $\boldsymbol{X_i}$ includes dummy controls for experimental strata and week. To derive average value curve, I combine the information on take-up rates with reported realized gains across accepters and decliners of leases. First, I use values in Table 4 to compute average experimental breakeven offers, residualized by strata- and week-fixed effects, separately for accepters and decliners of lease offers. I then combine these estimates with information from Table 6, which reports average gains above breakeven offers and share driving more than zero hours separately by accepters and decliners of experimental offers. From Table 4, the average residualized breakeven value among decliners is \$274. From Table 6, the share of decliners who drove more than zero hours is $423/679 = 62\%$. Among those who drove, accepters gained an average of 115. So the average earnings among decliners is $(\$115 + \$274) \times 0.62 = \$242$. Because this value is computed among decliners in all experimental groups,[49] I let it corresponds to the average fare revenue among the 55 percent drivers who opt out across all lease offers after controlling for stata and week, so

$$AV(0.55) \equiv E[Y_i|\theta \leq 0.55] = \$242. \tag{73}$$

Meanwhile, the average residualized breakeven value among accepters in Table 4 is \$271. From Table 6, the share of accepters who drove more than zero hours is $515/560 = 92\%$. Among those who drove, accepters gained an average of 97. So the average earnings among accepters is $(\$97 + \$271) \times 0.92 = \$338$. This value corresponds to the average fare revenue among the 45 percent drivers who opt in across all lease offers after controlling for stata and week, so $E[Y_i|\theta > 0.55] = \$338$.[50] I combine this value with $AV(0.55)$ from Equation (73) to take the total expectation,

$$\begin{aligned} AV(1) &\equiv E[Y_i|\theta \leq 1] = E[Y_i] \\ &= 0.55 \times E[Y_i|\theta \leq 0.55] + (1 - 0.55) \times E[Y_i|\theta > 0.55] \\ &= 0.55 \times \$242 + (1 - 0.55) \times \$338 \\ AV(1) &= \$286. \end{aligned} \tag{74}$$

I therefore calibrate the average value curve by fitting a line between two points:

[49]Unfortunately, Angrist et al. (2021) does not report statistics by take-up status at the strata, week, or breakeven level, so I must infer the average value curve from accepter and decliner averages across all treatment conditions. As a result, the average value curve is calibrated using just two points—one on either side of the average log wage offer and its corresponding supply share. Note that this aggregation likely attenuates the estimated slope of $AV(\theta)$, resulting in smaller estimates of welfare loss.

[50]Note that Table 6 values in Angrist et al. (2021) are already adjusted to remove the labor-supply effects of leases. As such value-curve estimates correspond to $AV_1(\theta)$ and $MV_1(\theta)$—potential output under the partial fixed wage contract.

$AV(0.55) = \$242$ and $AV(1) = \$286$, yielding the following average value curve:

$$AV(\theta) = 189.42 + 95.91\theta. \tag{75}$$

With a linear estimate of the average value curve in hand, the marginal value curve can be computed as a simple derivative:

$$\begin{aligned} MV(\theta) &= \frac{\partial}{\partial\theta}\left(\theta AV(\theta)\right) \\ &= \frac{\partial}{\partial\theta}\left(189.42\theta + 95.91\theta^2\right) \\ MV(\theta) &= 189.42 + 191.81\theta. \end{aligned} \tag{76}$$

With average value, marginal value, and supply curves in hand, I can calculate equilibrium and efficient shares of lease-free driving. The equilibrium share of lease-free contracts is $\theta^{EQ} = 0.55$. The associated "breakeven price" of $w_B(\theta^{EQ}) = \$242$ represents the breakeven value on the hypothetical lease that drivers would need to pay in lieu of the proportional fee on rider fares to generate the same net revenue for Uber. Meanwhile, the efficient share of lease-free contracts we would expect in a full-information equilibrium is $\theta^{EF} = 0.59$. The difference of $\theta^{EF} - \theta^{EQ} = 0.05$ represents potential drivers who would generate profitable levels of fare revenue if they were charged a lower proportional fee or paid some additional fixed weekly compensation that implicitly valued their labor product somewhere between \$242 and \$303 per week.[51] However, the cost of adverse selection among less productive drivers would make offering this compensation unprofitable. The corresponding welfare loss, shaded in orange, is \$1.32 per week. Table 3 of Angrist et al. (2021) reports the average driving hours per week as 14.16, so the deadweight loss is \$1.32/14.16 = \$0.09 per hour worked, comparable to my estimates of welfare loss in the market for online data-entry.

There are several limitations to this calibration exercise. Calibrated curves, particularly the average value curve, rely on transformations across a small number of point estimates. Linear extrapolating market-wide selection patterns from these

[51]One way to frame this comparison is to fix a weekly "lease" that all drivers must pay at $\bar{L} \equiv w_B^{EQ} t_0$ and imagine an equilibrium fixed wage, w, that values a t_0-share of weekly labor product to exactly offset the weekly lease, so at $\frac{w}{t_0} = w_B^{EQ}$. A higher breakeven value, $w_B > w_B^{EQ}$, could be accomplished with a lower proportional fee, $w_B = \frac{w}{t_0 - \delta} > w_B^{EQ}$, or with a higher fixed wage, $w_B = \frac{w+\epsilon}{t_0} > w_B^{EQ}$ (i.e., drivers receive a fixed $\epsilon = w_B - \bar{L}$ per week).

points comes with strong functional-form assumptions, and the absence of standard errors prevents any meaningful discussion of statistical significance. Moreover, the experimental sample in Angrist et al. (2021) consists of *existing* Uber drivers. Observed selection into taxi-style lease offers likely excludes drivers with the strongest preference for this type of compensation because they are already working as taxi drivers! More generally, studies of workers under existing employment contracts are likely to understate the effects of information asymmetries, which depend upon marginal treatment and selection across all workers in a hypothetical market.Finally, while drivers in Angrist et al. (2021) are stratified into high- and low-hour groups with separate experimental offers, this coarse conditioning likely falls short of the kind of dynamic contract that's feasible on modern rideshare platforms. For example, the "Uber Pro" program gives drivers with favorable histories access to more favorable rates and amenities, potentially mitigating welfare loss from adverse selection (Uber Technologies Inc., 2025). Despite these limitations, however, the calibration exercise provides an example of how my framework can be applied to a variety of labor markets where workers selection on potential productivity can prevent efficient contracting.