Valuing the Time of the Self-Employed*

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Abstract

People's value of their own time is essential to the evaluation of public policies affecting recipients' time use: these evaluations should account for time spent on the intervention rather than other work or leisure. Using choice data collected from farming households in western Kenya, we find that households exhibit behavioral biases resulting in non-transitive preferences over their own time. Consequently, our data imply a range of possible values of time rather than a single number. We discuss possible interpretations of these preferences, including loss aversion and self-serving biases, and the welfare implications of these different interpretations. A reasonable rule of thumb is to value time at 60% of the local wage. We suggest steps experimenters can take to obtain and interpret estimates of value of time in the field.

Keywords: value of time, welfare, labor rationing, non-transitivity, loss aversion, self-serving biases.

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1 Introduction

Valuing time is essential to understanding the welfare impacts of potential policies and interventions. For example, whether or not a new agricultural technology which doubles yields for smallholder farmers with 50% more of their labor increases welfare depends on the value of time to the farmer. This is particularly important as many development interventions aim to decrease global poverty by increasing the profitability of small owner-operated businesses and farms, the primary source of income for the vast majority of poor households (Merotto et al., 2018). Yet most studies ignore the value of time (for example, Aragón et al., 2020, Goldstein et al., 2018), or use prevailing local wages to estimate it (for example, Emerick et al., 2016). The former approach seems clearly too extreme. The latter approach is only accurate in the presence of well-functioning local labor markets—but in many developing economies there is evidence of involuntary unemployment that drives a wedge between the prevailing local wage[1] and the marginal value of time (Breza et al., 2020). Using both of these extremes can be a way to bound potential welfare impacts, but this may yield imprecise estimates. Surveying the literature, Rosenzweig (2012) notes, "[I]t is currently unsettled as to what the shadow value of family labor is on farms or in enterprises... It is a challenge for many evaluations... to properly impute labor costs in environments where family labor predominates." To our knowledge, no study since has sought to produce methods for reliably estimating the value of time in impact evaluations.

We develop, implement, and examine the results of two independent methods to measure the marginal value of time (MVT). Our first method is a direct wage auction for common tasks. Our second method elicits willingness to pay for a good in both cash and time. Neither method depends on well-functioning labor markets, and together do not require full ratio-

[1] We use the term "local wage" to refer to the average wage for casual laborers in our sample. We measure this using the most recent observed wage among those who have worked in the past 3 months, and imputing wages for those who have not. We impute wages by regressing observed wages on the set of control variables listed in footnote 9 and assigning fitted values based on values of those controls.

nality of participants. Our main finding is that these two methods generate vastly different estimates of the value of time. We show that this indicates a substantial departure from the standard model of economic decision-making, which cannot be explained by incomplete markets for labor or for credit. Rather, farmers' choices can be rationalized by a class of behavioral models incorporating either a *self-serving bias*—which causes workers to discount the value of what they receive in negotiations—or *loss aversion*—which causes workers to inflate the value of what they give away in negotiations—or both. The degree of the behavioral bias is substantial, equal to 28% of the value of the transaction on average. While the vast majority (81%) of farmers exhibit some bias, there is significant heterogeneity: the behavioral bias is more severe when workers are cash constrained, inexperienced in wage negotiation, or less educated. The patterns in our choice data suggest that both types of biases are at play, but they are specific to transactions over money.

These biases complicate measures that rely on people's willingness to spend or receive cash. Loss aversion can drive a wedge between private valuation and willingness to pay in cash: we estimate that cash-constrained farmers are willing to pay only about half of their private valuation for a good. A self-serving bias may disequilibrate labor markets if it extends to negotiations outside of an experimental setting. We find suggestive evidence that a self-serving bias causes labor to be withheld from the market: the average MVT is significantly lower than the local wage. We do not find evidence of widespread involuntary unemployment: on average reservation wages are very close to the local wage. However, behavioral biases may magnify differences between behavior within an experiment and natural decision making (Carney et al., 2019), and evaluating welfare requires taking a stance on how to incorporate behavioral parameters (see Bernheim, 2009). We therefore offer a range of estimates for the value of time based on our data, varying on average from about 40% to 100% of the local wage. We show that a general behavioral model that incorporates multiple biases permits identification of the value of time, purged of bias, at 60% of the local wage.

One of our methods—the wage auction for simple tasks—can be relatively easily deployed to help future researchers gauge the value of time to include in welfare calculations. Our data indicate that this method, when deployed on experienced laborers, provides a fairly accurate measure of MVT because experienced labors are much less prone to self-serving bias in negotiations, and therefore their elicited reservation wage is closer to their MVT. As many experimental interventions target similar groups of people—often in the same region of the same country—the value of time elicited by one study may be useful for others conducted nearby. If this is not possible in a particular context, assuming an MVT equal to 60% of the local wage is a good rule of thumb.

Our results inform a broad literature that evaluates the welfare impacts of interventions, many of which affect the labor supply of recipients. For example, interventions that provide farm inputs—such as fertilizer or seeds—increase hours worked on the farm (Duflo et al., 2011, Emerick et al., 2016). Likewise, interventions that improve tenancy contracts (Burchardi et al., 2018) or property rights (Goldstein et al., 2018) affect work hours. Measuring the effects of these interventions on welfare requires an estimate of workers' marginal value of time, but the absence of credible measures of the MVT in low-income countries has led to widely varying methodologies. For example, Goldstein et al. (2018) assume the household does not face an opportunity cost of supplying labor when studying the effect of a change in property rights. In contrast, Emerick et al. (2016) value all labor at the average wage when estimating the profitability of a flood-resistant type of rice in India. Ignoring the cost of inputs such as family labor can lead researchers to overstate the value of labor-intensive interventions or technologies, and may rationalize the apparent under-utilization of certain technologies (Suri, 2011). A similar issue arises among researchers studying labor misallocation: when workers in one sector earn more *and* work more, the value of changing sectors depends on the value of time lost or gained by the move. For example, there is a substantial wage premium in the non-agricultural sector of most low-income countries (Gollin et al., 2014, Restuccia et al., 2008, Caselli, 2005). Non-agricultural workers also work longer hours on average, and this difference explains about one-fifth of the non-agricultural premium (Pulido and Święcki, 2018). There is again no consensus on how to value workers' time when testing for misallocation: Gollin et al. (2014) control for hours worked in their measure of the agricultural productivity gap, while Pulido and Święcki (2018) do not. Finally, the MVT is a key parameter in the literature on business cycles (Hornstein et al., 2011, Shimer, 2005, Hagedorn and Manovskii, 2011). Mas and Pallais (2019) offer some of the first experimental estimates of the MVT among jobseekers in the U.S. but do not consider behavioral biases. Our paper offers what we believe are the first experimental estimates of the MVT in a low-income country, where we might expect more severe labor market frictions to drive the MVT below local wages (Kaur, 2018).

Our paper also contributes to the behavioral literature. Our framework and design offer a novel approach to identifying biases influencing decisions in an incentivized setting at the individual level. The biases we observe are consistent with at least two popular behavioral models—self-serving bias (see Babcock and Loewenstein, 1997) and loss aversion (see Kahneman et al., 1991, Kahneman and Tversky, 1979). However, these biases appear to be specific to transactions involving cash, and are more pronounced among farmers who report being unable to find cash in an emergency. Finally, we provide evidence that behavioral biases distort two incentivized measures commonly used in research: reservation wages and willingness to pay cash.

We proceed as follows. Section 2 describes our experimental setting and auction design, then offers a benchmark model of auction choices and preliminary evidence of a behavioral bias. Section 3 presents a series of behavioral models that rationalize the observed choices. Section 4 estimates the behavioral models with choice data from our field experiment. Section 5 presents a general model which allows us to distinguish between behavioral mechanisms. Section 6 discusses implications of our findings for labor market efficiency and future research.

2 Study setting and auction design

Our study elicits the marginal value of time from farmers by allowing them both to bid on short-term job contracts and to place bids in both cash and time for a chance to win a manual irrigation pump. We present the setting and auction designs, then present a benchmark model to characterize optimal choices in this setting.

2.1 Setting

The study took place from April through May of 2019 in rural western Kenya. We selected households with land suitable for manual irrigation. All households in our study do agricultural work, and nearly all households regularly sell part of their harvest. Most also engage in micro-entrepreneurship or provide casual labor on neighbors' farms. Each household selected a single adult member to participate in the study. Table 1 displays sample summary statistics for households and individual participants. The average participant is 47.8 years old and has 6.8 years of education. Participants are more likely to be women than men: women comprise 69% of our sample. The average household earns about 50,000 KSh ($461) per year, of which 45% comes from the sale of crops. Aside from farming, casual labor is by far the most common source of income, with 42% of participants having performed casual labor and 46% of households having hired casual laborers within the past 3 months. Those who had performed casual labor worked an average of 12 days in the past 3 months for 4.2 hours per workday. Average wages are 81 KSh (about $0.77) per hour. Casual labor usually involves labor-intensive agricultural work such as weeding and preparing land. The job contracts we offered were designed to mimic these casual labor tasks.

The pumps are made by KickStart International, a non-profit social enterprise that markets manually-powered irrigation pumps (branded as "MoneyMaker") which are specifically designed for smallholder farmers. KickStart's observational studies, comparing farmers be-

Table 1: Summary statistics

	Mean	Std. Dev.	N
Panel A: Demographics			
Age of participant	48	14	328
Education of participant (years)	6.8	3.6	307
Female participant = 1	0.69	0.46	332
No male head in household = 1	0.14	0.35	332
Number of adults (age 18 or over) in household	2.7	1.2	324
Number of children (under 18 years) in household	3.9	2.2	322
Panel B: Household income and wealth			
Land area under cultivation (acres)	2.3	1.9	323
Household income (Ksh, past year)	49,271	68,408	329
Income share from sale of crops	0.45	0.38	296
Cash constrained (unable to find 5,000 Ksh)	0.66	0.47	332
Panel C: Experience with casual labor			
Performed or hired casual labor within past 3 months = 1	0.75	0.43	332
Performed casual labor within past 3 months = 1	0.42	0.50	332
of which, days worked in last 3 months	13	17	141
during which, hours worked per day	4.2	1.4	141
among which, hourly earnings	81	66	129
Hired casual labor within past 3 months = 1	0.46	0.50	332
of which, days hired in last 3 months	6.5	8.5	154
during which, number of workers hired	3.2	3.4	154
among which, hours hired per day	4.0	1.3	154
among which, hourly wage paid	60	33	137
Panel D: Exposure to irrigation pump			
Owns a MoneyMaker irrigation pump	0.01	0.09	332
Has used a MoneyMaker irrigation pump	0.11	0.32	332
Familiar with the MoneyMaker irrigation pump	0.99	0.09	332
Self-reported valuation of pump (Ksh)	4,432	3,318	303

Note: An observation is a farmer. Data on casual labor and pump exposure from 2019 auctions. Other data from earlier household surveys. All monetary units are expressed in 2019 Kenyan shillings (Ksh).

fore and after they acquire a MoneyMaker pump, estimate that those who adopt the pump move from subsistence to irrigated farming, increase both their food and income security and their ability to invest in health and education. KickStart estimates that around 800,000 rural farming families (or around 4 million people) could benefit from using a shallow water irrigation pump in Kenya alone, but only 70,000 KickStart pumps—the cheapest pumps available—had been sold by 2013, despite marketing activities by KickStart throughout the country since 1998. Only 11% of farmers in our study had tried a KickStart pump themselves.

2.2 Auction design

We designed three auctions to elicit farmers' value of time both directly and indirectly. In the first auction, farmers could receive a cash payment for casual labor. In the second auction, farmers could pay cash for a lottery ticket offering 1 in 10 odds of winning a KickStart irrigation pump worth 9500 KSh (about $89), or about 20% of average yearly income in our study. In the third auction, farmers could perform casual labor for the lottery ticket. Each auction used a Becker-DeGroot-Marschak mechanism (Becker et al., 1964). This incentive-compatible mechanism elicits each farmer's reservation wage in the first auction, and each farmer's maximum willingness to pay for a lottery ticket in cash and time in the second and third auctions, respectively. In all mechanisms revealing this information is a strictly dominant strategy.

Auction 1: work for cash. Auction 1 is designed to elicit each farmer's reservation wage. We explained to each farmer that we were offering 2-hour jobs performing casual agricultural labor in a different village. We asked each farmer whether he or she would be willing to accept the job at 120 KSh per hour. If she answered "no," we asked about her reservation wage directly. If she answered "yes," we asked whether she would accept the job at incrementally lower wages until she changed her answer to "no." We recorded her reservation wage as the lowest wage at which she was willing to take the job. After this exercise, we drew a random wage. If her reservation wage was less than or equal to the random wage, she was eligible for the job at the random wage. If her reservation wage was greater than the random wage, she was not eligible.

Auctions 2 and 3: pay cash, or work, for a lottery ticket. Auctions 2 and 3 are designed to elicit each farmer's value of time indirectly. We explained to each farmer that we were selling lottery tickets offering 1 in 10 odds of winning a MoneyMaker pump. We collected bids from each farmer in both cash and time, beginning each exercise by asking whether the farmer would be willing to pay a low price—20 KSh or 30 minutes of casual agricultural work—and then asking the same question for increasingly higher prices. We recorded a farmer's willingness to pay as the highest price she was willing to pay for the ticket. After both exercises, we drew a random price in a random numeraire (either cash or time). If a cash price was drawn, we compared the farmer's willingness to pay in cash to the price. If her willingness to pay was at least as high as the drawn price, she was eligible to purchase the ticket at the drawn price. Otherwise, she could not purchase a ticket. If a time price was drawn, we compared her willingness to pay in time to the price. If her willingness to pay was at least as high as the drawn price, she was eligible to perform casual work for the ticket for the drawn number of hours. Otherwise, she was not eligible to work for the ticket.

3 Benchmark model and empirical evidence against it

3.1 Model set-up

We model farmers' choices in our three lotteries and derive two measures of the value of time. Two features of our environment differ from the basic labor-leisure model with complete markets. First, we allow for *labor rationing*, which implies that a farmer's reservation wage is strictly less than the local wage. The literature discusses a number of mechanisms that may result in workers being off of their labor supply curve, for example, downward wage rigidity resulting from social norms or effort retaliation (Kaur, 2018), or workers acting as a cartel to withhold work from the market and increase wages (Breza et al., 2019). We do not take a stand on what might be driving this mismatch between labor supply and demand; we simply allow for it in the model. Second, we allow for borrowing constraints to influence the value of cash on hand. In Section 4.1 we extend the model to include a number of possible behavioral biases.

Each farmer chooses:

1. whether to buy a lottery ticket $\tau \in \{0, 1\}$
2. a monetary payment $m \in \mathbb{R}_+$
3. time spent on work $h \in \mathbb{R}_+$

Preferences are represented by the utility function

$$V(\tau, m, h) = \max_{c,l} u(c, l + h) + k(I + wl - c - m) + \mathbb{E}[v(I + wl + \tau\theta - c - m)] \qquad (1)$$
$$l \text{ s.t. } l \leq \bar{l}$$

Choice variables c and l denote current consumption and labor supply respectively. Utility function u captures preferences over consumption and labor, k is the value of cash on hand, and v is the continuation value over next period wealth. Finally, I denotes non-labor income, w is the wage per unit of labor, and $\theta \in [0, \overline{\theta}]$ is a random variable capturing the returns to the lottery. This setup explicitly accommodates both labor rationing (through $\bar{l}$) and borrowing constraints (through k).

In the benchmark model, we make the following assumption.

Assumption 1 (smooth preferences)**.** *u, k, and v are strictly concave, and continuously differentiable.*

We assume without loss of generality that $V(\tau = 0, m = 0, h = 0) = 0$. We denote by $u_{c,0}$, $u_{l,0}$, k'_0 and v'_0 the derivatives of u, k and v at the unique optimal choices c_0, l_0 made when $\tau = m = h = 0$. Then the following first order approximation (using the familiar Big O notation) holds.

Theorem 1 (first-order approximation)**.** *Under Assumption 1,*

$$V(\tau, m, h) = \tau V_\tau + m V_m + h V_h + O\left(\overline{\theta}^2 + m^2 + h^2\right) \tag{2}$$

with

$$V_\tau = v_0' \mathbb{E}[\theta]; \quad V_m = -k_0' - v_0'; \quad \text{and} \quad V_h = u_{l,0}.$$

In addition

$$u_{c,0} = k_0' + v_0' \quad \text{and} \quad -u_{l,0} + \lambda = w \times (k_0' + v_0'),$$

where λ *is the Lagrange multiplier associated with* (1)*.*

3.2 Measuring the value of time

Our setup permits two ways to measure the value of time: directly through the choice over work for pay, and indirectly through lottery bids in cash and time.

3.2.1 Direct measurement

Auction 1 elicits the smallest monetary amount m^A needed to work h^A hours. That is, it elicits m^A and h^A such that $V(\tau = 0, m = -m^A, h = h^A) = V(\tau = 0, m = 0, h = 0)$. Using the first order approximation in Theorem 1, this implies $-m^A V_m + h^A V_h = 0$, or

$$w^A \equiv \frac{m^A}{h^A} = \frac{V_h}{V_m} = -\frac{u_l}{k' + v'}.$$

We call w^A the *reservation wage*, which is a direct measure of a person's marginal value of time.

3.2.2 Indirect measurement

Our indirect measure of the value of time comes from combining the information from Auctions 2 and 3. Auction 2 elicits the maximum willingness to pay, m^τ, for the lottery τ. That is, it elicits m^τ such that $V(\tau = 1, m = m^\tau, h = 0) = V(\tau = 0, m = 0, h = 0)$. Applying the first order approximation from Theorem 1, we have

$$m^\tau = -\frac{V(\tau = 1, m = 0, h = 0)}{V_m} \tag{3}$$

Auction 3 elicits the maximum willingness to work, h^τ, for the lottery τ. That is, it elicits h^τ such that $V(\tau = 1, m = 0, h = h^\tau) = V(\tau = 0, m = 0, h = 0)$. Once again applying the first-order approximation from Theorem 1 we have

$$h^\tau = -\frac{V(\tau = 1, m = 0, h = 0)}{V_h} \tag{4}$$

Combining (3) and (4) gives what call the *implied value of time* (IVT):

$$w^\tau \equiv \frac{m^\tau}{h^\tau} = \frac{V_h}{V_m} = -\frac{u_l}{k' + v'}$$

Thus, in the absence of behavioral distortions, the direct and implied measures for the marginal value of time should be equal:

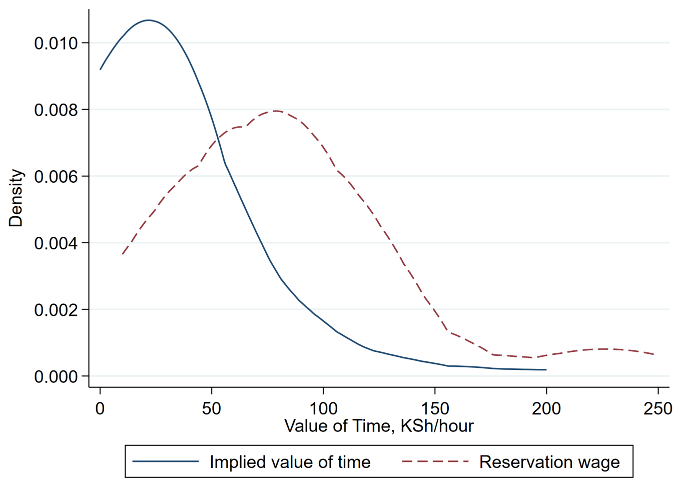
$$w^A = w^\tau = \frac{V_h}{V_m} = \frac{-u_l}{-u_l + \lambda} \times w \tag{5}$$

The next subsection shows that they are not. We then turn to discuss behavioral models that can accommodate the patterns in the data.

3.3 Auction results: Evidence of behavioral bias

Our first measure of the value of time relies on reservation wages w^A elicited through Auction 1. The average reservation wage is 83 KSh/hour. This is almost identical to the average reported wage for casual labor. Our second measure, w^τ—the implied value of time (IVT)—is the ratio of bids in cash and time for a lottery ticket elicited in Auctions 2 and 3. The average implied value of time is 30 KSh/hour, substantially below the average reservation wage. Figure E1 plots kernel density estimates of the value of time using both measures. The distribution of the IVT is shifted substantially to the left relative to the distribution of reservation wages.

Figure 1: The value of time is smaller when estimated indirectly through bids than when estimated directly through reservation wages.



Note: "Implied value of time" is the ratio of a bidder's cash to time bid for a lottery ticket. See Section 2.2 for details on design of the auctions.

These data suggest not only that, in general, $w^A \neq w^\tau$, but that preferences are, on average, cyclical. Treating the mean observed values of w^A, m^τ, and h^τ as the preferences elicited from a representative agent, our measurements roughly indicate $w^A = 80$ KSh, $m^\tau = 100$ KSh, and $h^\tau = 4$ hours. This implies the following preferences:

- 200 KSh $\prec$ 3 hours (since $w^A = 80$),
- $\tau = 1 \prec$ 200 KSh (since $m^\tau = 100$) , and
- 3 hours labor $\prec \tau = 1$ (since $h^\tau = 4$),

resulting in a cycle: 3 hours $\prec \tau = 1 \prec$ 200 KSh $\prec$ 3 hours. This is inconsistent with decision making under the model described above, which accommodates heterogeneity in the value of time, the valuation of the irrigation pump, the effort cost of performing casual labor, access to credit, and labor supply constraints. The next section formulates a set of behavioral models which accommodate these data.

4 Behavioral biases

4.1 Behavioral models

Motivated by the literature on self-serving bias and loss aversion in negotiations, we formulate a set of behavioral models that rationalize the choices we observe.[2] We begin with a set of models that incorporate a bias *either* in the reservation wage *or* in the implied value of time, but not both. In Section 5 we relax this assumption and estimate a model that incorporates bias in both measures.

For notational simplicity, we define preference parameters $a \equiv V(\tau = 1, m = 0, h = 0)$ (the valuation for the lottery ticket); $b \equiv -V_h$ (this is the MVT, our parameter of interest); and we normalize $V_m = -1$ (in addition to our earlier normalization $V(\tau = 0, m = 0, h = 0) = 0$). We can then re-write (2) as:

$$V(\tau, m, h) = \tau a - m - hb$$

[2] For a general discussion of behavioral welfare economics, see Bernheim and Rangel (2009), Bernheim (2009).

Model 1: Self-serving bias

Consider a decision maker who, in a transaction with another party, shrinks the value of what she obtains from the other party by an amount $1 - r$ (see Loewenstein et al., 1993, Babcock et al., 1995, Babcock and Loewenstein, 1997). In this case, r is a *self-serving bias*, although we will use the general preference parameter $r \in [0, 1]$, which we call the *behavioral discount rate* in each of our different behavioral models.

Under this model, the three auctions correspond to the following choices, respectively:

1. Receive m^A for h^A hours of work: $V(0, -(1-r)m^A, h^A) = 0 \Rightarrow (1-r)m^A - bh^A = 0$.

2. Pay m^τ for the lottery τ: $V((1-r)\tau = 1, m^\tau, 0) = 0 \Rightarrow (1-r)a - m^\tau = 0$.

3. Work h^τ hours for the lottery τ: $V((1-r)\tau = 1, 0, h^\tau) = 0 \Rightarrow (1-r)a - bh^\tau = 0$.

Under this model, the direct elicitation of MVT is distorted, whereas when the MVT is elicited indirectly it is undistorted. Specifically,

$$\begin{aligned} w^A \equiv \frac{m^A}{h^A} &= \frac{b}{1-r} \\ w^\tau \equiv \frac{m^\tau}{h^\tau} &= \frac{(1-r)a}{(1-r)a/b} = b. \end{aligned}$$

The latter expression matches (5) under the parameterization $b = -V_h$ and $V_m = -1$, whereas the former does not. The former is distorted by the self-serving bias $1 - r$, whereas in the latter w^τ is derived from choices where the distortion affects each choice in the same way, so those distortions cancel out.

Model 2: Money-specific self-serving bias

Consider a decision maker who shrinks only the value of money she receives from the other party. The choice problems are now, respectively:

1. Receive m^A for h^A hours of work: $(1-r)m^A - bh^A = 0$

2. Pay m^τ for the lottery τ: $a - m^B = 0$

3. Work h^τ hours for the lottery τ: $a - bh^C = 0$

Under this model, the direct elicitation of MVT is again distorted, whereas when the MVT is elicited indirectly it is undistorted. Specifically,

$$\begin{aligned} w^A \equiv \frac{m^A}{h^A} &= \frac{b}{1-r} \\ w^\tau \equiv \frac{m^\tau}{h^\tau} &= \frac{a}{a/b} = b. \end{aligned}$$

Model 3: Loss aversion

Consider a decision maker who inflates the cost of unplanned losses (Kahneman et al., 1991, Kahneman and Tversky, 1979). The choice problems are:

1. Receive m^A for h^A hours of work: $m^A - \frac{1}{1-r}bh^A = 0$

2. Pay m^τ for the lottery τ: $a - \frac{1}{1-r}m^B = 0$

3. Work h^τ hours for the lottery τ: $a - \frac{1}{1-r}bh^C = 0$

Under this model, the direct elicitation of MVT is again distorted, whereas when the MVT is elicited indirectly it is undistorted. Specifically,

$$\begin{aligned} w^A \equiv \frac{m^A}{h^A} &= \frac{b}{1-r} \\ w^\tau \equiv \frac{m^\tau}{h^\tau} &= \frac{(1-r)a}{(1-r)a/b} = b. \end{aligned}$$

Model 4: Money-specific loss aversion

If the decision maker is averse only to unplanned monetary losses, the choice problems are:

1. Receive m^A for h^A hours of work: $m^A - bh^A = 0$

2. Pay m^τ for the lottery τ: $a - \frac{1}{1-r}m^B = 0$

3. Work h^τ hours for the lottery τ: $a - bh^C = 0$

Under this model, the direct elicitation of MVT is now undistorted, whereas when the MVT is elicited indirectly it is distorted. Specifically,

$$\begin{aligned} w^A \equiv \frac{m^A}{h^A} &= b \\ w^\tau \equiv \frac{m^\tau}{h^\tau} &= \frac{(1-r)a}{a/b} = (1-r)b. \end{aligned}$$

The behavioral discount rate

The preference parameter r_i, which we call the *behavioral discount rate* of person i, appears in each model with a different interpretation. However, in each case it can be determined from the same choice data:

$$r_i = 1 - \frac{w_i^\tau}{w_i^A} = 1 - \frac{m_i^\tau}{h_i^\tau w_i^A} \tag{6}$$

4.2 Revisiting the auction results

In our sample, 81% of farmers expressed a reservation wage strictly greater than their IVT. In the behavioral models of Section 4.1, this is rationalized by a single preference parameter r. A test of the benchmark model is therefore $E[r_i] = 0$. In our sample we observe an average behavioral bias r of 0.28 (p-val < 0.001). That is, the average farmer applies a discount when negotiating equal to 28% of the transacted value.

The implications of this bias for measuring the value of time depend on which transactions farmers are discounting. If farmers discount all transactions (Models 1 and 3) or discount money earned through work only (Model 2), then reservation wages will be biased upward and the IVT will accurately measure the value of time. If farmers inflate the value of cash they must pay (Model 4), then the IVT will be biased downward and reservation wages will accurately measure the value of time. Remaining agnostic about the form of the behavioral bias therefore implies a range of estimates of the value of time. Table D3 displays this range, expressed relative to the prevailing local wage. The smallest estimate is 30 KSh/hour, or about 40% of the local wage. The largest estimate is 83 KSh/hour, roughly equal to the local wage.

A self-serving bias may become reduced with experience. Columns 2 and 3 of Table D3 focus on individuals who have recently provided or hired casual labor, respectively. We find that both subgroups, especially sellers of casual labor, exhibit less severe discounting. They bid more for the lottery ticket in both cash and time, and have lower reservation wages.[3]

Loss aversion that applies specifically to cash is likely to be amplified by cash constraints. Column 4 of Table D3 focuses on individuals facing cash constraints—specifically, those who report that they would be unable to find 5,000 KSh (about $47) to cover an emergency (Dupas et al., 2018). We find that these farmers exhibit greater bias. They behave no differently when paying in time (for a ticket or for a wage), but bid significantly less in cash.

An accurate estimate of the value of time depends on the degree to which each auction choice is influenced by behavioral bias. Our findings suggest that both our direct and indirect measures are affected. Experienced casual laborers exhibit less bias and lower reservation wages, suggesting that on average reservation wages overestimate the value of time. Cash constrained farmers exhibit more bias and offer lower cash bids, suggesting that the IVT underestimates the value of time. In the next section, we present a generalized behavioral model that, under stronger assumptions, allows us to identify the relative importance of each bias and offers a single estimate of the average value of time.

[3]We present formal regression analysis showing the predictive power of these two and other covariates in Appendix C.

Table 2: Auction choices imply cyclic preferences and can be rationalized by a behavioral bias, which is heterogeneous across farmer subsamples.

	(1) Full sample	(2) Supplies casual labor	(3) Hires casual labor	(4) Cash constrained
Reservation wage (w^A)	82.8	72.2	84.7	82.6
	(3.0)	(3.9)	(4.5)	(3.6)
Implied value of time (w^τ)	29.8	31.3	34.8	25.1
	(1.9)	(3.1)	(3.0)	(2.2)
Cash bid (m^τ)	110.8	129.1	126.2	92.2
	(6.9)	(10.9)	(11.4)	(7.2)
Time bid (h^τ)	4.0	4.6	4.1	4.1
	(0.1)	(0.2)	(0.2)	(0.1)
Local wage (w)	82.4	80.3	85.9	79.6
	(2.6)	(5.4)	(3.7)	(3.0)
Behavioral bias (r)	0.278	0.159	0.205	0.438
	(0.073)	(0.125)	(0.105)	(0.072)
Relative IVT (w^τ/w)	0.36	0.39	0.41	0.32
Relative res. wage (w^A/w)	1.00	0.90	0.99	1.04
p-val $r = 0$	<0.01	0.21	0.05	<0.01
p-val $w^A = w^\tau$	<0.01	<0.01	<0.01	<0.01
p-val $w^A = w$	0.18	0.23	0.32	0.62
p-val $w^\tau = w$	<0.01	<0.01	<0.01	<0.01
Observations	332	141	154	216

Note: Each observation is a farmer. Currency units are Kenyan shillings (1 USD = 107 Ksh). Each cell reports the mean and its standard error. Cash bids, time bids, and reservation wage elicited through a Becker-DeGroot-Marschak mechanism. "Local wage" is most recent hourly wage earned from casual labor and is imputed for farmers who have not performed casual labor recently. IVT stands for implied value of time and is equal to the ratio of a cash bid to a task bid. Column (1) shows results on the full sample. Columns (2) and (3) show results among farmers who have done casual work, or hired casual laborers, respectively in the past 3 months. Column (4) shows results among farmers who report that they could not find 5,000 Ksh within 3 days in the event of an emergency. Robust standard errors in parentheses.

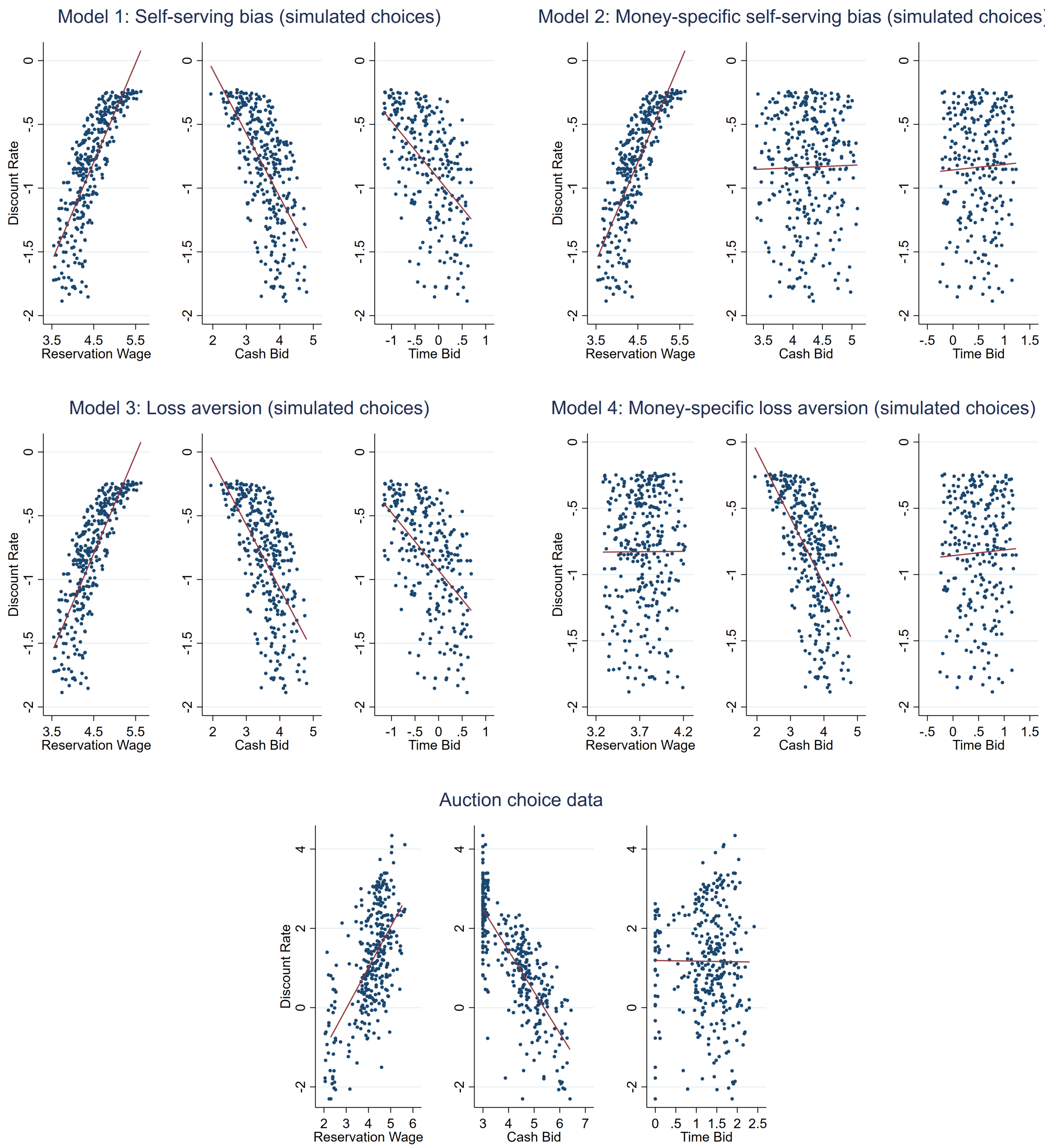
5 Decomposing the behavioral bias

In this section we present a generalized behavioral model which allows us to identify the magnitude of discounting in each of our three auctions. Recall that any auction choice triplet (a reservation wage, a cash bid, and a time bid) is rationalized by any of the four behavioral models of Section 3 with the same discount rate. Additionally, the behavioral models we have considered up to this point have different implications for how to correctly measure the value of time. For example, if only cash bids are biased, then reservation wages accurately measure the value of time. If only reservation wages are biased, then the IVT—calculated from cash and time bids—accurately measures the value of time.

The following numerical example illustrates the need for a general model. A farmer bids 100 KSh and 2 hours for the lottery. Her reservation wage elicited through Auction 1 is 75 KSh/hour. These choices are inconsistent with our benchmark model and indicate cyclic preferences. But from these choices alone we cannot distinguish whether her reservation wage is inflated, her cash bid is deflated, or her time bid is inflated. To do so we turn to features of the aggregate choice data. The key is that a bias in one auction induces a relationship between the choice made in that auction and the calculated behavioral discount rate. Figure 2 plots the relationship between simulated choice data and discount rates that would arise under each of the four behavioral models in Section 4.1, along with observed choices in auctions. To simulate choices, we draw preference parameters a, b, and r independently for each farmer, then solve for auction choices using first-order constraints. Consider Model 4, in which farmers exhibit a money-specific loss aversion: their cash bids will be biased but their time bids and reservation wages will not. Farmers with greater discount rates will tend to place lower cash bids. Variation in reservation wages will be driven only by variation in the value of time, and not by variation in the discount rate. In our data, farmers with high discount rates tend to place low cash bids and have high reservation wages; time bids are uncorrelated with discounting. This suggests that a mixture of Models 2 and 4—in which farmers deflate cash bids and inflate reservation wages—best describes our setting.

We formalize this argument in a model that allows the discount rate to vary across auctions. We identify the degree of bias in each auction and compute the debiased value of time. Our identifying assumption is that the discount rate is uncorrelated with preference parameters a and b. We present evidence supporting this assumption in Section 5.3.

Figure 2: Aggregate auction data allow us to distinguish between behavioral mechanisms.



Note: Each observation is a farmer. OLS line in red. Choices are simulated under four possible behavioral models. Actual choice data from incentivized auctions with a 3% jitter. All variables are log-transformed.

5.1 Model setup

We revisit the choice problems of Section 4.1, but allow the farmer to bias each of her three choices with a different discount rate. The three auctions correspond to the following choices, respectively:

1. Receive m^A for h^A hours of work: $V(0, -(1-r^A)m^A, h^A) = 0 \Rightarrow (1-r^A)m^A - bh^A = 0$.

2. Pay m^τ for the lottery τ: $V((1-r^B)\tau = 1, m^\tau, 0) = 0 \Rightarrow (1-r^B)a - m^\tau = 0$.

3. Work h^τ hours for the lottery τ: $V((1-r^C)\tau = 1, 0, h^\tau) = 0 \Rightarrow (1-r^C)a - bh^\tau = 0$.

Define parameters ρ_i and $\vec{\gamma} = (\gamma^A, \gamma^B, \gamma^C)$ such that

- $1 - r_i^A = \exp(-\rho_i \gamma^A)$
- $1 - r_i^B = \exp(-\rho_i \gamma^B)$
- $1 - r_i^C = \exp(-\rho_i \gamma^C)$,

with $\gamma^A + \gamma^B + \gamma^C = 1$ and $\gamma^A + \gamma^B - \gamma^C > 0$. From the first order conditions above,

$$\log(m_i^A/h^A) = \log b_i + \rho_i \gamma^A \tag{7}$$

$$\log m_i^\tau = \log a_i - \rho_i \gamma^B \tag{8}$$

$$\log h_i^\tau = \log a_i - \log b_i - \rho_i \gamma^C \tag{9}$$

Solving for ρ_i gives

$$\rho_i = \frac{\log(m_i^A/h^A) - \log m_i^\tau + \log h_i^\tau}{\gamma^A + \gamma^B - \gamma^C}$$

5.2 Identifying bias shares

To identify the bias shares γ^A, γ^B, and γ^C that apply to reservation wages, cash bids, and time bids respectively, we make the following assumptions.

Assumption 2 (independence). *ρ is independent of preference parameters a and b.*

Then the bias shares are identified as follows.

Theorem 2 (identification of bias shares). *Let $\hat{\rho}_i \triangleq \log(m_i^A/h^A) - \log m_i^\tau + \log h_i^\tau = \rho_i(\gamma^A + \gamma^B - \gamma^C)$. Then, under Assumption 2 and the first order conditions (7), (8), and (9), the bias shares γ^A, γ^B, and γ^C are identified by*

$$\gamma^A = \frac{\hat{\gamma}^A}{\hat{\gamma}^A + \hat{\gamma}^B + \hat{\gamma}^C} \quad ; \quad \gamma^B = \frac{\hat{\gamma}^B}{\hat{\gamma}^A + \hat{\gamma}^B + \hat{\gamma}^C} \quad ; \quad \gamma^C = \frac{\hat{\gamma}^C}{\hat{\gamma}^A + \hat{\gamma}^B + \hat{\gamma}^C}$$

Where $\hat{\gamma}^A$, $\hat{\gamma}^B$, and $\hat{\gamma}^C$ are the OLS solutions to

$$\log(m_i^A/h^A) = \bar{A} + \hat{\gamma}^A \hat{\rho}_i + \epsilon_i^A \tag{7'}$$

$$\log m_i^\tau = \bar{B} - \hat{\gamma}^B \hat{\rho}_i + \epsilon_i^B \tag{8'}$$

$$\log h_i^\tau = \bar{C} - \hat{\gamma}^C \hat{\rho}_i + \epsilon_i^C \tag{9'}$$

and $\bar{A}$, $\bar{B}$, and $\bar{C}$ are constant terms.

5.3 Estimation results

We estimate (7′), (8′), and (9′) under the constraints $\gamma^k \geq 0$ for $k \in \{A, B, C\}$. Table 3 Column 1 displays results for the full sample. We estimate that reservation wages, cash bids, and time bids represent 39%, 61%, and 0% of the total bias respectively. This accords with the logic of Figure 2: farmers exhibiting greater bias tend to be those who express high reservation wages or place low cash bids. The value of time, debiased using (7), is on average 49 KSh/hour, or 60% of the average wage for casual labor. As expected, this lies inside the range of estimates produced by the behavioral models of Section 4.1, in which the overall bias is expressed entirely through reservation wages or the implied value of time, but not both at once.

Identification requires that the total behavioral bias ρ_i be independent of preference parameters a and b,[4] the valuation of the lottery ticket and the marginal value of time. Testing this assumption requires proxies of a and b that are not themselves influenced by a behavioral bias. Our survey data suggest that the behavioral bias measured as in (6) does not appear in unincentivized reports: when we ask farmers how much they would be willing to pay or work for a lottery ticket, and whether they would be willing to spend time to collect various amounts of cash, the implied "unincentivized discount rate" is very close to 0 (mean=0.03, p-val=0.52). We therefore re-estimate the model controlling for unincentivized proxies of a and b—reported valuation of the irrigation pump and the minimum amount of money for which the respondent would be willing to travel 1 hour, respectively. Table 3 Column 4 shows results. These controls have very little effect on our results, which lends support to Assumption 2. As an additional test of whether correlation between preference parameters a and b and behavioral discounting is driving our results—and whether the fixed-share structure of our model is reasonable—we estimate our model separately within groups of economically similar farmers. We argue that there is likely to be less confounding variation in preferences within these groups, so that Assumption 2 is more likely to hold. We divide our sample into 3 groups using cluster analysis.[5] Table C3 displays results. Our estimated bias shares vary surprisingly little across groups, and the estimated value of time is quite

[4]This assumption is sufficient but not necessary. We only require that ρ be uncorrelated with $\log a$ and $\log b$.

[5]We choose three groups based on a kink in the within-cluster sum of squares criterion (see Figure E1).

stable at 52–65% of the local wage across groups. This is true despite the fact that the overall magnitude of the bias ρ varies substantially across clusters—from 0.741 to 1.594—supporting our assumption of bias shares that are fixed across our sample.

Because we bottom-code cash and time bids that are outside the range of allowed prices—bids below 20 KSh or 1 hour respectively—and top-code reservation wages above 250 KSh/hour, we also show results estimated on the subset of farmers who placed at least 1 "allowed" bid (Columns 2 and 5) and the subset of farmers with 3 "allowed" bids (Columns 3 and 6) in Table 3. The estimated bias shares change little across specifications, and the estimated relative value of time is very stable at 60–61% of the local wage.

Table 3: The total behavioral bias is driven primarily by deflated cash bids, followed by inflated reservation wages.

	(1) Full sample	(2) Placed $\geq$1 bid	(3) Placed all bids	(4) Full sample	(5) Placed $\geq$1 bid	(6) Placed all bids
Reservation wage bias (γ^A)	0.385	0.384	0.452	0.384	0.383	0.454
	(0.023)	(0.024)	(0.032)	(0.023)	(0.023)	(0.031)
Cash bid bias (γ^B)	0.612	0.616	0.548	0.616	0.617	0.546
	(0.029)	(0.030)	(0.042)	(0.029)	(0.030)	(0.041)
Time bid bias (γ^C)	0.003	0.000	0.000	0.000	0.000	0.000
	(0.025)	(0.025)	(0.036)	(0.025)	(0.026)	(0.036)
Debiased Value of Time (DVT)	48.8	48.6	47.0	49.0	48.6	46.9
	(2.47)	(2.48)	(2.62)	(2.48)	(2.48)	(2.61)
Local Wage (w)	82.4	82.4	76.8	82.4	82.4	76.8
	(6.01)	(6.02)	(5.99)	(6.01)	(6.02)	(5.99)
Relative Value of Time (DVT/w)	0.592	0.589	0.612	0.595	0.590	0.611
	(0.057)	(0.057)	(0.061)	(0.057)	(0.057)	(0.060)
Observations	332	329	231	332	329	231
Controls?	N	N	N	Y	Y	Y

Note: Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 Ksh). See Section 5 for details on identifying bias shares and DVT. Columns (4)-(6) include controls that proxy for two preference parameters—the value of time and the valuation of the irrigation pump—which determine auction choices together with the behavioral discount rate. "Local wage" is most recent hourly wage earned from casual labor. Columns (1) and (4) show results on the full sample, with cash and time bids bottom-coded at 20 KES and 1 hour respectively. Columns (2) and (4) show results estimated using farmers who placed eligible bids in at least 1 auction. Columns (3) and (6) show results estimated using farmers who placed eligible bids in all 3 auctions. An eligible bid is a cash bid > 0, a time bid > 0, or a reservation wage below 250 Ksh/hour. Bootstrap standard errors in parentheses.

Figure 3 Panel A plots the estimated distribution of the debiased value of time against reservation wages and actual wages earned for casual labor. We find that both reservation wages and earned wages lie significantly above the value of time. We discuss possible implications for labor markets in Section 6.1. Panel B plots the estimated distribution of the debiased ticket valuation against cash bids for those tickets. We find that cash bids lie significantly below farmers' private valuations of the ticket. We discuss implications for willingness to pay as a measure of valuation in Section 6.2.

Figure 3: The effects of behavioral biases on auction choices

Panel A: Kernel densities estimated on all farmers in sample. "Debiased value of time" is the preference parameter b (see Section 4.1) identified as described in Section 5.2. "Reservation wage" is elicited through Auction 1 (see Section 2.2 for design details). "Wage for casual labor" is the most recent wage earned for casual labor (imputed for those who have not recently worked). All variables top-coded at 150 KSh/hour.
Panel B: Kernel densities estimated on all farmers in sample. "Debiased ticket valuation" is the preference parameter a. "Cash bid for ticket" is the willingness to pay (WTP) in cash for a lottery ticket, elicited through Auction 2. All variables top-coded at 400 KSh.

6 Discussion and conclusion

We collect auction choice data from 332 farmers in western Kenya to measure the marginal value of time. We uncover a substantial behavioral bias affecting choices. The bias is more severe among cash constrained farmers, farmers with low levels of education, and farmers with no recent casual labor experience. We test alternative explanations for the behavioral bias in Appendix D—including non-linear effort costs of casual work, risk aversion, order effects of the auctions, anchoring to common wages for casual work, non-compliance within our auctions, and social suppression of labor supply—and find that none of these explanations appears to explain the choices we observe. Our findings suggest that willingness to pay in cash is biased downward by loss aversion—possibly due to cash scarcity—and reservation wages are biased upward by a self-serving bias, possibly due to inexperience with the casual labor market. Taking both biases into account, we estimate an average value of time of 60% of the local wage.

6.1 Implications for labor markets

Self-serving bias can cause impasse in negotiations even when information is complete (Babcock and Loewenstein, 1997). In our context, self-serving bias appears to partially explain the cyclic choices observed in our auctions. This bias is substantial: farmers appear to inflate their reservation wages by almost 50% relative to their value of time. Experience seems to matter: casual laborers, who must frequently engage in negotiation over wages, display a less severe behavioral bias. A key question is whether this bias affects real-world labor market negotiations. If the self-serving bias observed in our auctions is also present in labor markets, it may lead prospective workers to turn down job offers that would be welfare-improving in the absence of the bias, thereby driving unemployment or underemployment levels above the bias-free equilibrium. Our data on market wages suggests that this may indeed be the case: typical market wages are substantially greater than most farmers' value of time. We do not find evidence of labor rationing creating involuntary unemployment: on average reservation wages are very close to the local wage. We also do not find evidence that reservation wages are inflated by social norms which prevent workers from accepting low-wage work (see Appendix D).

6.2 Implications for measuring willingness to pay

Researchers often use willingness to pay as a mechanism to assign goods to agents who value them most. Our model of loss aversion, which disproportionately affects cash payments, implies that agents will not be willing to pay their full valuation for a good. The evidence we find for this loss aversion appears particularly striking among cash-strapped farmers, who by our measure constitute two-thirds of our sample. Farmers not strapped for cash were willing to pay 82% of their estimated valuation for a lottery ticket; cash-strapped farmers were willing to pay only 53%. The bias we uncover is likely to affect researchers who employ similar methods to measure willingness to pay. In our setting, willingness to pay in cash does not even produce a good ordinal ranking of private valuation. A valuation ranking of our 332 farmers based on willingness to pay in cash is off by an average of 66 ranks. This echoes findings in similar contexts that willingness to pay in cash is a poor assignment mechanism for health technologies (Cohen and Dupas, 2010).

6.3 Implications for future research

How should researchers value non-work time in low-income settings? For researchers already conducting field work, implementing our first auction to elicit reservation wages from a subset of the sample may be a practical way to estimate the marginal value of time. When doing so, researchers should consider whether bids are likely to be bias-free, and may need to take a stand on how to incorporate behavioral parameters into welfare evaluations. Our first auction does present some challenges—it requires scheduling workdays and transporting workers to and from work sites—and so may be expensive at scale. Given our finding that experienced workers discount less severely, we suggest selecting a heterogeneous subset of experienced casual laborers for this activity and then mapping the results onto the target population. Based on our data, a researcher looking to estimate reservation wages within

10% of the population mean at $\alpha = 0.05$ would need 125 casual laborers to take part in a wage auction.

Of course, implementing this mechanism will be prohibitively difficult in some contexts, and for researchers working with secondary data. In these cases, researchers will need to rely on estimates of the MVT from similar contexts. Even the most conservative interpretation of our results yields an estimate of the average MVT of about 40% of the local wage, and 60% is probably a more reasoned estimate. Studies that do not account for changes in working hours may therefore overstate welfare gains from any labor-increasing reallocation, such as implementing a new technology on the farm, or transitioning to a sector where working hours are higher.

This study leaves many questions about the nature of the observed behavioral bias unanswered. In particular we do not take a stand on whether the observed biases are welfare-decreasing. The possibility remains that these biases can improve outcomes in other types of negotiation. An additional limitation is that our estimates are local to the season in which our auctions took place—in this case, the end of sowing season. We cannot rule out that labor is rationed only during lean seasons, as in Breza et al. (2020), or that the severity of behavioral biases varies across seasons. We cannot say conclusively whether these biases operate outside of an experimental setting. Finally, our finding that discounting is less severe among active laborers points to experience as debiasing, and suggests training as an avenue for future research.

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Appendix

A Proofs

Proof of Theorem 1. Let $x = (c, l)$, and $z = (\tau, m, h)$. Because maximization problem (1) is continuous in x, z and strictly concave in z, it follows that for every z, problem (1) admits a unique solution x_z, and it is continuous in z.

Let $u \in \mathbb{R}^3$ be a direction of change. Let

$$V(x, z) \equiv u(c, l + h) + k(I + wl - c - m) + \mathbb{E}[v(I + wl + \tau\theta - c - m)].$$

Corollary 5 of Milgrom and Segal (2002) implies that V is absolutely continuous in z and for any z, u, satisfies

$$V(z + u) = V(z) + \int_{s=0}^{1} \langle \nabla_x V(x_{z+su}, z + su), u \rangle \, \mathrm{d}s.$$

Under Assumption 1, $\nabla_x V(x, z)$ is continuous in x and z. Since x_z is continuous in z, it follows that V is differentiable, with derivative $\nabla_x V(x_z, z)$. This implies that

$$V(\tau, m, h) = \tau V_\tau + m V_m + h V_h + O\left(\overline{\theta}^2 + m^2 + h^2\right)$$

with

$$u_{c,0} = k_0' + v_0' \quad \text{and} \quad - u_{l,0} + \lambda = w \times (k_0' + v_0').$$

The fact that

$$u_{c,0} = k_0' + v_0' \quad \text{and} \quad - u_{l,0} + \lambda = w \times (k_0' + v_0'),$$

follows from first-order conditions with respect to c and l in program (1). ■

Proof of Theorem 2. Consider the regression equations $7'$, $8'$, and $9'$. Substituting $\hat{\rho}_i = \rho_i(\gamma^A + \gamma^B - \gamma^C)$ gives

$$\log(m_i^A/h^A) = \bar{A} + \rho_i \hat{\gamma}^A(\gamma^A + \gamma^B - \gamma^C) + \epsilon_i^A$$

$$\log m_i^\tau = \bar{B} - \rho_i \hat{\gamma}^B(\gamma^A + \gamma^B - \gamma^C) + \epsilon_i^B$$

$$\log h_i^\tau = \bar{C} - \rho_i \hat{\gamma}^C(\gamma^A + \gamma^B - \gamma^C) + \epsilon_i^C$$

The first order conditions (7), (8), and (9) imply that

$$\bar{A} + \epsilon_i^A = \log b_i$$

$$\bar{B} + \epsilon_i^B = \log a_i$$

$$\bar{C} + \epsilon_i^C = \log a_i - \log b_i.$$

Under Assumption 2, ρ_i is independent of a_i and b_i and therefore also independent of $\log a_i$ and $\log b_i$. This implies that $cov(\rho, \epsilon^k) = 0$ for $k \in \{A, B, C\}$. Because $\hat{\rho}$ is a linear transformation of ρ, it follows that $cov(\hat{\rho}, \epsilon^k) = 0$ for $k \in \{A, B, C\}$. Therefore OLS estimates of ($7'$), ($8'$), and ($9'$) identify

$$\hat{\gamma}^A = \frac{\gamma^A}{\gamma^A + \gamma^B - \gamma^C} \quad ; \quad \hat{\gamma}^B = \frac{\gamma^B}{\gamma^A + \gamma^B - \gamma^C} \quad ; \quad \hat{\gamma}^C = \frac{\gamma^C}{\gamma^A + \gamma^B - \gamma^C}$$

■

B Implementation details

We selected villages for our sample to ensure a sufficient number of farmers with land suitable for irrigation, that is, close enough to a water source but with land not too steep for pumping up water. In each village, we identified an "anchor farmer" who lived close to a water source, and used the snowball technique to generate a list of 15 to 25 neighboring farmers with land suitable for manual pump irrigation. Although 61% of farmers were using some form of irrigation, the overwhelming majority use "bucket irrigation" (which is extremely time consuming and dramatically limits the area that can be irrigated) and only 6% of farmers had used a manual pump in the past 3 years.[6]

Before the auctions, our project staff explained the auction design and quizzed bidders on hypothetical outcomes to ensure comprehension. Staff gave bidders information on the irrigation pump, including its market price, hose length, maximum pumping height, and flow rate. Staff explained that casual labor would be performed in groups in a nearby village, and that workers would be monitored by project staff to ensure the work was performed. Because the work was done for a stranger in a different village, we do not expect bidders to internalize the direct value of their work. Additionally, because the work was similar to casual agricultural work that is commonly done throughout all of our villages, there should not be any learning value from completing the work.

If the head of household was unable to perform casual labor, a different household member was selected at the outset.

[6]The majority of the world's poor lives in sub-Saharan Africa and earns very little money as small-scale farmers. Without irrigation, it is difficult for these farmers to grow multiple cycles of high value crops throughout the year and to harvest and sell their crops in the dry season when prices are higher. Yet, according to a 2010 FAO report, less than 4% of arable land in Sub-Saharan Africa is irrigated.

BDM Step 1: Eliciting willingness to pay

The cash and task auctions occurred at the beginning of the survey, in random order. The day work auction came next. Prices were drawn at the end of the three auctions. Scripts read to each farmer explained that there could be absolutely no bargaining once the prices were drawn.

Cash for ticket. Each bidder was asked whether she would be willing to purchase the lottery ticket for a series of increasing prices, beginning from 20 KSh and increasing in 20-KSh increments up to 500 KSh. If the bidder was willing to pay 500 KSh, we asked for her maximum willingness to pay (WTP) in a single question. Bidders were not aware that there was a price ceiling during the elicitation. Once her WTP was determined, it was explained once more that if the price drawn were 20 KSh higher than her stated WTP, she would be unable to purchase the ticket. At this point, she was given the option to revise her answer.

Work for ticket. Each bidder was asked whether she would be willing to perform casual labor for the lottery ticket for a series of increasing hours, beginning from 30 minutes and increasing in 30-minute increments up to 6 hours. If the bidder was willing to work for 6 hours, we asked for her maximum WTP (in hours) in a single question. Bidders were not aware that there was an hours ceiling during the elicitation. Once her WTP was determined, it was explained once more that if the price drawn were 30 minutes greater than her stated WTP, she would be unable to purchase the ticket. At this point, she was given the option to revise her answer.

Work for cash. Each bidder was asked whether she would be willing to perform casual labor for a series of decreasing wages, beginning from 120 KSh/hr and decreasing in 10-KSh/hour increments down to 10 KSh/hr. If the bidder was not willing to work at 120 KSh/hr, we asked for her reservation wage in a single question. Once her reservation wage was determined, it was explained once more that if the wage drawn were 10 KSh lower than her stated reservation wage, she would be unable to take the job. At this point, she was given the option to revise her answer.[7]

BDM Step 2: Assignment of a numeraire

Each village was randomly assigned (by a pseudo-random number generator) to one of three assignment types: Cash, Cash + Day Work, or Task. Bidders in *Cash* villages received a lottery ticket price payable in cash only, and were not eligible for wage work. Bidders in *Cash + Day Work* villages received a lottery ticket price payable in cash only, and were eligible for wage work. Bidders in *Task* villages received a lottery ticket price payable in hours of work only, and were not eligible for day work. We randomized at the village level to simply logistics, as this reduced the number of work sites we needed to set up. In practice, the randomization was conducted on a computer prior to the field visit, but bidders did not learn about their assignment until their lottery ticket price was drawn (see step 3 below). To reduce the possibility that bidders might share information with each other and, we completed all surveys within each village in the same day.[8]

BDM Step 3: Lottery ticket price and wage draw

Each farmer received a random ticket price and a random day work wage. Prices and wages were drawn independently from distributions stratified at the village level. In particular, each

[7]22% of bidders declined to place a cash bid for a lottery ticket. We code these as bids of 0 KSh. 10% of bidders declined to place a time bid for a lottery ticket. We bottom-code these as bids of 0.5 hours so that the discount rate r is defined. Results are not sensitive to excluding these bids. 9% of bidders declined to participate in the day work auction, as we told bidders ahead of time that the maximum possible wage was 120 KSh/hour. For these bidders, we ask their reservation wage directly.

[8]Note that even if bidders did talk during the survey day, in principle this should not affect their bidding behavior. Without seeing the results of a high number of draws, one can not be certain that the numeraire assignment occurred at the village-level rather than household-level. As long as there is some uncertainty over the numeraire, and the effort cost of bidding is not too high, it is optimal to take each bidding exercise seriously.

farmer was assigned two pseudo-random numbers (one for ticket price and one for wage), and price and wage assignment were based on the within-village percentile of the random price and wage numbers. Figure A1 shows the empirical distributions of ticket prices and day work wages.

In practice, the random prices and wages were decided prior to the surveys. Each bidder's ticket price and wage were written on cards and inserted into sealed envelopes, which were shown to the bidder at the beginning of the survey. At the end of the survey, the envelope was opened and the ticket price and wage revealed. A bidder could thus be sure that her answers in the auctions had no bearing on her draws.

Ticket winners whose prices were denominated in cash were required to make a down payment of 20 KSh ($0.20) at the end of the survey, and were given about 1 week to collect the remaining money to pay for the ticket. This was done to mimic real-world conditions in which cash constrained farmers gather money from friends and family to pay for unexpected expenses.

Cash collection and day work

Farmers who won lottery tickets were given approximately one week before collection day. On collection day, enumerators returned to the village to collect the remaining amount owed by cash winners, and to take task winners out to perform their work.

Work days for bidders who won a lottery ticket priced in time were scheduled about one week out from the auction. Work days for bidders eligible for wage work were scheduled about two weeks out from the auction. A random subset of villages was selected for day work after lotteries were held. Work days were organized in groups at the village level: all eligible bidders were asked to complete their work on a farm outside of their village. Work sites were selected by project staff in nearby villages, and transportation was provided. Work involved common tasks performed by casual laborers, including weeding and land preparation.

Compliance was high: 88% of bidders paying cash and 75% of bidders performing casual labor completed their payments or work (see Section D for details on compliance). After payments and work were complete, lotteries were held publicly. Farmers who were eligible for a lottery ticket or day work but did not complete payment or show up for work were ineligible for the rest of the study. This was made salient to bidders throughout the auctions to discourage bids that bidders were not truly willing to accept.

Lotteries

In *Cash* and *Task* villages, lotteries were conducted immediately following collection, at which point farmers were informed that their village had not been selected for day work. In *Cash + Day Work* villages, enumerators returned to the village approximately one week after collection to take eligible day workers to the job site. Lotteries were held immediately following the day work.

Lotteries were held in groups with all present ticket winners. Farmers were ordered randomly from position $n \in \{1, ..., N\}$, and given a lottery card numbered $c = \mathrm{mod}(n, 10)$. For villages with $\geq N$ ticket winners, a single number between 1 and 10 was drawn and all farmers holding that card won a pump. For villages with fewer than N ticket winners, a single number between 1 and N was drawn to determine the winner. The minimum number of winners per village was therefore 1, and the maximum was $ceiling(N/10)$.

Farmers who drew a ticket price or reservation wage that they had agreed to during the BDM elicitations but then reneged by not paying for the ticket, showing up for task work, or showing up for day work were ineligible for the rest of the study. This was made salient to farmers throughout the elicitations so that they would only bid in amounts they were truly willing to pay or work for.

C Covariates of Bias

To understand which farmers discount more severely, we estimate specifications of the form:

$$y_i = \alpha + \beta P_i + X_i' \Gamma + \epsilon_i, \tag{10}$$

where y_i is an auction choice, P_i is a predictor variable we expect to influence choices through a behavioral channel, X_i is a vector of possible controls, and ϵ_i is an error term. To account for censoring in the auction choice variables, we estimate (10) using Tobit models. Table C1 shows results with controls chosen through post double-selection lasso regression (Belloni and Chernozhukov, 2013, Tibshirani, 1996).[9] We standardize all non-binary predictor and control variables. Standard errors and p-values are computed by estimating (10) in 1,000 bootstrap samples. Table C2 shows estimates of (10) excluding control variables.

The characteristics we analyze are not randomly assigned, and so estimates of β should not be interpreted as causal. However, recall that in the model, the behavioral discount rate r is invariant to both observed and unobserved farmer characteristics. Characteristics that are non-behavioral—including the farmer's value of time, valuation of the pump, risk aversion, wealth, and effort cost of providing casual labor—influence both measures of the value of time proportionately. We therefore view estimates of (10) as informative of the characteristics of farmers that exhibit a more severe behavioral bias.

The literature on self-serving bias and loss aversion motivates our selection of behavioral predictors. Questioning one's own judgement before negotiating reduces self-serving bias (Babcock et al., 1998), though it is not clear whether experience reduces bias over time. To

[9] In the set of possible controls we include the farmer's age, years of education, gender, an indicator for whether the household has no male head, household size, cultivated land area, total household income, the share of household income from crop farming, self-reported valuation of the irrigation pump, an index of knowledge about the pump, an indicator for whether the farmer has used a pump in the past, an indicator for whether the farmer has considered buying the pump in the past, three occupation dummies (corresponding to vendors, traders, and business owners), an index of intra-household altruism, and network centrality as measured by the number of farmers in the village who report receiving farming advice from that household.

Table C1: Farmers who exhibit a greater behavioral bias tend to be younger, less educated, inexperienced at wage negotiation, and cash constrained.

	(1) Discount rate	(2) Reservation wage	(3) Implied value of time	(4) Cash bid	(5) Time bid
Performs or hires casual labor	-0.597***	-9.7	17.6***	71.7***	0.690**
	(0.168)	(8.3)	(5.3)	(16.8)	(0.294)
Performs casual labor	-0.380*	-16.8**	6.5	34.9*	0.720***
	(0.194)	(6.6)	(5.2)	(18.1)	(0.250)
Hires casual labor	-0.047	8.1	8.5*	24.3	0.091
	(0.188)	(6.6)	(4.8)	(17.9)	(0.258)
Age	-0.145	-4.3	-2.3	-16.0	-0.326**
	(0.097)	(4.0)	(2.8)	(9.9)	(0.147)
Years of education	-0.260***	-7.7	7.4***	19.7**	-0.042
	(0.090)	(4.7)	(2.9)	(8.7)	(0.152)
Female	-0.003	-12.9	-1.3	-15.9	-0.568*
	(0.227)	(8.7)	(6.0)	(22.2)	(0.329)
No male head of household	0.113	7.7	4.8	22.1	0.574
	(0.269)	(9.7)	(10.2)	(30.8)	(0.351)
Cash constrained	0.562***	-0.6	-14.5***	-58.8***	0.319
	(0.217)	(6.9)	(5.5)	(21.6)	(0.285)
Land area under cultivation	-0.189*	-1.6	3.2	4.7	-0.058
	(0.100)	(4.0)	(2.6)	(8.1)	(0.163)
Household income	0.191	4.2	-4.9	-9.9	-0.210
	(0.140)	(6.3)	(4.1)	(14.8)	(0.261)
Altruism	0.072	-3.2	-1.1	-4.8	0.098
	(0.077)	(3.2)	(2.3)	(8.0)	(0.121)
Observations	332	332	332	332	332
Controls?	Y	Y	Y	Y	Y
Estimator	Tobit	Tobit	Tobit	Tobit	Tobit

Note: Each observation is a farmer. Currency units are Kenyan shillings (1 USD = 107 Ksh). Each cell is estimated from a Tobit regression of an auction choice on the predictor of interest. Controls in each regression are chosen using double lasso. All non-binary predictors are standardized to mean 0, standard deviation 1. Bootstrap standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

test this, we include dummy variables indicating whether the farmer has recently provided or hired casual labor—proxies for negotiating experience—following the logic that these farmers are likely to have thought more carefully about wage bargaining. We find that sellers of casual labor in particular exhibit less severe discounting (coeff=-0.38; p-val=0.05). They bid more for the lottery ticket in both cash and time, and have lower reservation wages. We also include age and education as proxies for experience. We find that older farmers discount less (coeff=-0.145; p-val=0.14). The relationship between the discount rate and age is non-monotonic: the young and the very old discount more (see Figure C1). More educated farmers also discount less (coeff=-0.26; p-val<0.01).

A large body of work finds that scarcity affects decision-making (see Mullainathan and Shafir, 2013, for a review). We use a survey-based measure of cash constraints—whether the farmer reports that she would be unable to find 5,000 KSh (about $47) to cover an emergency (Dupas et al., 2018)—to test whether farmers who are strapped for cash discount transactions more severely. We find that these farmers exhibit greater bias (coeff = 0.562; p-val $<$ 0.01). They place lower cash bids (coeff = -59; p-val $<$ 0.01), but not time bids, and have very similar reservation wages compared to less cash-constrained farmers. We also include two measures of wealth: land area cultivated, and total household income. We find that these measures have much less predictive power than our measure of cash constraints.

Scarcity can potentially affect decision-making in many ways. One possibility, following the framework of Shah et al. (2012), is that scarcity focuses attention on immediate needs and away from other economic decisions. Our preferred interpretation is that cash constraints amplify a loss aversion that applies specifically to cash. This would explain our finding that cash constrained farmers behave no differently when paying in time (for a ticket or for a wage), but bid significantly less in cash. One possibility is that scarcity increases present bias (Schofield, 2014). We do not believe this explains our results. In our design, transactions occurred at least one week after the auctions, with no substantial differences in wait times for cash payments, work, or wages paid.

There is some evidence in the loss aversion literature that women exhibit greater loss aversion than men (Rau, 2014). We include two dummy variables related to gender: whether the bidder is female, and whether the household has no male head. We find little differences based on the gender of the bidder. Bidders who head households with no male head (most commonly because the bidder is a widow) exhibit a greater behavioral bias, though the estimate is imprecise (coeff=0.113; p-val=0.67).

Altruism may mitigate self-serving bias (Di Tella et al., 2015). We test whether more altruistic farmers—measured using the share donated to an unspecified person in their village in a hypothetical dictator game—discount less. A one standard-deviation increase in our measure of altruism corresponds with an insignificant 0.072 reduction in the discount rate (p-val=0.35).

Alternative model specifications

Table C2: Which bidders discount the most (excluding control variables)?

	(1) Discount rate	(2) Reservation wage	(3) Implied value of time	(4) Cash bid	(5) Time bid
Performs or hires casual labor	-0.777***	-15.0*	21.4***	91.4***	0.960***
	(0.178)	(8.3)	(5.4)	(17.7)	(0.297)
Performs casual labor	-0.324*	-18.8***	5.7	39.8**	1.016***
	(0.188)	(6.8)	(5.0)	(17.8)	(0.257)
Hires casual labor	-0.252	3.8	12.5**	39.5**	0.165
	(0.182)	(6.9)	(5.0)	(17.7)	(0.265)
Age	-0.044	1.3	-3.1	-19.9**	-0.284**
	(0.084)	(3.6)	(2.5)	(8.8)	(0.134)
Years of education	-0.316***	-7.3*	8.3***	30.2***	0.114
	(0.091)	(4.1)	(2.6)	(8.0)	(0.147)
Female	0.286	-5.0	-3.3	-18.3	-0.406
	(0.218)	(8.0)	(5.5)	(19.4)	(0.304)
No male head of household	0.363	11.4	-2.3	-25.9	-0.282
	(0.241)	(8.5)	(9.0)	(27.7)	(0.319)
Cash constrained	0.669***	0.9	-17.7***	-71.9***	0.295
	(0.218)	(7.4)	(5.3)	(19.8)	(0.280)
Land area under cultivation	-0.280**	-2.6	4.9*	12.1	-0.017
	(0.113)	(4.3)	(2.6)	(7.9)	(0.157)
Household income	-0.058	3.1	2.5	12.7	-0.174
	(0.089)	(5.0)	(2.6)	(10.3)	(0.144)
Altruism	-0.026	-4.1	0.8	5.7	0.174
	(0.069)	(3.0)	(2.4)	(8.1)	(0.112)
Observations	332	332	332	332	332
Controls?	Y	Y	Y	Y	Y
Estimator	Tobit	Tobit	Tobit	Tobit	Tobit

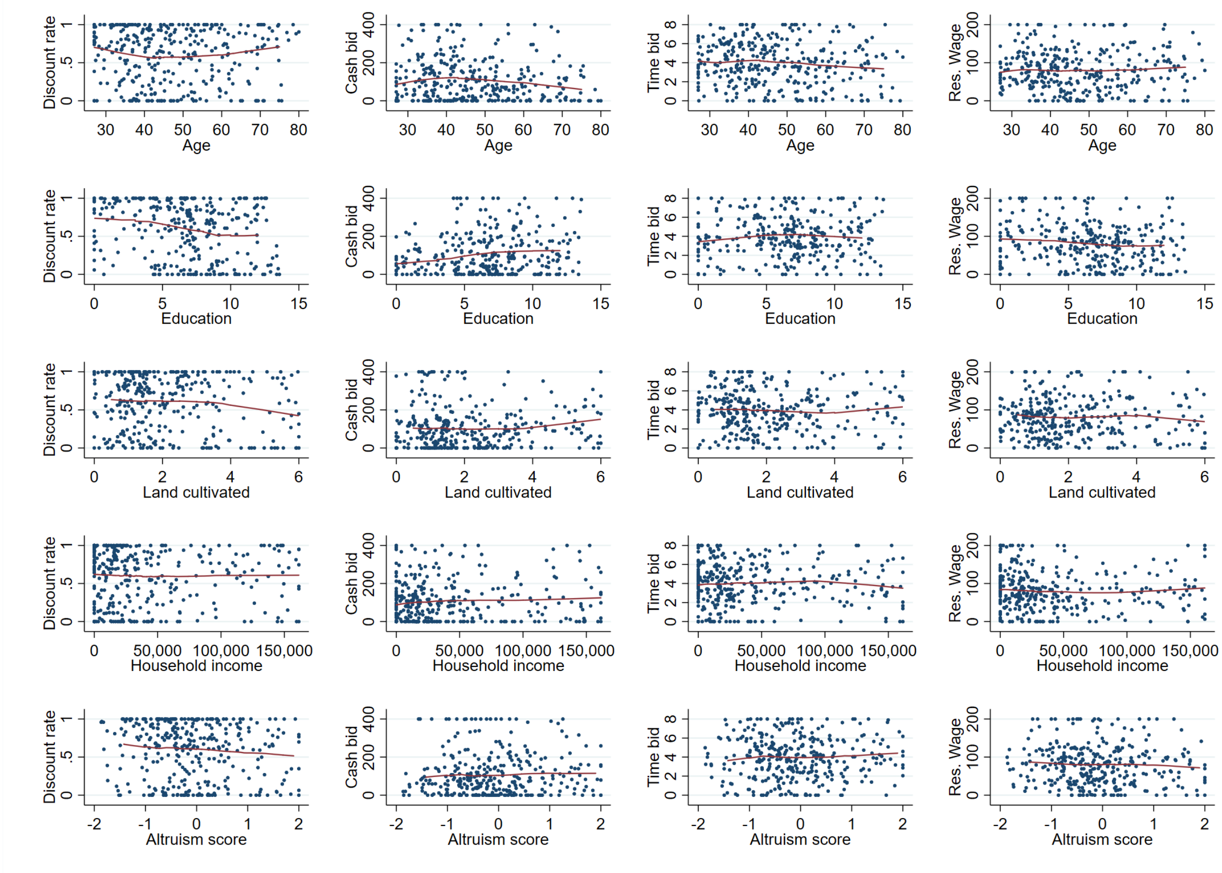
Note: Each observation is a farmer. Currency units are Kenyan shillings (1 USD = 107 Ksh). Each cell is estimated from a Tobit regression of an auction choice on the predictor of interest. All non-binary predictors are standardized to mean 0, standard deviation 1. Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C3: Estimated bias shares are fairly stable across subgroups.

	(1) Full sample	(2) Cluster 1	(3) Cluster 2	(4) Cluster 3	(5) Cash constrained	(6) Casual laborers
Magnitude of bias (ρ)	1.176	0.741	1.124	1.594	1.356	1.026
	(0.073)	(0.191)	(0.090)	(0.153)	(0.087)	(0.115)
Reservation wage bias (γ^A)	0.384	0.364	0.378	0.449	0.375	0.395
	(0.023)	(0.069)	(0.034)	(0.042)	(0.027)	(0.040)
Cash bid bias (γ^B)	0.616	0.614	0.622	0.551	0.613	0.605
	(0.029)	(0.097)	(0.038)	(0.069)	(0.040)	(0.048)
Time bid bias (γ^C)	0.000	0.022	0.000	0.000	0.012	0.000
	(0.025)	(0.085)	(0.031)	(0.057)	(0.028)	(0.042)
Debiased Value of Time (DVT)	49.0	52.6	49.2	42.5	46.4	46.2
	(2.48)	(6.43)	(3.04)	(6.32)	(3.40)	(3.51)
Local Wage (w)	81.4	81.4	81.4	81.4	81.4	81.4
	(5.99)	(5.99)	(5.99)	(5.99)	(5.99)	(5.99)
Relative Value of Time (DVT/w)	0.602	0.646	0.604	0.522	0.570	0.568
	(0.057)	(0.094)	(0.060)	(0.092)	(0.061)	(0.064)
Observations	332	52	201	79	216	157
Controls?	Y	Y	Y	Y	Y	Y

Note: Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 Ksh). See Section 5 for details on identifying bias shares and DVT. Columns (2)-(4) estimate the model of Section 5.2 within clusters of similar farmers. Cluster analysis conducted using kmeans. "Cash constrained" means farmer self-reports being unable to come up with 5,000 Ksh in an emergency. "Casual laborers" are farmers who have sold casual labor within the past 3 months. "Local wage" is most recent hourly wage earned from casual work (imputed for those who have not worked recently). Cash and time bids bottom-coded at 20 KES and 1 hour respectively. Bootstrap standard errors in parentheses.

Figure C1: Lowess regressions of auction choices against possible behavioral predictors.



Note: Each chart shows a lowess regression of an auction choice on a behavioral predictor. “Household income” is annual income from crop sales, wage earnings, and profits. “Altruism score” defined as in Section 5. “Discount rate” is the behavioral discount rate computed from (6) and is bottom-coded at 0. Scatters are shown using a 5% jitter.

D Alternative explanations of the behavioral bias

Effort costs of casual work

For observed bids to correctly measure the value of non-work time, it is important that the work in our field exercises mimic real-world working conditions. For example, if work effort is costly, farmers will express a lower reservation wage to sit idly than they would to work for the same amount of time. The correct measure of the value of time is the one that accounts for the real-world disutility of effort. With this in mind, we designed the work activity to be as commonplace as possible: work involved casual agricultural tasks which are extremely common in this context. The short-term nature of the contract was also typical: in our data, the median real-world casual labor contract lasts for 12 hours spread over 3 days.

One possible explanation for the observed gap between the implied value of time and the reservation wage is that bidders viewed the two task activities differently. We do not think this can explain our results. The two activities were designed to be as similar as possible: they involved the same type of work and were monitored the same way. If effort costs are convex in labor supply (for example, because of increasing marginal fatigue), then the average effort cost per hour of work for a wage may differ than the effort cost of work for the lottery ticket. However, time bids for the ticket were on average greater than the fixed length of the day work contract (4 hours versus 2 hours), so any convexity in effort costs will cause us to underestimate the true gap. Scheduling costs may also matter: bidders must make room in their schedule to attend the task day. Task days for lottery tickets were scheduled on average one week out from auctions; task days for a wage were scheduled on average two weeks out from auctions. Assuming that rescheduling is more costly the sooner the event, differential scheduling costs should lead us to underestimate the true gap. The same logic applies if bidders discount the value of time in the distant future more than that in the near future.

Risk aversion

If farmers are risk averse, their bids for lottery tickets will be lower than their private expected value. Importantly, the benchmark model of section 3 accounts for simple risk aversion. It is possible, however, that bidders are more or less risk averse when paying in cash than when paying in time. If so, this could rationalize the apparently low cash bids. To test for this, we elicit risk aversion in our survey instrument by directly asking respondents about their general willingness to take risks,[10] a measure that correlates well with risk-taking behavior in a paid lottery (Dohmen et al., 2011). Table D1 presents results. Risk aversion appears to have at most a modest effect on bidding behavior: cash and time bids are both somewhat lower among the risk averse, with no significant differences in the implied value of time (coeff = 5.0 KSh/hour; p-val = 0.34) or the reservation wage (coeff = −2.2 KSh/hour; p-val = 0.72).

[10]We assume that any gap in risk aversion across payment numeraires is likely to be positively correlated with the degree of overall risk aversion.

Table D1: Alternative explanations of the bidding gap

	(1) Cash bid for ticket	(2) Time bid for ticket	(3) Cash bid / task bid	(4) Reservation wage
Risk averse	-6.6	-0.52**	5.0	-2.3
	(13.5)	(0.24)	(5.2)	(6.1)
Cash auction appeared first	-9.7	-0.29	2.6	-0.0
	(13.6)	(0.24)	(5.3)	(6.0)
Perceived typical wage	2.6	-0.25**	2.5	-0.2
	(6.5)	(0.12)	(2.8)	(2.9)
Observations	332	332	332	332
Dep Var Mean	110.8	4.012	34.48	82.75

An observation is a farmer. Currency units are Kenyan shillings (1 USD=107 Ksh). Each column reports restimates from a regression of an auction choice on three predictors. "Risk averse" is a dummy = 1 if the bidder reports a willingness to take risks below the sample median. "Cash auction appeared first" is a dummy = 1 if the cash auction was done prior to the task auction (the order was randomized prior to the survey). "Perceived typical wage" is the wage the bidder reports as typical for casual agricultural work in their village and is standardized to have mean 0 and standard deviation 1. Robust standard errors in parentheses.

Order effects

To test for order effects, we randomized the order of the cash and time auctions.[11] Table D1 shows the effect on auction choices of having the cash auction appear first. We find no evidence of significant order effects.

Anchoring

Another alternative explanation for the gap we observe is that bidders anchor their reservation wage to what they believe to be the prevailing wage in their village, even if their true value of time is below that prevailing wage. To test for anchoring effects, we ask bidders what the typical hourly wage is for casual agricultural work in their village and regress auction choices on their perception of the typical wage. Table D1 shows results. We find no evidence

[11]The auction for wage work always came third.

of significant anchoring effects.

Non-compliance

If bidders do not comply with the auction rules—either by bidding a value higher than their true willingness to pay and then not following through with payment, or by not showing up to complete their casual work—then our estimates may be biased. We attempted to reduce non-compliance by requiring a down payment among cash winners, giving bidders $1-2$ weeks before the full payment was due or casual work was scheduled, and stressing from the beginning that non-compliance in one auction made the bidder ineligible for the remaining auctions. Overall, compliance rates were high, and we do not find evidence that non-compliance is driving our results. Among bidders who received a cash price below their willingness to pay (and so were eligible for a ticket), 88% paid the correct price on or before collection day. Among bidders who received a time price below their willingness to pay, 75% completed their work on the scheduled work day. Among bidders selected for wage work who had a reservation wage weakly below their wage draw, 74% completed their work on the scheduled work day. The higher compliance rate in cash is possibly due to the screening effect of the down payment, which is difficult to mimic in time. Another possible explanation is that bidders' time obligations on the scheduled work day may be difficult to substitute inter-temporally in the face of unexpected shocks.

If compliance is non-random, then our measures of the value of time may be biased. To test for non-random compliance, we regress bid amounts on a dummy for compliance within the sample of eligible bidders.[12] Table D2 present results. Compliance is uncorrelated with willingness to pay in time (coeff = 0.16 hours on a base of 4.8; p-val = 0.76) or with the reservation wage (coeff = 0.6 KSh/hour on a base of 46; p-val = 0.95), the two measures

[12]Eligible bidders are those with bids higher than the price draw in cash and task, or reservation wages lower than the wage draw.

Table D2: Testing for non-compliance bias

	(1) Cash bid for ticket	(2) Time bid for ticket	(3) Reservation wage
Complied = 1	48.9**	-0.16	0.1
	(21.2)	(0.50)	(4.7)
Observations	118	83	163
Dep Var Mean	184.5	4.76	46.4
Compliance rate	0.88	0.75	0.74

An observation is a bidder who was eligible for a lottery ticket or day work. Currency units are Kenyan shillings (1 USD=107 Ksh). Each column reports restimates from a regression of an auction choice on a dummy for compliance, defined as completing payment or work. Robust standard errors in parentheses.

for which the compliance rate was lower (about 75%). The correlation between the cash bid and compliance is positive (coeff = 49 KSh on a base of 185; p-val = 0.02). The effect of this on our average measure is likely small, as compliance was high for cash payments (88%). Additionally, because higher cash bids predict compliance, true willingness to pay among the non-compliers may be even lower, suggesting that our measure of the behavioral discount rate is a lower bound. To test for the effect of non-compliance bias on our estimates, we restrict the sample to bidders with high predicted compliance[13] in all 3 auctions. The effect on our results is generally very small (see Table **??**).

Social suppression of labor supply

An alternative explanation for the observed gap between reservation wages and the implied value of time is that stigma surrounding working for low wages increases stated reservation wages. For example, if workers feel ashamed of accepting low-wage work, or anticipate

[13] We do not observe compliance for every farmer. We only observe compliance in cash and task for those with a sufficiently high bid and who were randomly offered a price in cash or hours of work, respectively. We only observe compliance among wage bidders for those villages that we visited for work—a random subset of all villages. We therefore predict compliance with a probit model fitted on those for whom we observe compliance, and restrict the sample to bidders with $\geq 50\%$ predicted compliance on all three measures.

Table D3: Auction choices imply cyclic preferences and can be rationalized by a behavioral bias, which is heterogeneous across farmer subsamples

	(1) Full sample	(2) Supplies casual labor	(3) Hires casual labor	(4) Cash constrained
Reservation wage (w^A)	85.9	75.1	86.5	85.6
	(3.2)	(4.1)	(4.7)	(3.9)
Implied value of time (w^τ)	32.2	33.3	37.0	28.0
	(2.1)	(3.3)	(3.2)	(2.4)
Cash bid (m^τ)	122.2	141.0	135.0	103.8
	(7.4)	(12.1)	(11.1)	(7.8)
Time bid (h^τ)	4.2	4.9	4.3	4.4
	(0.1)	(0.2)	(0.2)	(0.1)
Local wage (w)	81.8	80.5	86.2	78.6
	(2.7)	(5.7)	(3.9)	(3.2)
Behavioral bias (r)	0.269	0.177	0.181	0.395
	(0.073)	(0.119)	(0.108)	(0.077)
Relative IVT (w^τ/w)	0.39	0.41	0.43	0.36
Relative res. wage (w^A/w)	1.05	0.93	1.00	1.09
p-val $r = 0$	<0.01	0.14	0.09	<0.01
p-val $w^A = w^\tau$	<0.01	<0.01	<0.01	<0.01
p-val $w^A = w$	0.32	0.44	0.96	0.16
p-val $w^\tau = w$	<0.01	<0.01	<0.01	<0.01
Observations	298	128	143	190

Note: Each observation is a farmer with a predicted compliance above 50% for all three auctions (see Appendix D subsection "Non-compliance"). Currency units are Kenyan shillings (1 USD = 107 Ksh). Each cell reports the mean and its standard error. Cash bids, time bids, and reservation wage elicited through a Becker-DeGroot-Marschak mechanism. "Local wage" is most recent hourly wage earned from casual labor and is imputed for farmers who have not performed casual labor recently. IVT stands for implied value of time and is equal to the ratio of a cash bid to a task bid. Column (1) shows results on the full sample. Columns (2) and (3) show results among farmers who have done casual work, or hired casual laborers, respectively in the past 3 months. Column (4) shows results among farmers who report that they could not find 5,000 Ksh within 3 days in the event of an emergency. Robust standard errors in parentheses.

sanctions from other workers, they may report a reservation above their true value of time. Such an explanation would be consistent with findings in rural India (Breza et al.).

To test whether stated reservation wages are inflated by stigma, we elicited emotional responses to a story about a farmer accepting a wage well below the market rate. Our setup was modeled on the Test of Self-Conscious Affect (TOSCA), which yields scales for shame and guilt. The TOSCA measure of shame correlates well with psychological adjustment

(Woien et al., 2003). We elicited feelings of shame, anger, and pride surrounding working for low wages. We then run three regressions of the form:

$$w_i^A = \alpha_0 + \alpha_1 Emotion_i + \epsilon_i$$

where $Emotion_i \in \{0, 1\}$ is a dummy variable indicating a positive emotional response to the story.

Table D4 presents results. Negative emotional responses to the vignettes were uncommon: 81% of respondents said that they did not think the low-wage worker should feel any shame *at all* (possible answers were "Not at all ashamed," "A little ashamed," "Moderately ashamed," and "Very ashamed") and 83% said that they did not feel any anger *at all* toward the low-wage worker. Positive responses were more common: 67% report feeling "very proud" of the low-wage worker, 22% felt "moderately proud" or "a little proud," and 11% felt "not at all proud." Importantly, none of the emotional responses to low-wage work correlate with the reservation wage. This finding is robust to including demographic controls selected from a rich set of covariates with Lasso regression (see Column 5). We interpret this as evidence that, unlike in the context of Breza et al. (2019), workers do not feel that they need to report a high reservation wage to avoid stigma.

Table D4: Reservation wages are not distorted by social norms against expressing low value for time.

	Dep Var: Reservation Wage				
	(1)	(2)	(3)	(4)	(5)
Reaction to low-wage work:					
Shame = 1	2.1			2.1	3.6
	(4.4)			(8.0)	(8.9)
Anger = 1		1.2		-1.4	-0.9
		(5.1)		(10.1)	(10.7)
Pride = 1			-2.5	-1.9	-4.0
			(3.9)	(7.0)	(5.7)
Observations	332	332	332	332	332
Demographic Controls?	N	N	N	N	Y

Notes: An observation is a farmer. Currency units are Kenyan shillings (1 USD=107 KSh). Dependent variable is the farmer's reservation wage. Shame, anger, and pride reactions to low-wage work are elicited in relation to a story about a hypothetical farmer. Robust standard errors in parentheses.

E Alternative method to identify bias shares

In this section we offer an alternative formulation of the bias identification framework presented in Section 5 in which multiple population biases emerge from a mixture of individuals exhibiting a single bias. That is, farmers exhibit either a cash bid bias, a time bid bias, or a reservation wage bias. As in the model of Section 5, identification of shares comes from the relationship between auction choices and the calculated bias.

Consider a set of bidders who face the same choice problems but who draw their behavioral type from a common probability distribution. Define parameters $(\delta_i^A, \delta_i^B, \delta_i^C) \in \{(1,0,0),(0,1,0),(0,0,1)\}$ with respective probabilities ϕ^A, ϕ^B, ϕ^C satisfying $\phi^A + \phi^B + \phi^C = 1$ such that

- $1 - r_i^A = (1 - r_i)^{\delta_i^A}$
- $1 - r_i^B = (1 - r_i)^{\delta_i^B}$
- $1 - r_i^C = (1 - r_i)^{\delta_i^C}$

From the first order conditions,

$$\tfrac{m_i^A}{h^A} = \tfrac{b_i}{(1-r_i)^{\delta_i^A}} \quad ; \quad m_i^\tau = a_i \times (1 - r_i)^{\delta_i^B} \;\; ; \quad h_i^\tau = \tfrac{a_i}{b_i} \times (1 - r_i)^{\delta_i^C}$$

Let

$$\chi_i \triangleq \frac{h^A m_i^\tau}{m_i^A h_i^\tau} = \frac{(1 - r_i)^{\delta_i^A}(1 - r_i)^{\delta_i^B}}{(1 - r_i)^{\delta_i^C}}$$

Then we have that

$$\chi_i = \begin{cases} 1 - r_i & \text{with probability } \phi^A + \phi^B \\ \frac{1}{1-r_i} & \text{with probability } \phi^C \end{cases}$$

Because $(1-r) \in [0,1]$ by assumption, we have

$$1 - r_i = \begin{cases} \frac{1}{\chi_i} & \text{if } \chi_i \geq 1 \\ \\ \chi_i & \text{if } \chi_i < 1 \end{cases}$$

As in Section 5.2, we maintain the assumption that $r \perp\!\!\!\perp (a, b)$ and that $\vec{\phi} = (\phi^A, \phi^B, \phi^C)$ is fixed at the population level. Let $(1 - r_i) = \exp(-\xi_i)$. Then we have, from the FOCs,

$$\log(m_i^A/h^A) = \log b_i + \delta_i^A \xi_i \implies \mathbb{E}(\log(m_i^A/h^A)|\xi_i) = \mathbb{E}(\log b_i) + \phi^A \xi_i$$

$$\log m_i^\tau = \log a_i - \delta_i^B \xi_i \implies \mathbb{E}(\log m_i^B|\xi_i) = \mathbb{E}(\log a_i) - \phi^B \xi_i$$

$$\log h_i^\tau = \log a_i - \log b_i - \delta_i^C \xi_i \implies \mathbb{E}(\log h_i^C|\xi_i) = \mathbb{E}(\log a_i - \log b_i) - \phi^C \xi_i$$

And therefore that the following regressions identify $\vec{\phi}$:

$$\log(m_i^A/h^A) = \bar{A} + \phi^A \xi_i + \nu_i^A \tag{11}$$

$$\log m_i^\tau = \bar{B} - \phi^B \xi_i + \nu_i^B \tag{12}$$

$$\log h_i^\tau = \bar{C} - \phi^C \xi_i + \nu_i^C \tag{13}$$

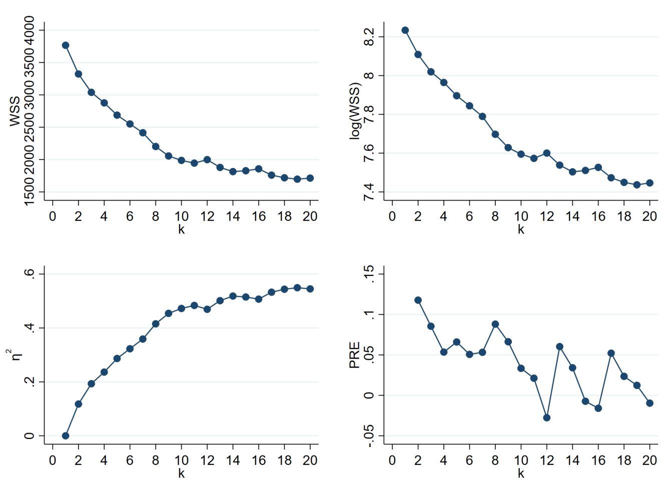
And offer two tests of overidentifying restrictions:

1. $\phi^A + \phi^B + \phi^C = 1$
2. $\bar{A} - \bar{B} + \bar{C} = 0$

We estimate this model under the constraints $\phi^k \geq 0, k \in \{A, B, C\}$. Results are displayed in Table E1. We find the bias shares of reservation wages, cash bids, and time bids are 23%, 68%, and 0% respectively. Restricting the estimation sample to bidders who participated in at least 1 bid (Column 2) or all three bids (Column 3) has little effect on our results, as does including controls for survey measures of the bidder's valuation of the irrigation pump and hypothetical reservation wage (see Section 5.2). Both of our identifying restrictions are statistically rejected at the 5% level, but the differences are modest in magnitude, with $\phi^A + \phi^B + \phi^C = 0.91$ and $\bar{A} - \bar{B} + \bar{C} = -0.2$ in the full sample.

Although this model yields qualitatively similar results to our preferred model, it predicts that farmers some farmers are discounting their time bids while others are discounting their cash bids or reservation wages. This appears inconsistent with the results in Table C3, which point to a fairly stable type of bias across subgroups.

Figure E1: The within sum of squares criterion suggests $n = 3$ groups for cluster analysis.



Note: Cluster analysis performed using kmeans over all behavioral predictor variables. "WSS" is the within sum of squares. $\eta_k^2 = 1 - \frac{WSS(k)}{WSS(1)}$. "PRE" is the proportionate reduction in error, given by $PRE_k = \frac{WSS(k-1) - WSS(k)}{WSS(k-1)}$.

Table E1: Decomposing the behavioral bias (probabilistic bias model)

	(1) Full sample	(2) Placed ≥1 bid	(3) Placed all bids	(4) Full sample	(5) Placed ≥1 bid	(6) Placed all bids
Reservation wage bias (ϕ^A)	0.231	0.223	0.259	0.228	0.221	0.259
	(0.035)	(0.036)	(0.051)	(0.035)	(0.035)	(0.052)
Cash bid bias (ϕ^B)	0.677	0.673	0.596	0.678	0.673	0.598
	(0.033)	(0.033)	(0.047)	(0.034)	(0.033)	(0.047)
Time bid bias (ϕ^C)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.033)	(0.032)	(0.032)	(0.033)	(0.032)	(0.033)
Mean log time value ($\bar{A}$)	3.828	3.800	3.740	3.824	3.800	3.737
	(0.073)	(0.074)	(0.071)	(0.072)	(0.073)	(0.071)
Mean log pump value ($\bar{B}$)	5.220	5.259	5.412	5.222	5.259	5.414
	(0.062)	(0.063)	(0.062)	(0.063)	(0.063)	(0.063)
Mean log pump/time value ($\bar{C}$)	1.195	1.266	1.429	1.195	1.266	1.429
	(0.063)	(0.064)	(0.048)	(0.064)	(0.065)	(0.049)
$\phi^A + \phi^B + \phi^C$	0.907	0.896	0.855	0.906	0.894	0.858
$\bar{A} - \bar{B} + \bar{C}$	-0.197	-0.194	-0.243	-0.203	-0.193	-0.248
p-val $\phi^A + \phi^B + \phi^C = 1$	0.040	0.021	0.042	0.038	0.020	0.049
p-val $\bar{A} - \bar{B} + \bar{C} = 0$	0.000	0.000	0.000	0.000	0.000	0.000
Observations	332	320	233	332	320	233
Controls?	N	N	N	Y	Y	Y

Note: Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 Ksh). See Appendix C for details on identifying bias shares and DVT. Columns (4)-(6) include controls that proxy for two preference parameters—the value of time and the valuation of the irrigation pump—which determine auction choices together with the behavioral discount rate. Columns (1) and (4) show results on the full sample, with cash and time bids bottom-coded at 20 KES and 1 hour respectively. Columns (2) and (4) show results estimated using farmers who placed eligible bids in at least 1 auction. Columns (3) and (6) show results estimated using farmers who placed eligible bids in all 3 auctions. An eligible bid is a cash bid > 0, a time bid > 0, or a reservation wage below 100 Ksh/hour. Bootstrap standard errors in parentheses.