# Valuing the Time of the Self-Employed*

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**Abstract**

People's value for their own time is a key input to evaluate public policies affecting recipients' time use: evaluations should account for recipients' time substituted away from work or leisure. Possible estimates of value of time include local wages, as well as individual measures obtained by offering participants trade-offs between money and time (Becker et al., 1964, henceforth BDM). Using rich choice data collected from farming households in western Kenya, we show that households exhibit non-transitive preferences consistent with behavioral biases such as loss aversion. As a result, local wages and BDM estimates can mismeasure participants' value of time. Using a structural model, we identify the mix of behavioral biases driving our choice data, and take a stand on the welfare interpretation of our findings. We argue that valuing time at 60% of the local wage is a reasonable rule of thumb. Alternatively, adequate BDM estimates can be obtained by focusing on the subset of recipients experienced with wage bargaining.

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

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# 1 Introduction

Many development interventions aim to increase 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). Importantly, when households are self employed, the opportunity cost of their time is not automatically reflected in bottom-line monetary outcomes. This means that valuing individuals' time should be an important component of studies evaluating interventions that potentially affect time use.

In practice, a large share of intervention studies ignore the value of participants' time (for example, Aragón et al., 2020, Goldstein et al., 2018). The most typical alternative is to use prevailing local wages as an estimate (see for example Emerick et al., 2016). The difficulty here lies in the intuition that both valuations are too extreme. A value of zero clearly underestimates participants' value of time. In turn, prevailing local wages overestimate participants' value of time whenever labor market frictions cause involuntary unemployment, prevalent in many developing economies (Kaur, 2018, Breza et al., 2020).[1] Using both values can provide bounds on potential welfare impacts, but often yields 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."

A natural way to obtain more precise, individual estimates of value of time is to use BDM mechanisms offering participants trade-offs between money and time. However, there is reason to worry that because of self-serving biases (Babcock et al., 1995), endowment effects (Kahneman et al., 1991), or loss-aversion (Kahneman and Tversky, 1979), BDM may also mis-measure participants' value of time. This paper proposes a way to identify biases, and infer welfare relevant values of time by exploiting richer choice data.

In the context of a larger field experiment conducted in western Kenya, we elicit partici-

[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 impute wages for those who have not. We impute wages by regressing observed wages on the set of control variables listed in Appendix D and assigning fitted values based on values of those controls.

pants' preferences over trade-offs involving three goods: money, time, and lottery tickets for an irrigation pump. Including this third good allows us to measure failures of transitivity and identify sources of bias. Specifically, we use BDM mechanisms to elicit participants' willingness to accept money for time, and their willingness to pay for lottery tickets either in time, or money. This gives us two measures of participants' value of time: a direct measure corresponding to their willingness to accept money for time; and an indirect measure corresponding to the ratio of their willingness to pay for lottery tickets in money, divided by their willingness to pay for tickets in time. Our main motivating finding is that on average, direct measures of value of time are 2.8 times larger than indirect measures. In addition, the choices of 81% of farmers exhibit non-transitivities: a farmer may value their time at 75 Kenyan shillings (KSh) per hour, be willing to pay 100 KSh for a lottery ticket, and yet be willing to work 4 hours for the same ticket.

We show that this choice data is inconsistent with standard decision-making models, even if we account for labor market rigidities and credit constraints. However, this wedge between direct and indirect value of time is potentially consistent with several behavioral biases. We focus on four: self-serving bias (Babcock et al., 1995) leading participants to discount the value of what they receive; a money-specific version of self-serving bias applying only to money; loss-aversion (Kahneman and Tversky, 1979); and a money-specific version of loss-aversion. Identifying the contribution of different biases to observed choice behavior matters to the extent that it changes the welfare-relevant measure of value of time that would apply when participants make their time-use decisions on their own, and in a stable setting where expectations have ample time to adjust.[2] For instance, we argue that the indirect measure of value of time is the correct one if participants exhibit either form of self-serving bias, whereas the direct measure of time is the welfare relevant one if participants exhibit money-specific loss aversion.

Using a structural model of choice that nests these four models as special cases, we are

[2]This is consistent with the view that behavioral biases manifest themselves differently in experimental versus natural decision making settings (Carney et al., 2019).

able to recover the contribution of different biases to choice behavior, under the assumption that the magnitude and nature of bias are uncorrelated. Money-specific self-serving bias, and money-specific loss aversion appear to drive the bulk of our empirical findings. We estimate welfare-relevant values of time roughly equal to 60% of the local wage. In addition, we show that frequent laborers, experienced with wage bargaining, are much less subject to bias. Direct measures of value of time elicited from this sub-population may be treated as a welfare-relevant value of time.

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 (henceforth MVT), 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 underutilization 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 and take as given BDM estimates.

Our paper also contributes to literature on preference elicitation using mechanisms proceduraly similar to BDM (Crockett and Oprea, 2012, Holt and Smith, 2016, Azrieli et al., 2018). We use BDM mechanisms over a richer choice space to identify behavioral biases. Pinning down the relative importance of different sources of bias allows us to evaluate counterfactual decisions in a non-experimental setting and take a stand on the correct welfare interpretation of our experimental measures of value of time. This contributes to the small but important literature on welfare analysis when decision makers exhibit choice inconsistencies (Bernheim and Rangel, 2009, Bernheim, 2009, Chetty, 2015).

We proceed as follows. Section 2 describes our study design and the resulting choice data. Section 3 presents a benchmark model of behavior and argues that it is rejected by our data. Section 4 describes possible behavioral biases generating our choice data, discusses the corresponding welfare implications. Section 5 presents a structural model that allows us to identify the relative contribution of different behavioral mechanisms. Section 6 discusses implications of our findings for policy evaluation.

# 2 Study design and choice data

Our analysis exploits data from three choice problems, each of which follows the Becker et al. (1964) design. We elicit choices involving: (i) money and leisure; (ii) money and a good (here a lottery ticket for an irrigation pump); (iii) leisure and the same good. This allows to recover two measures of farmers' value of time: a direct one involving trade-offs between money and leisure; and an indirect one combining choices over money and the good, and leisure and the good. This section describes our study setting and the choice problems offered to farmers.

## 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. 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 13 days in the past 3 months for 4.2 hours per workday. Average wages are 82 KSh (about $0.77) per hour.[3] 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 choice of the third good is not essential for our analysis. We used lottery tickets for pumps for two reasons. First, a surplus of unused pumps was made available to us from a finishing project. Second, lotteries for a one-in-ten chance of winning the pump reduced the value of the object to monetary values on the order of 120 KSh, representing roughly 1.5 hours of work at the average hourly wage. This ensures that the trade-offs considered by the farmers were relatively small with respect to their overall budget. This plays a role in the benchmark analysis of Section 3.2.

[3]These wages are high relative to average daily household earnings of 135 KSh. This is because average working hours are low—about 4 hours per week among those who worked—possibly suggesting that jobs are rationed.

Table 1: Summary statistics

| | Mean | Std. Dev. | N |
|---|---|---|---|
| **Panel A: Demographics** | | | |
| Age of participant | 47.7 | 14.3 | 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 | 1.3 | 324 |
| Number of children (under 18 years) in household | 4.0 | 2.4 | 322 |
| **Panel B: Household income and wealth** | | | |
| Land area under cultivation (acres) | 2.3 | 2.0 | 323 |
| Household income (KSh, past year) | 49,271 | 68,408 | 329 |
| Income share from sale of crops | 0.45 | 0.38 | 296 |
| **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 | 82 | 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 | 3.5 | 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 = 1 | 0.01 | 0.09 | 332 |
| Has used a MoneyMaker irrigation pump = 1 | 0.11 | 0.32 | 332 |
| Familiar with the MoneyMaker irrigation pump = 1 | 0.99 | 0.09 | 332 |
| Has considered buying a MoneyMaker irrigation pump = 1 | 0.59 | 0.48 | 332 |
| Self-reported valuation of pump (KSh) | 4,432 | 3,318 | 303 |

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).

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 before 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. The main reason for this low adoption is that the pumps are expensive (they retail for 9500 KSh, or about $89), and farmers fear that they may be costly or painful to operate.

## 2.2 Choice problems

Each farmer in our sample was exposed to three decision problems along the lines of Becker et al. (1964) and close to the design of Crockett and Oprea (2012). Farmers were asked to submit their preferences before a specific choice problem was drawn, and a decision was made according to the preferences they had submitted. Concrete implementation details are provided in Appendix B.

**Choice A: Money vs. time.** In the first choice problem, farmers were offered the option to receive a cash payment for casual labor.

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 denote by $m^A$ the lowest amount of money the farmer was willing to accept.

**Choice B: Lottery ticket vs. money.** In the second choice problem, farmers were offered the option to obtain a lottery ticket for the MoneyMaker pump in exchange for money.

We explained to each farmer that we were selling lottery tickets offering 1 in 10 odds of winning a MoneyMaker pump. We collected cash bids by asking the farmer whether they would be willing to pay a low price of 20 KSh and then asking the same question for increasingly higher prices, until the farmer declined the offer.

We denote by $m^B$ the maximum amount of money the farmer was willing to pay for the lottery ticket.

**Choice C: Lottery ticket vs. time.** Finally, the third choice problem, farmers were offered the option to obtain a lottery ticket for the MoneyMaker pump in exchange for casual agricultural work.

We explained to each farmer that we were selling lottery tickets offering 1 in 10 odds of winning a MoneyMaker pump. We collected time bid by asking the farmer whether they would be willing to work 30 minutes for the ticket, and then asking the same question for increasingly higher prices, until the farmer declined the offer.

We denote by $h^C$ the maximum amount of time the farmer was willing to work for the lottery ticket.

**Offer revelation and payment.** Choices B and C occurred at the beginning of the survey, in random order. Choice A came next. Prices were drawn at the end of the three activities. Scripts read to each farmer explained that there could be absolutely no bargaining once the prices were drawn.

Before the experiment, we assigned each farmer a random ticket price in either cash or time, and a random cash wage. Farmers were assigned a single ticket price in either cash or time, but not both. Cash wages were assigned independently of ticket price. This information was written on a card and inserted into a sealed envelope, which was shown to the farmer at the beginning of the survey. After the farmer had made their three decision choices, the envelope was opened and the ticket price, payment denomination (cash or time), and wage revealed. Farmer could thus be sure that their bids did not influence the drawn prices.

Cash winners—farmers who drew a cash price weakly lower than $m^B$—were asked to make a down payment of 20 KSh ($0.19) at the end of the experiment, and were given about 1 week to collect the remaining money to pay for the ticket. Time winners—farmers who drew a time price weakly lower than $h^C$—were scheduled for casual work approximately 1 week from the date of the experiment. Casual jobs for eligible wage workers—farmers who drew an hourly cash wage weakly greater than $m^A/2$—were scheduled approximately 2 weeks from the date of the experiment.

**Direct and indirect value of time.** Our design lets us compute to different measures of each farmer's value of time: a *Direct Value of Time* (DVT) $m_A/2$ obtained from preferences over direct trade-offs between time and money; and an *Indirect Value of Time* (IVT) defined as $m_B/h_C$, combining information from trade-offs between money and the lottery, and time and the lottery.

In the next section, we show that under a smooth benchmark model of decision making, these two different value of time should be approximately equal.

# 3 The Benchmark Model and Evidence Against It

## 3.1 Model

We model farmers' choices in a framework that allows for *labor rationing* and credit constraints. Labor rationing implies that a farmer's reservation wage may be 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. We model borrowing constraints by assigning a direct utility to cash-on-hand.

This captures credit constraints that are either binding now, or may plausibly be binding in the future.

Specifically, a farmer makes decisions over bundles $(\tau, m, h)$ corresponding to

- obtaining or not the lottery ticket $\tau \in \{0, 1\}$
- a monetary transfer $m$ that can be sent $(m > 0)$ or received $(m < 0)$
- time spent on work $h \in \mathbb{R}^+$

Preferences over $\tau, m, h$ are represented by the indirect 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. Labor rationing is captured through $\bar{l}$, while borrowing constraints are captured through $k$.

We extend $V$ to values of $\tau$ in $(0, 1)$ using the right-hand side of (1), capturing scaled-down returns to owning a pump. We impose without loss of generality that $V(\tau = 0, m = 0, h = 0) = 0$ and make the following assumption.

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

Let us denote by $u_{c,0}$, $u_{l,0}$, $k'_0$ and $v'_0$ the derivatives of $u$, $k$ and $v$ at the uniquely optimal choices $c_0$, $l_0$ made when $\tau = m = h = 0$. Let $\lambda$ denote the Lagrange multiplier associated with labor rationing under these conditions. The following first order approximation (using the familiar Big O notation) holds.

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

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

*with*

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

*In addition*

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

This result follows from a generalization of the Envelope Theorem allowing for constraints (Milgrom and Segal, 2002). The key observation is that the first-order approximation holds, and that the derivative $V_h$ of value $V$ with respect to additional hours worked $h$ is continuous with respect to bundle $(\tau, m, h)$. Small changes in optimization problem (1) have a small impact on the shadow value of labor provision.

## 3.2 A test of the benchmark model

Importantly, we believe that our choice problems satisfy the premise of Theorem 1: farmers are making decisions over bundles whose magnitude is small compared to their overall optimization problem. Choice problem A (money vs. labor) involved 2 hours of work. Average highest monetary bids $m_B$ for lottery tickets in choice problem B were 111 KSh on average (equivalent to about 1.3 times the local hourly wage). Time bids $h_C$ for lottery tickets in choice problem $C$ were 4 hours on average. As a result, the remainder of this section attempts to interpret choice data using linearized preferences (2). We show this leads to a contradiction.

**Direct value of time.** A farmer's optimal choice $m_A$ in choice problem A corresponds to the amount of money for which the farmer is indifferent between performing two hours of work for money $m_A$, and the status-quo:

$$V(\tau = 0, m = -m^A, h = 2) = V(\tau = 0, m = 0, h = 0).$$

Using first order approximation (2), this implies that $-m^A V_m + 2V_h = 0$. As a result the DVT satisfies

$$DVT \equiv \frac{m^A}{2} = \frac{V_h}{V_m} = -\frac{u_l}{k' + v'}.$$

**Indirect value of time.** The indirect value of time $IVT \equiv \frac{m_B}{h_C}$ can also be interpreted using (2). A farmer's optimal choices $m_B$ and $h_C$ in choice problems B and C respectively satisfy

$$V(\tau = 1, m = m^B, h = 0) = V(\tau = 0, m = 0, h = 0), \quad \text{and}$$
$$V(\tau = 1, m = 0, h = h^C) = V(\tau = 0, m = 0, h = 0).$$

Using Theorem 1, this implies that

$$m^B = -\frac{V_\tau}{V_m} \quad \text{and} \quad h^C = -\frac{V_\tau}{V_h}.$$

Hence, we obtain that

$$IVT \equiv \frac{m^B}{h^C} = \frac{V_h}{V_m} = DVT. \tag{3}$$

Under our benchmark model the direct and indirect measures for the marginal value of time should be equal. The next subsection shows that they are not.

## 3.3 Evidence from choice data and interpretation

Table 2 shows summary statistics of the choice data. The data clearly reject the benchmark model. The average direct value of time $DVT$, elicited through choice problem A is 83

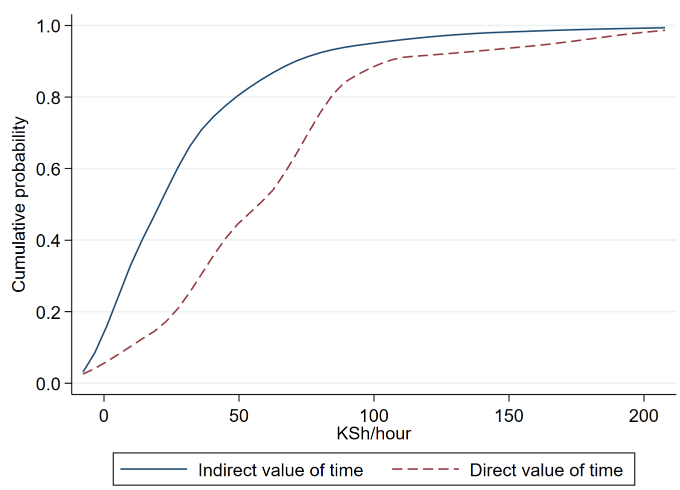
KSh/hour. This is very close to the average reported wage for casual labor (82 KSh/hour). In contrast the average indirect value of time $IVT$, inferred from choice problems B and C, is 30 KSh/hour, substantially below the mean $DVT$ (diff = 53 KSh/hour ; p-val< 0.0001). As Figure 1 illustrates, the distribution of $DVT$ first-order stochastically dominates the distribution of $IVT$.

Table 2: Experimental choice data (N=332)

| | Mean | Std. Dev. | p25 | p50 | p75 |
|---|---|---|---|---|---|
| Direct value of time ($DVT = m^A$) | 83 | 54 | 50 | 80 | 100 |
| Indirect value of time ($IVT$) | 30 | 35 | 3 | 20 | 40 |
| Cash bid ($m^B$) | 111 | 126 | 20 | 100 | 155 |
| Time bid ($h^C$) | 4.0 | 2.2 | 3.0 | 4.0 | 5.0 |
| Behavioral discount ($\widehat{r}$) | 0.30 | 1.22 | 0.28 | 0.71 | 0.98 |

Each observation is a farmer. Currency units are Kenyan shillings (1 USD = 107 KSh). Cash bids, time bids, and $DVT$ elicited through BDM. $IVT$ = cash bid / time bid. Behavioral discount = $1 - IVT/DVT$. p25, p50, and p75 are the 25th, 50th, and 75th percentiles.

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




At the individual level, these data suggests that a majority of farmers have cyclical, non-transitive preferences. For instance, a farmer choosing $m^A/2 = 80$ KSh, $m^B = 100$ KSh, and

$h^C = 4$ hours (matching average choice values) would exhibit the following choice behavior:

- 200 KSh $\prec$ 3 hours (since $m^A/2 = 80$),
- $\tau = 1 \prec$ 200 KSh (since $m^B = 100$) , and
- 3 hours labor $\prec \tau = 1$ (since $h^C = 4$),

resulting in a cycle: 3 hours $\prec \tau = 1 \prec$ 200 KSh $\prec$ 3 hours.

At the level of individual farmers, we define

$$\widehat{r} = 1 - \frac{IVT}{DVT}$$

as a measure of preference intransitivity.[4] The average value of $\widehat{r}$ is 0.3, substantially higher than the benchmark prediction $\widehat{r} = 0$ (p-val<0.0001).[5]

We interpret such failures of transitivity as an expression of behavioral biases. Indeed, we show in Section 4 how several prominent behavioral models involving kinked preferences around reference bundles can generate this gap between direct and indirect values for time. Correspondingly, we refer to $\widehat{r}$ as a farmer's *behavioral discount*.

**Alternative explanations.** Because our benchmark model accommodates credit constraints and labor supply constraints, Theorem 1 implies that to a first-order, these frictions cannot explain the wedge between DVT and IVT.

In principle, second-order effects of credit and labor constraints may explain the wedge between DVT and IVT, but we find this implausible. Here is a potential scenario. In the absence of the lottery ticket, farmers have a relatively low value for cash and hence demand high wages in exchange for their labor (choice A). They find the lottery ticket potentially

[4] We use hatted notation to emphasize that $\widehat{r}$ is an empirically observable object, defined using choice data.

[5] The median value of $\widehat{r}$ is even larger, at 0.71, because of a long left tail in the distribution. One possible explanation is that second-order effects are nontrivial for farmers with very high willingness to pay cash, as this is rationalized by a very high number of working hours in the work activity for Choice C. Our results are robust to truncating these high values.

very attractive, so that they are willing to supply a relatively large amount of labor for it (choice C). However, even though farmers find the lottery ticket an attractive proposition, they are only willing to pay a relatively small amount for it (choice B). This would require farmers facing choice A to make consumption decisions that take them right below a binding credit constraint.[6]

This is highly implausible. Farmers operate in an environment that includes many opportunities for useful investment, and are likely already credit constrained when we offer them choice problems. Furthermore, as the valuations expressed by the farmers reflect, the acquisition of a lottery ticket constitutes a relatively small change in their economic environment, worth at most a few hours of labor. We do not believe it would radically change farmers' shadow cost of capital.

We discuss (and rule out) other explanations for the gap between DVT and IVT in Appendix E. These include differential effort or scheduling costs of work tasks between choice problem A and choice problem C, risk aversion, order effects of the bidding activities, anchoring, bid censoring, and stigma surrounding low wages.

# 4 Behavioral Models and their Welfare Interpretation

In this section we delineate different models of behavioral decision-making that can potentially explain the wedge between DVT and IVT, and highlight how different models result in different welfare-relevant interpretations of the data. Section 5 proposes and estimates a general structural model that nests the biases discussed in this section.

## 4.1 Possible biases

The wedge between DVT and IVT can be explained by two classes of biases that have received extensive attention: self-serving biases (Loewenstein et al., 1993, Babcock et al., 1995, Babcock and Loewenstein, 1997) in which a farmer discounts the value of goods obtained

[6] Or equivalently right below a sudden kink in the cash-on-hand value function $k$.

from other parties; and reference-dependence (Kahneman et al., 1991, Kahneman and Tversky, 1979) in which a farmer discounts the value of goods they did not expect to acquire. While the two biases generate kinks in preferences, they are distinct: self-serving biases are relevant during social interactions, while loss-aversion is specific to unanticipated decision-making problems. In each case, we discuss two variants of the bias: a version that treats all goods symmetrically, and a version that applies specifically to monetary transactions.

We find it useful to start with baseline preferences following the linearized benchmark model (2), and express biases as modifications of this model applying in specific circumstances. We normalize $V(\tau = 0, m = 0, h = 0) = 0$, $V_m = 1$ and define $a \equiv V_\tau$ and $b = -V_h$. Under this notation, have:

$$V(\tau, m, h) = \tau a - m - hb. \tag{4}$$

Recall that

$$\widehat{r} = 1 - \frac{DVT}{IVT}$$

denotes the empirically observable behavioral discount rate.

**Model 1: Symmetric self-serving bias.** We model symmetric self-serving bias by assuming that in a transaction with another party, the farmer shrinks the value of what they obtain from the other party by an amount $1 - r$. Under this model, choices $m^A$, $m^B$ and $h^C$ must satisfy

$$\begin{aligned} V(0, -(1-r)m^A, 2) &= 0, \\ V(1-r, m^B, 0) &= 0, \\ V(1-r, 0, h^C) &= 0, \end{aligned} \qquad \iff \qquad \begin{aligned} (1-r)m^A - 2b &= 0, \\ (1-r)a - m^B &= 0, \\ (1-r)a - bh^C &= 0. \end{aligned} \tag{5}$$

This implies that the DVT and IVT take the form

$$DVT \equiv \frac{m^A}{2} = \frac{b}{1-r} \quad \text{and} \quad IVT \equiv \frac{m^B}{h^C} = \frac{(1-r)a}{(1-r)a/b} = b. \tag{6}$$

As a result $IVT/DVT = 1 - r$, so that $\widehat{r} = r$: we can interpret the measured behavioral discount as self-serving parameter $r$.

**Model 2: Money-specific self-serving bias.** Under money-specific self-serving bias, the farmer discounts the value of money they receive from the other party with a factor $1 - r$. Choices $m^A$, $m^B$ and $h^C$ must satisfy

$$\begin{aligned} V(0, -(1-r)m^A, 2) &= 0, \\ V(1, m^B, 0) &= 0, \\ V(1, 0, h^C) &= 0, \end{aligned} \qquad \Longleftrightarrow \qquad \begin{aligned} (1-r)m^A - 2b &= 0, \\ a - m^B &= 0, \\ a - bh^C &= 0. \end{aligned} \tag{7}$$

This implies that the DVT and IVT take the form

$$DVT \equiv \frac{m^A}{2} = \frac{b}{1-r} \quad \text{and} \quad IVT \equiv \frac{m^B}{h^C} = \frac{a}{a/b} = b. \tag{8}$$

As in the previous model $IVT/DVT = 1 - r$, so that the empirical behavioral discount $\widehat{r}$ is equal to parameter $r$. Note that although symmetric self-serving bias and money specific self serving bias yield the same values for DVT and IVT, they do not predict the same patterns of correlation across choices $m^A$, $m^B$ and $h^C$ – this will matter for inference when we turn to our structural model.

**Model 3: Symmetric loss aversion** We now turn to models of loss aversion (Kahneman et al., 1991, Kahneman and Tversky, 1979). We consider experiment-related deviations from the status quo as unexpected, and assume that the farmer inflates the cost of unexpected losses with a factor $1/(1 - r)$. Choices $m^A$, $m^B$ and $h^C$ must satisfy

$$
\begin{aligned}
V(0,-m^A,2/(1-r)) &= 0, & & & m^A - 2b/(1-r) &= 0,\\
V(1,m^B/(1-r),0) &= 0, & &\iff & a - m^B/(1-r) &= 0,\\
V(1,0,h^C/(1-r)) &= 0, & & & a - bh^C/(1-r) &= 0.
\end{aligned} \tag{9}
$$

This implies that the DVT and IVT take the form

$$
DVT \equiv \frac{m^A}{2} = \frac{b}{1-r} \quad \text{and} \quad IVT \equiv \frac{m^B}{h^C} = \frac{a(1-r)}{a(1-r)/b} = b. \tag{10}
$$

Again, we have that $\widehat{r} \equiv 1 - IVT/DVT = r$.

**Model 4: Money-specific loss aversion** Under money-specific loss aversion the farmer inflates the cost of unexpected monetary losses with a factor $1/(1-r)$. Other losses are undiscounted Choices $m^A$, $m^B$ and $h^C$ must satisfy

$$
\begin{aligned}
V(0,-m^A,2) &= 0, & & & m^A - 2b &= 0,\\
V(1,m^B/(1-r),0) &= 0, & &\iff & a - m^B &= 0,\\
V(1,0,h^C) &= 0, & & & a - bh^C &= 0.
\end{aligned} \tag{11}
$$

This implies that the DVT and IVT take the form

$$
DVT \equiv \frac{m^A}{2} = b \quad \text{and} \quad IVT \equiv \frac{m^B}{h^C} = \frac{a(1-r)}{a/b} = b(1-r). \tag{12}
$$

## 4.2 Welfare interpretation

The reason it is useful to consider different behavioral models, even though they all generate the same gap between DVT and IVT, is that different models can lead to different welfare interpretations of our data.

Welfare economics for behavioral decision-makers exhibiting inconsistent preferences in inherently tricky. Bernheim and Rangel (2009) provides foundations for welfare analysis based on the subset of preference rankings that are unambiguous, i.e. that are not associated with cycles.

This is not possible in our context: we are specifically trying to evaluate welfare over a domain where preferences exhibit cycles. In other to make discerning welfare assessments we must take a stand on which choices reflect welfare-relevant preferences, and which choices do not.

**Experimental vs. natural decision-making.** The key difficulty is to understand how the context in which farmers make decisions within our experimental setting, and the context they face when making decisions as part of an intervention, affect their choices.

Echoing Carney et al. (2019), we believe that our experimental setting elicits strong behavioral responses: these are unexpected choices, and they involve trading with an external party, the experimenter. In the context of a policy intervention, a farmer's time use decisions are likely to: first, be well integrated into reference-expectations (Kőszegi and Rabin, 2006) at the time of decision-making; second, time use decisions likely do not affect trading with third parties.

As a result, we think that linearized preferences (2) do capture welfare relevant preferences, while behavioral preferences reflect non-welfare-relevant biases specific to the experimental context. As a result, the welfare-relevant value of time corresponds to parameter $b$ in (4), which we refer to as the *Structural Value of Time* (SVT).[7]

**Inference from different models.** Different behavioral models lead to different welfare-relevant interpretations of choice data. Under models 1, 2 and 3 (self-serving biases, and symmetric loss aversion), the structural value of time coincides with the indirect value of

[7]In situations where decision-makers are surprised or negotiating with third parties, the measure of value of time incorporating the behavioral bias is likely to be more welfare relevant.

time: $SVT = IVT$. In contrast, under model 4 (money-specific loss aversion), the structural value of time is equal to the direct value of time: $SVT = DVT$.

If we remain agnostic about the form of the behavioral bias, our analysis so far yields a range of values for farmers' value of time. The lower bound, corresponding to models 1, 2, and 3, is 30 KSh/hour, or about 40% of the local wage. The higher bound, corresponding to model 4, is 83 KSh/hour, roughly equal to the local wage.

We now seek to refine this range using a structural model of behavioral choice nesting all 4 biases discussed in Section 4.

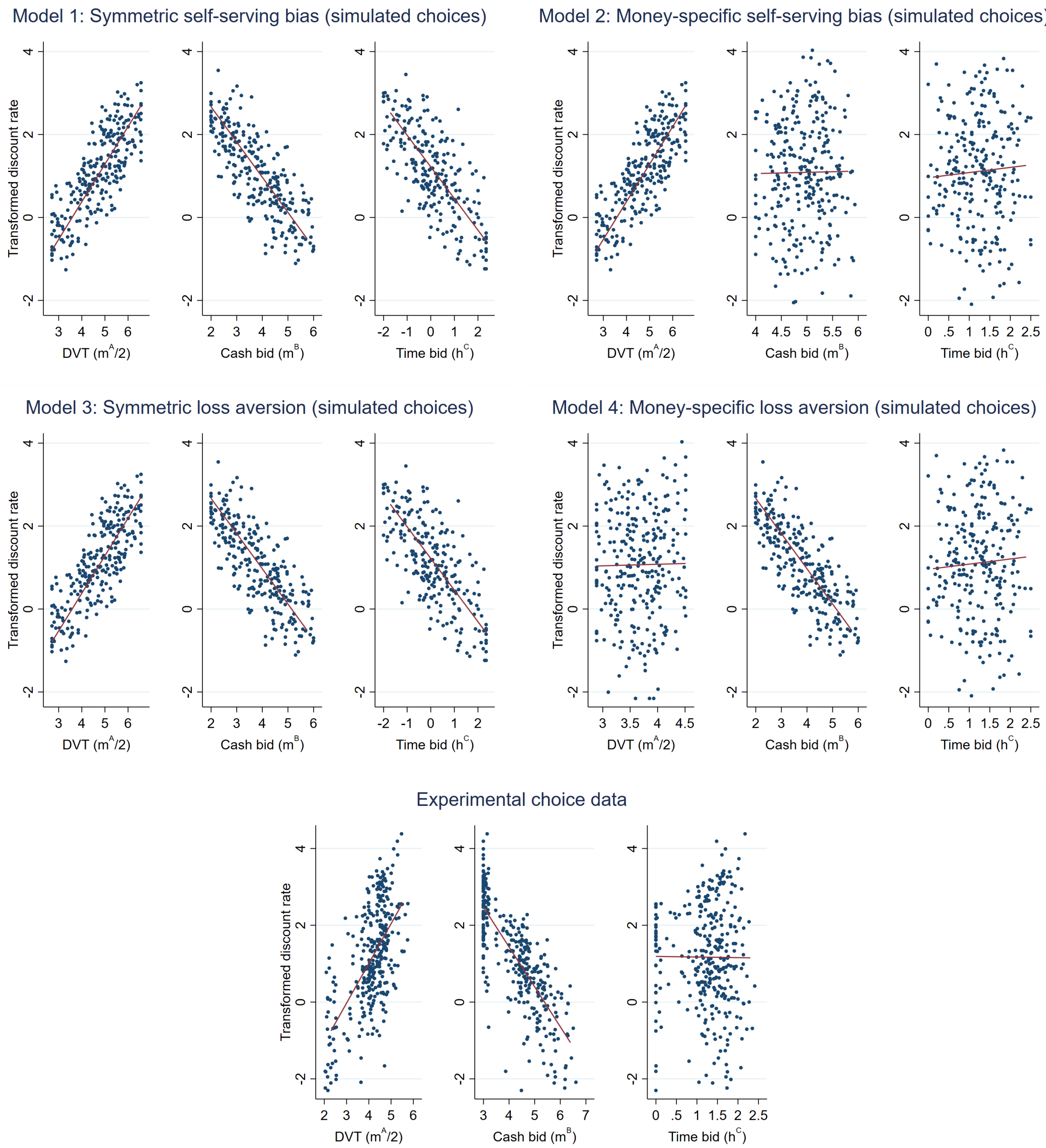
# 5 Structural Estimation

Before we turn to a formal model, we find it use to provide an intuitive argument why identification may be possible under assumptions. Figure 2 plots both the relationship between choice data $m^A$, $m^B$, $h^C$ and the behavioral discount rate $\widehat{r}$ measured in our experimental data, and simulated using the models studied in Section 4. Simulated choices assume that parameters $a$, $b$, and $r$ are drawn independently across farmers, according to log-normal distributions with parameters chosen to match our experimental data.

In our data, farmers' time bids $h^C$ are uncorrelated with behavioral discount rate $\widehat{r}$. Our behavioral models exhibit either negative correlation between $h^C$ and $\widehat{r}$ (models 1 and 3) or zero correlation (models 2 and 4). This means that our data can only be explained using mixtures of models putting weight on models 2 and 4: money specific self-serving bias, and money specific loss aversion.

In turn, in our data, the behavioral discount rate $\widehat{r}$ is positively correlated with choice $m^A$ (reservation wage), and negatively correlated with choice $m^B$ (cash bid for a lottery ticket). These correlations can only be explained by a mixture putting weight on both models 2 and 4. We now formalize this intuitive argument.

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




Each observation is a farmer. OLS line in red. Choices are simulated under four possible behavioral models. Actual choice data from incentivized bids with a 3% jitter. All variables are log transformed. Transformed discount rate $= -\log(1 - \widehat{r})$.

## 5.1 Framework

We generalize the models presented Section 4 by allowing behavioral biases to affect each choice $m^A$, $m^B$ and $h^C$ differently. We assume that there exist discount rates $r^A, r^B$ and $r^C$

such that choices $m^A$, $m^B$ and $h^C$ satisfy

$$\begin{aligned} V(0,-(1-r^A)m^A,2) &= 0, \\ V(1-r^B,m^B,0) &= 0, \\ V(1-r^C,0,h^C) &= 0, \end{aligned} \qquad \Longleftrightarrow \qquad \begin{aligned} (1-r^A)m^A-2b &= 0, \\ (1-r^B)a-m^B &= 0, \\ (1-r^C)a-bh^C &= 0. \end{aligned} \tag{13}$$

This framework nests model 1 and 3 (symmetric self-serving bias and loss aversion) when $r^A = r^B = r^C \in (0,1)$. It nests model 2 (money-specific self-serving bias) when $r^A \in (0,1)$ and $r^B = r^C = 0$. It nests model 4 (money-specific loss aversion) when $r^B \in (0,1)$ and $r^A = r^C = 0$.

**Data-generating process.** We now specify a particular model of variation in preferences across farmers. We index farmers by $i \in \mathbb{N}$ and allow for farmer-level heterogeneity so that (13) takes the form

$$(1-r_i^A)m_i^A - 2b_i = 0, \quad (1-r_i^B)a_i - m_i^B = 0, \quad (1-r_i^C)a_i - b_i h_i^C = 0. \tag{14}$$

We impose two main assumptions. The first is conditional on characteristics observed by the econometrician, behavioral parameters $r_i^A, r_i^B$ and $r_i^C$ be independently distributed from preference parameters $a_i$, and $b_i$. We derive our identification results under the assumption that we are conditioning on observables so that behavioral and preference parameters are independent.

Our second assumption is that farmers vary in the strength of their behavioral bias but not in the relative importance of each bias.[8] Specifically, we assume that farmer $i$'s discount

[8]An alternative model in which farmers are randomly affected by one bias but not the other, and the relative probabilities of being affected is constant is also identified, and does not lead to qualitatively different results.

rates $r_i^A$, $r_i^B$ and $r_i^C$ take the form

$$
\begin{aligned}
1 - r_i^A &= \exp(-\rho_i \gamma^A) \\
1 - r_i^B &= \exp(-\rho_i \gamma^B) \\
1 - r_i^C &= \exp(-\rho_i \gamma^C)
\end{aligned}
$$

with $\gamma^A + \gamma^B + \gamma^C = 1$ and $\gamma^A + \gamma^B - \gamma^C \neq 0$.

**Identification.** Condition (14) implies that

$$
\begin{aligned}
\log(m_i^A/2) &= \log b_i + \rho_i \gamma^A \\
\log m_i^B &= \log a_i - \rho_i \gamma^B \\
\log h_i^C &= \log a_i - \log b_i - \rho_i \gamma^C
\end{aligned}
\tag{15}
$$

Recall that a farmer's empirical behavioral discount $\widehat{r}_i$ satisfies

$$
1 - \widehat{r}_i = \frac{IVT_i}{DVT_i} = \frac{2m_i^B h_i^C}{m_i^A}.
$$

Hence, it follows from (15) that

$$
\log \frac{1}{1 - \widehat{r}_i} = \log(m_i^A/2) - \log(m_i^B) + \log(h_i^C) = \rho_i(\gamma_A + \gamma_B - \gamma_C). \tag{16}
$$

Let $\widehat{\delta}^A$, $\widehat{\delta}^B$, and $\widehat{\delta}^C$ denote the OLS estimates (under the constraint that $\widehat{\delta}^X \geq 0$) obtained from the linear model:

$$
\begin{aligned}
\log(m_i^A/h^A) &= c_A + \widehat{\delta}^A \log \frac{1}{1 - \widehat{r}_i} + \epsilon_i^A \\
\log m_i^B &= c_B - \widehat{\delta}^B \log \frac{1}{1 - \widehat{r}_i} + \epsilon_i^B \\
\log h_i^C &= c_C - \widehat{\delta}^C \log \frac{1}{1 - \widehat{r}_i} + \epsilon_i^C.
\end{aligned}
\tag{17}
$$

**Theorem 2** (identification)**.** *With probability one as the sample size gets large: for all* $X \in \{A, B, C\}$,

$$\widehat{\gamma}^X \equiv \frac{\widehat{\delta}^X}{\widehat{\delta}^A + \widehat{\delta}^B + \widehat{\delta}^C} \to \gamma^X;$$

*for all* $i \in \mathbb{N}$,

$$\widehat{\rho}_i \equiv (\widehat{\delta}_A + \widehat{\delta}_B + \widehat{\delta}_C) \log \frac{1}{1 - \widehat{r}_i} \to \rho_i.$$

Given estimates $(\widehat{\gamma}^A, \widehat{\gamma}^B, \widehat{\gamma}^C)$ and $\widehat{\rho}_i$, consistent estimates of the structural value of time $b_i$ of farmer $i$ can be recovered using (15):

$$\widehat{SVT}_i = \widehat{b}_i \equiv \frac{m_i^A}{2} \exp(-\widehat{\rho}_i \widehat{\gamma}^A). \tag{18}$$

## 5.2 Empirical findings

**Main estimates.** Column 1 of Table 3 displays full-sample estimates of bias parameters $\widehat{\gamma}^A, \widehat{\gamma}^B$ and $\widehat{\gamma}^C$ as well as the estimated mean structural value of time $\mathbb{E}[SVT_i]$ using Theorem 2 and (18).[9] Bias paramters estimates take values $\widehat{\gamma}^A = 39\%$, $\widehat{\gamma}^B = 61\%$, and $\widehat{\gamma}^C = 0\%$. This is consistent with Figure 2: behavioral biases appear to be cash specific. As a result, the mean structural value of time is equal to 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 (40% to 100% of the local wage).

**Robustness checks.** Our key identification assumption is that farmers behavioral discount $\widehat{r}$ be independent of their preference parameters $a$ and $b$, farmers' welfare relevant valuation of the lottery ticket and value of time.

One way to test this assumption is to evaluate the correlation between $\widehat{r}$ and proxies of $a$ and $b$ that are not themselves influenced by a behavioral bias. In principle, if we accept the

[9]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 test for sensitivity to recoding in Table E4. The estimated bias parameters $\widehat{\gamma}^A, \widehat{\gamma}^B, \widehat{\gamma}^C$ change little across specifications, and the estimated mean structural value of time is very stable at 59–60% of the local wage.

premise that biases are exacerbated by incentives inherent to the experiment design, then unincentivized choices may be less affected by behavioral biases, but still serve as proxies for preference parameters. We investigate whether this is the case using unincentivized responses collected in a prior survey.

We use stated willingness to work in hours for the lottery ticket, and the stated minimum amount of money for which the respondent would be willing to travel 1 hour as proxies for parameters $a$ and $b$. Unincentivized proxies are strongly correlated with bids but uncorrelated with the behavioral bias. The $p$-values from bivariate regressions of $\log \frac{1}{1-\widehat{r}}$ on the logarithm of the unincentivized willingness to work for the ticket and on the logarithm of the unincentivized reservation payment for traveling 1 hour are 0.50 and 0.29 respectively. The p-values from bivariate regressions of $\log(m_i^B)$ and $\log(h_i^C)$ on the logarithm of the unincentivized willingness to work for the ticket are 0.03 and 0.00 respectively, and the p-value from the bivariate regression of $\log(m_i^A/2)$ on the logarithm of the unincentivized reservation payment for traveling 1 hour is 0.01.

We re-estimate the model controlling for these unincentivized proxies of $a$ and $b$. Table E4 Column 4 shows results. These controls have very little effect on our results, supporting the assumption that behavioral discount $\rho_i$ is independent of preference parameters $a_i$ and $b_i$.

Table 3: The behavioral bias appears only in transactions over cash—cash bids and reservation wages—across several subgroups.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | | | Cluster breakdown | | | |
| | Full sample | Casual laborers | Considered buying pump | Low-skill employees | Low-skill self-employed | Hires casual workers | Small, low-edu households |
| Reservation wage bias ($\widehat{\gamma}^A$) | 0.385 | 0.392 | 0.402 | 0.418 | 0.378 | 0.381 | 0.368 |
| | (0.023) | (0.041) | (0.031) | (0.062) | (0.041) | (0.045) | (0.041) |
| Cash bid bias ($\widehat{\gamma}^B$) | 0.612 | 0.608 | 0.598 | 0.582 | 0.619 | 0.619 | 0.59 |
| | (0.025) | (0.041) | (0.032) | (0.061) | (0.043) | (0.050) | (0.056) |
| Time bid bias ($\widehat{\gamma}^C$) | 0.003 | 0.000 | 0.000 | 0.000 | 0.004 | 0.000 | 0.042 |
| | (0.014) | (0.007) | (0.017) | (0.015) | (0.022) | (0.021) | (0.036) |
| Structural value of time ($\widehat{SVT}$) | 48.8 | 45.4 | 44.1 | 41.1 | 47.9 | 58.3 | 44.4 |
| | (2.443) | (3.561) | (2.731) | (4.785) | (3.899) | (5.604) | (5.267) |
| Market wage ($w$) | 81.6 | 73.4 | 81.9 | 83.0 | 76.4 | 88.5 | 79.5 |
| | (1.798) | (3.208) | (2.276) | (5.058) | (3.473) | (2.945) | (3.204) |
| Relative Value of Time ($\widehat{SVT}/w$) | 0.598 | 0.619 | 0.538 | 0.495 | 0.627 | 0.659 | 0.558 |
| | (0.033) | (0.058) | (0.037) | (0.064) | (0.058) | (0.068) | (0.072) |
| Observations | 332 | 216 | 141 | 58 | 99 | 90 | 85 |

Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 KSh). $\widehat{\gamma}^A$, $\widehat{\gamma}^B$, and $\widehat{\gamma}^C$ are the estimated share of the behavioral bias present in reservation wages, cash bids, and time bids respectively (see Section 5 for details on identifying bias shares). Structural value of time ($SVT$) is the preference parameter $b$ (see Section 4). Market wage is most recent hourly wage earned from casual work and is imputed for those who have not done casual work within the past 3 months. Column (2) shows results estimated on recent casual workers. Column (3) shows results estimated on farmers who report that they have considered buying a MoneyMaker irrigation pump in the past. Columns (4)-(7) show results estimated separately within clusters of similar farmers (see Section 5.2). Cash and time bids bottom-coded at 20 KES and 1 hour respectively. Bootstrap standard errors in parentheses.

To further investigate whether omitted variable bias 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 form 4 groups using partition around medoids (PAM) cluster analysis, which is described in Appendix D. We argue that there is likely to be less confounding variation in preferences within these groups, so that independence between behavioral discount rate $\widehat{r}$ and welfare-relevant parameters $a$ and $b$ is more likely to hold. Table 4 characterizes each cluster using post-LASSO OLS regressions (Belloni and Chernozhukov, 2013, Tibshirani, 1996) of membership in the cluster on the set of control variables listed in Appendix D. We characterize these 4 clusters—sorted from least to most subject to behavioral bias—as consisting of low-skill employees, the low-skill self employed, hirers of casual labor, and small, low-education households who do not hire or provide casual labor. Columns (4)-(7) of Table 3 present the results of within-cluster estimation. Estimated bias shares are highly stable across clusters. The estimated value of time is also quite stable at around 50–65% of the average wage. This is true despite the fact that the overall magnitude of the bias $\hat{\rho}$ varies substantially across clusters—from 0.827 to 1.475—supporting our assumption of bias shares that are fixed across our sample. Estimates for cash-constrained workers, and for casual laborers, are also shown separately in Table 3.

## 5.3 Behavioral bias across sub-populations

Experience negotiating may mitigate the bias induced by experimental conditions. Similarly, individuals who have well-formed expectations about the good being transacted may be less surprised by the BDM choice problems and thus behave more naturally within the experiment. Columns 1 and 2 of Table 4 show descriptive statistics and experimental choice data for casual laborers and individuals who have considered purchasing a MoneyMaker irrigation pump in the past, respectively. We find that both subgroups exhibit less severe behavioral discounting. We present formal regression analysis showing the predictive power of these two and other covariates in Appendix C. Older, less educated, and land-poor farmers

Table 4: Characteristics and experimental choices across farmer subgroups

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | Cluster breakdown | | | |
| | Casual laborers | Considered buying pump | Low-skill employees | Low-skill self-employed | Hires casual workers | Small, low-edu households |
| **Panel A: Farmer characteristics** | | | | | | |
| Years of education | | | | | | -0.06 |
| Household size | | | | | | -0.07 |
| No male head in household | | -0.09 | | | | |
| Farm income | | 0.07 | | | | |
| Non-farm income | | | | | | -0.02 |
| Performs casual labor | | | 0.10 | 0.14 | -0.13 | -0.12 |
| Hires casual labor | | | -0.10 | 0.08 | 0.27 | -0.24 |
| Irrigates | | | 0.09 | 0.11 | -0.10 | -0.09 |
| Agricultural employee | 0.14 | | | | | |
| Low-skill non-ag. employee | | | 0.18 | -0.07 | | -0.09 |
| Low-skill self-employed | | | -0.06 | 0.27 | -0.10 | -0.10 |
| Network centrality | | 0.13 | | | | |
| **Panel B: Experimental choices** | | | | | | |
| Direct value of time ($DVT$) | 72 | 73 | 62 | 79 | 97 | 86 |
| | (3.9) | (3.2) | (4.9) | (4.7) | (6.8) | (6.0) |
| Indirect value of time ($IVT$) | 31 | 29 | 31 | 31 | 37 | 20 |
| | (3.1) | (2.4) | (4.5) | (3.5) | (4.4) | (2.9) |
| Cash bid ($m^B$) | 129 | 123 | 130 | 128 | 113 | 76 |
| | (11.4) | (9.6) | (17.9) | (13.6) | (13.4) | (10.4) |
| Time bid ($h^C$) | 4.6 | 4.4 | 4.4 | 4.4 | 3.6 | 3.8 |
| | (0.2) | (0.2) | (0.3) | (0.2) | (0.3) | (0.2) |
| Behavioral discount ($\widehat{r}$) | 0.193 | 0.175 | 0.007 | 0.244 | 0.256 | 0.612 |
| | (0.113) | (0.103) | (0.198) | (0.128) | (0.136) | (0.080) |
| Observations | 141 | 189 | 58 | 99 | 90 | 85 |

Each observation is a farmer. Each column is a subgroup. "Casual laborers" are those who have performed casual labor within the past 3 months. "Considered buying pump" are those who self-report that they have considered buying a MoneyMaker pump. Columns (3)-(6) divide the full sample into 4 clusters (see Appendix D). **Panel A:** Each column shows post-estimation OLS coefficients from LASSO regressions of a dummy variable equal to 1 if the farmer is a member of the corresponding subgroup. All variables are standardized to have mean 0, standard deviation 1. **Panel B:** Currency units are Kenyan shillings (1 USD = 107 KSh). Cash bids, time bids, and $DVT$ elicited through BDM. $IVT$ = cash bid / time bid. Behavioral discount = $1 - IVT/DVT$.

exhibit a more severe bias.

If preference parameters are independent of $\widehat{r}$, then the DVT among farmers exhibiting no behavioral bias should approximate the average value of time in the sample. Consistent with this prediction, we find that farmers with $|\widehat{r}|< 0.15$ have an average DVT of 54 KSh/hour, or 66% of the local wage. This is very close to the average SVT in the full sample of 49 KSh/hour.

# 6 Discussion

This paper seeks to better understand how to account for participants' value of time in policy evaluations. We show that a direct BDM approach to measuring value of time in an incentivized way need not produce reliable results because of behavioral biases: in particular, participants seem to over-value their time in the context of monetary transactions. Using a design involving choices between time, money, and a third good, we are able to identify the magnitude of the behavioral bias and recover a welfare-relevant structural value of time. This value of time is roughly 60% of the value elicited through a direct BDM mechanism, and roughly 60% of the local wage for casual labor.

To understand how the value of time affects estimates of returns to interventions or technologies, we review a selected sample of 57 recent empirical papers drawn from top agricultural and general interest journals.[10] There is substantial heterogeneity in the assumed value of time in the literature: 42% of papers value time at zero, 26% of papers value time at the local wage, and 5% report estimates using both approaches. The remaining papers are agnostic about the value of time: they focus only on direct output measures such as revenue or yield. The decision to focus on these gross output measures is in some cases explicitly motivated by uncertainty over the value of time. No reviewed paper valued family labor at a fraction of the local wage.

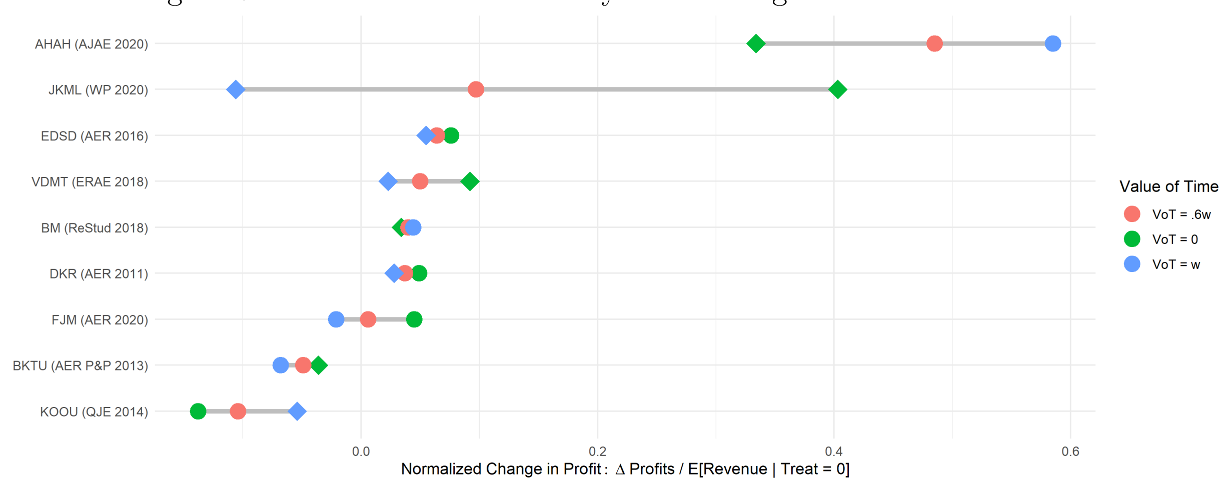
To measure the sensitivity of profit estimates to assumptions about the value of time, we require data on changes in labor inputs—disaggregated by paid and unpaid labor—

[10]Specifically, we prioritize papers already cited in our introduction, those cited in de Janvry et al. (2017), and recent agricultural field experiments in Sub-Saharan Africa. Papers were deemed to be relevant if they estimated an output (profit, yield, revenue, etc.) for which family or unpaid labor was an input and where the unit of analysis was an individual, household, or business.

an estimate of the local wage, and data on profits or revenues and costs. Only 47% of the reviewed papers provide data meeting these requirements based on the description of the data in the paper's text and inspection of replication files, when available. Family or otherwise unpaid labor is often not recorded, and thus implicitly valued at zero.

When possible, we compute the returns to each intervention valuing unpaid labor at zero, the local wage, and 60% of the local wage.[11] Figure 3 summarizes results. The effect of the assumed MVT on returns varies substantially across studies, and in some cases dramatically changes the estimated returns to a given intervention. This variation is driven by the technology's effect on labor input, as well as the level of wages. Note that accounting for the value of time will *increase* the value of a technology that is labor-saving. While practitioners often focus on increasing revenues and yields, there may be previously underestimated value in promoting interventions that have smaller impacts on outputs while decreasing labor input costs.

Figure 3: Different values of family labor change estimates of returns




Diamonds represent the value of time assumed by the authors.
AHAH (AJAE 2020): The impacts of GM foods: results from a Randomized Controlled Trial of Bt eggplant in Bangladesh - Ahmed, Hoddinott, Abedin, Hossain
DKR(AER 2011): How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya - Duflo, Kremer, Robinson
FJM (AER 2020): Seasonal Liquidity, rural labor markets and agricultural production - Fink, Jack, Masiye
JKML (WP 2020):Factor Market Failures and the Adoption of Irrigation in Rwanda - Jones, Kondylis, Loeser, Magruder
BKTU(AER P&P 2013): Profitability of Fertilizer: Experimental evidence from female rice farmers in Mali - Beaman, Karlan, Thuysbaert, Udry
VDMT (ERAE 2018): Labour, profitability and gender impacts of adopting row planting in Ethiopia - Vandercasteelen, Dereje, Minten, Taffesse
BM (ReStud 2018): Social Learning and Incentives for Experimentation and Communication - BenYishay, Mobarak
KOOU (QJE 2014): Agricultural Decisions after Relaxing Credit and Risk Constraints - Karlan, Osei, Osei-Akoto, Udry
EDSD (AER 2016): Technological Innovations, Downside Risk, and the Modernization of Agriculture - Emerick, de Janvry, Saoudlet, Dar

[11] Specifically, we calculate the returns to an intervention as the change in individual profits and normalize this value by the average revenue in the untreated group.

## 6.1 Practical implications for researchers

In this final discussion, we evaluate practical takeaways that researchers interested in accounting for participants' value of time can draw from our research. How might one evaluate the value of time of casual laborers?

One simple strategy:

**Use 60% of local wage.** Researchers evaluating interventions in similar contexts as ours could opt to rely on our rule-of-thumb estimate that the MVT is close to 60% of the local wage for casual labor. The main limitation is external validity: market failures that keep wages above the average MVT are likely to be context-specific. For example, because our estimates are local to the season in which our activities took place—in this case, the end of sowing season—we cannot rule out that labor is increasingly rationed during lean seasons, as in Breza et al. (2020), or that the severity of behavioral biases varies across seasons.

Two more complex approaches involve running experiments:

**Use direct BDM for experienced laborers.** We do not think that direct BDM for the overall population is likely to yield reliable estimates of the MVT. However, given that experienced laborers exhibit lower behavioral bias, we expect direct BDM within this group to be more reliable. This does present some challenges—it requires scheduling workdays and transporting workers to and from work sites—and so may be expensive at scale. Researchers concerned that experienced laborers have a significantly different value of time than other participants could consider mapping the BDM measure to the full sample based on an unincentivized measure collected from all participants, or based on observable characteristics the researcher believes are predictive of value of time. Additionally, debiasing participants through experience may represent an avenue for future research. Alternatively, researchers could design an activity to mitigate loss aversion by removing the factor of surprise. For example, offering short-term jobs at

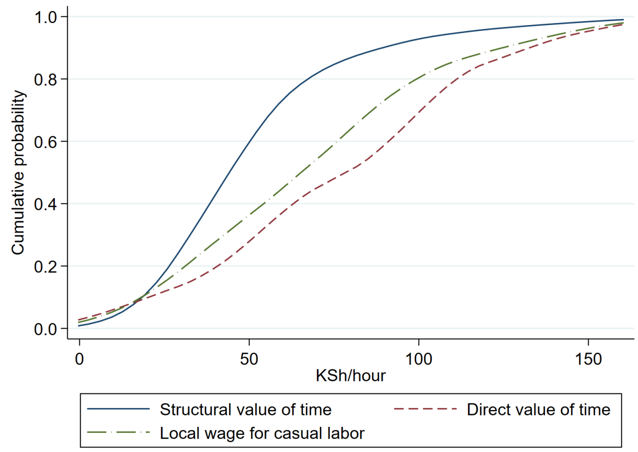
60% of the local wage and giving participants time to decide whether to accept it should produce a more reliable estimate of the labor supply curve at that price.

**Replicate our analysis.** Researchers who expect the MVT to significantly influence the value of an intervention can consider replicating our full study to estimate the SVT. Interventions that are likely to substantially increase or decrease family labor supply are the most likely to meet this criterion. Since this is likely to be difficult and costly at scale, conducting this exercise within a representative subset of participants may be best. Because second-order effects may create upward bias in the behavioral discount rate, researchers should consider whether their experiment is substantially affecting participants' shadow cost of capital.

## 6.2 Implications for labor markets

Self-serving bias can cause impasse in negotiations even when information is complete (Babcock and Loewenstein, 1997). Figure 4 displays the distributions of reservation wages elicited through BDM (DVT), the structural value of time, and local wages. DVT first-order stochastically dominates SVT, with local wages lying well above SVT and slightly below DVT. If the self-serving bias extends to natural decision-making, 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. We do not believe this is likely. As discussed in Section 4.2, experimental conditions are likely to induce behavioral response: the finding that experienced negotiators exhibit a lower bias is consistent with this. Instead, the results in Figure 4 appear consistent with the rationing of casual jobs. This could explain why wages in these jobs are high relative to total household earnings, but working hours are low. We do not take a stand on what mechanism could be driving labor rationing, although we do not find evidence of norms preventing workers from accepting low-wage work, as in Breza et al. (2019) (see Appendix Table E.7).

Figure 4: The structural value of time is lower than wages

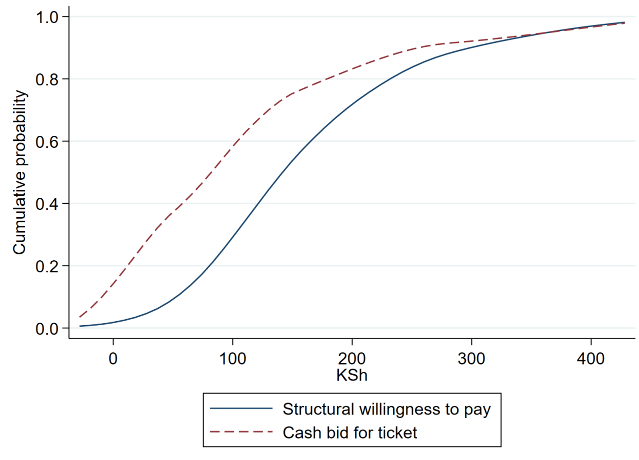



Kernel-smoothed cumulative distribution functions (Van Kerm, 2012) estimated on all farmers in sample. "Structural value of time" is the preference parameter $b$ (see Section 4) identified as described in Section 5. "Direct value of time" is elicited through Mechanism 1 (see Section 2.2 for design details). "Local 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.

## 6.3 Implications for measuring willingness to pay

Researchers often use willingness to pay as a mechanism to assign goods to agents who value them most. Mechanisms that are unusual or surprising to participants, or which involve negotiations with third parties, are likely to induce the same loss aversion that we observe. Figure 5 displays the distributions of cash bids for lottery tickets and the structural willingness to pay (preference parameter $a$). Structural willingness to pay first-order stochastically dominates cash bids. This has two implications for researchers using willingness to pay to measure valuation. First, loss aversion will lead willingness to pay within an experiment to understate the willingness to pay that would be observed in more natural conditions. Second, if the behavioral response is sufficiently heterogeneous across participants—as in our experiment—researchers will be unable to recover even an ordinal ranking of valuation using willingness to pay. To demonstrate this, we rank our 332 farmers based on willingness to pay in cash and compare it to the ranking of the same farmers based on their structural willingness to pay. We find that the ranking by willingness to pay 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).

Figure 5: The structural willingness to pay is higher than BDM cash bids




Kernel-smoothed cumulative distribution functions (Van Kerm, 2012) 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 Mechanism 2. All variables top-coded at 400 KSh.

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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

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

Let $\Delta z \in \mathbb{R}^3$ be a direction of change. Corollary 5 of Milgrom and Segal (2002) implies that $V$ is absolutely continuous in $z$ and for any $z$, $\Delta z$, satisfies

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

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). $\blacksquare$

**Proof of Theorem 2.** Equations (15) and (16) imply that

$$\begin{aligned}
\log(m_i^A/2) &= \log b_i + \frac{\gamma^A}{\gamma^A + \gamma^B - \gamma^C} \log \frac{1}{1 - \widehat{r}_i} \\
\log m_i^B &= \log a_i - \frac{\gamma^B}{\gamma^A + \gamma^B - \gamma^C} \log \frac{1}{1 - \widehat{r}_i} \\
\log h_i^C &= \log a_i - \log b_i - \frac{\gamma^C}{\gamma^A + \gamma^B - \gamma^C} \log \frac{1}{1 - \widehat{r}_i}.
\end{aligned}$$

Under the assumption that $\widehat{r}_i$ is independent from $a_i$ and $b_i$, it follows that for all $X \in \{A, B, C\}$, OLS coefficient $\widehat{\delta}^X$ consistently estimates $\gamma^X/(\gamma^A + \gamma^B - \gamma^C)$. In turn, the assumption that $\gamma^A + \gamma^B + \gamma^C = 1$ implies that $\widehat{\delta}^A + \widehat{\delta}^B + \widehat{\delta}^C = \frac{1}{\gamma^A + \gamma^B - \gamma^C}$.

This implies that for all $X \in \{A, B, C\}$, $\widehat{\delta}^X/(\widehat{\delta}^A + \widehat{\delta}^B + \widehat{\delta}^C)$ is a consistent estimator of $\gamma^X$. $\blacksquare$

# B Implementation details

We selected villages for our sample from a set of villages sampled for a separate project (Chassang et al., 2020) which auctioned off Kickstart irrigation pumps. We selected all control villages which had not received any pumps, and used remaining pumps from Chassang et al. (2020) to elicit willingness to pay in cash and time. Villages in Chassang et al. (2020) were selected 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, an "anchor farmer" was identified who lived close to a water source, and the snowball technique was used 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.[12]

Before the experiment, our project staff explained the experimental design and quizzed farmers on hypothetical outcomes to ensure comprehension. If the head of household was unable to perform casual labor, a different household member was selected at the outset. Staff gave farmers 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 farmers 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.

## BDM Step 1: Eliciting willingness to pay / willingness to accept

Choices B and C occurred at the beginning of the survey, in random order. Choice A came next. Prices were drawn at the end of the three activities. Scripts read to each farmer explained that there could be absolutely no bargaining once the prices were drawn.

**Choice A: Work for cash.** Each farmer 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 farmer 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

[12] 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.

was given the option to revise her answer.[13]

**Choice B: Cash for ticket.** Each farmer 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 farmer was willing to pay 500 KSh, we asked for her maximum willingness to pay (WTP) in a single question. farmers 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.

**Choice C: Work for ticket.** Each farmer 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 farmer was willing to work for 6 hours, we asked for her maximum WTP (in hours) in a single question. farmers 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.

## BDM Step 2: Assignment of prices

Each village was randomly assigned (by a pseudo-random number generator) to one of three assignment types: Cash, Cash + Day Work, or Task. Farmers in *Cash* villages received a

[13] 22% of farmers declined to place a cash bid for a lottery ticket. We code these as bids of 0 KSh. 10% of farmers declined to place a time bid for a lottery ticket. We bottom-code these as bids of 1 hour so that the discount rate $r$ is defined. Results are not sensitive to excluding these bids. 9% of farmers declined to participate in the day work activity, as we told farmers ahead of time that the maximum possible wage was 120 KSh/hour. For these farmers, we ask their reservation wage directly and top code them at 250 KSh/hour.

lottery ticket price payable in cash only, and were not eligible for wage work. farmers in *Cash + Day Work* villages received a lottery ticket price payable in cash only, and were eligible for wage work. farmers 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 simplify 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 farmers did not learn about their assignment until their lottery ticket price was drawn (see step 3 below). Farmers were not told the sample space of assignment types or the level of assignment, only that there was some positive probability that each choice would be used. To reduce the possibility that farmers might share information with each other, we completed all surveys within each village in the same day.[14]

## 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 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.

Before the experiment, we assigned each farmer a random ticket price in either cash or time, and a random cash wage. Farmers were assigned a single ticket price in either cash or time, but not both. Cash wages were assigned independently of ticket price. This information was written on a card and inserted into a sealed envelope, which was shown to the farmer at the beginning of the survey. After the farmer had made their three decision choices, the envelope was opened and the ticket price, payment denomination (cash or time),

[14]Note that even if farmers did talk during the survey day, in principle this should not affect their choices. Without seeing the results of a high number of price draws, farmers should not infer that price denomination assignment occurred at the village level.

and wage revealed. Farmer could thus be sure that their bids did not influence the drawn prices.

## Cash collection and day work

Cash winners—farmers who drew a cash price weakly lower than $m^B$—were asked to make a down payment of 20 KSh ($0.19) at the end of the experiment. Approximately one week later, enumerators returned to the village to collect the remaining amount owed. Time winners—farmers who drew a time price weakly lower than $h^C$—were scheduled for casual work approximately 1 week from the date of the experiment. Enumerators returned approximately one week later to transport time winners to and from the job site and monitor their work. Casual jobs for eligible wage workers—farmers who drew an hourly cash wage weakly greater than $m^A/2$—were scheduled approximately 2 weeks from the date of the experiment. Enumerators returned and this time to provide transport and monitoring.

Compliance was high: 88% of farmers paying cash and 75% of farmers performing casual labor completed their payments or work (see Section E.5 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 farmers throughout the activities to discourage bids that farmers 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 $c = \text{mod}(n, 10)$. 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 $ceiling(N/10)$.

# C Covariates of Bias

To understand which farmers exhibit more severe behavioral discounting, we estimate regressions of the form:

$$y_i = \alpha + X_i' \Gamma + \epsilon_i, \tag{19}$$

where $y_i$ is an experimental choice such as the behavioral discount rate $\widehat{r}$, $X_i$ is a vector of predictor variables, and $\epsilon_i$ is an error term. To account for censoring in bids, we estimate (19) using Tobit models. Table C1 shows results. Table C2 displays bivariate estimates of (19). Results are overall very similar across these two specifications.

The characteristics we analyze are not randomly assigned, and so estimates of $\Gamma$ should not be interpreted as causal. However, recall that in the benchmark model of Section 3, the behavioral discount rate $\widehat{r}$ 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 IVT and DVT proportionately. We therefore view estimates of (19) as informative of the characteristics of farmers that exhibit a more severe behavioral bias.

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

| | (1) Discount rate | (2) Direct value of time | (3) Indirect value of time | (4) Cash bid | (5) Time bid |
|---|---|---|---|---|---|
| Age | -0.157* | -4.9 | -0.5 | -8.3 | -0.218 |
| | (0.093) | (4.0) | (3.0) | (9.7) | (0.145) |
| Years of education | -0.286*** | -10.0** | 7.0** | 19.5** | 0.014 |
| | (0.093) | (4.6) | (2.8) | (8.8) | (0.151) |
| Household size | -0.130 | 0.9 | 1.6 | 6.2 | -0.004 |
| | (0.084) | (3.5) | (2.6) | (9.1) | (0.139) |
| Female = 1 | 0.007 | -12.7 | -0.0 | -9.2 | -0.424 |
| | (0.196) | (8.1) | (6.1) | (20.9) | (0.312) |
| Total income | 0.105 | 6.3 | -0.8 | -1.8 | -0.250 |
| | (0.093) | (4.6) | (2.8) | (11.2) | (0.153) |
| Considered buying pump = 1 | -0.333* | -22.6*** | -1.5 | 23.1 | 0.779*** |
| | (0.185) | (7.2) | (5.4) | (19.0) | (0.273) |
| Supplies casual labor = 1 | -0.371** | -19.9*** | 6.8 | 42.7** | 0.967*** |
| | (0.170) | (6.7) | (5.4) | (17.9) | (0.258) |
| Hires casual labor = 1 | -0.154 | 4.3 | 9.5* | 27.9 | 0.259 |
| | (0.165) | (6.8) | (5.0) | (17.5) | (0.261) |
| Altruism | -0.085 | -6.7** | -0.0 | 5.7 | 0.150 |
| | (0.092) | (3.0) | (2.2) | (9.3) | (0.103) |
| Cash scarse = 1 | 0.387* | -2.2 | -7.7 | -41.0* | 0.094 |
| | (0.216) | (8.5) | (5.7) | (22.9) | (0.352) |
| Overconfidence | -0.037 | 3.8 | 3.5 | 13.9* | -0.021 |
| | (0.092) | (2.9) | (2.3) | (7.9) | (0.120) |
| Observations | 332 | 332 | 332 | 332 | 332 |
| Estimator | Tobit | Tobit | Tobit | Tobit | Tobit |

Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 Ksh). Time units are hours. Each column is estimated from a Tobit regression of an auction outcome on a vector of predictors. 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

The literature on self-serving bias and loss aversion motivates our selection of behavioral predictors. Questioning one's own judgment before negotiating reduces self-serving bias (Babcock et al., 1998), though it is not clear whether experience reduces bias over time. To 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=$-0.37$; p-val=0.03). We also include age and education as proxies for experience. We find that older farmers discount less (coeff=$-0.16$; p-val = 0.09). Figure C1 shows that the relationship between the discount rate and age is non-monotonic: the young and the very old discount more. More educated farmers also discount less (coeff=$-0.29$; p-val$<0.01$).

Loss aversion may be amplified in the context of unexpected choices which are not well-integrated into reference-expectations (Kőszegi and Rabin, 2006, Carney et al., 2019). We include information from prior surveys on whether the farmer's household had considered buying an irrigation pump in the past. We expect these farmers to have thought more carefully through their willingness to pay for the lottery tickets in our choice problems, and therefore to be less subject to a behavioral bias in negotiations. Indeed, we find a lower bias among these farmers (coeff=$-0.33$; p-val=0.07).

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 scarcity—whether the farmer reports that she does that have savings to cover a 5,000 KSh ($47) emergency (Dupas et al., 2018)—to test whether farmers facing scarcity discount more severely. We find that these farmers do exhibit greater bias (coeff = 0.39; p-val = 0.07). We also include a measure of total household income. Farmers with more income exhibit a slightly higher bias, though the coefficient is not statistically significant.

Scarcity can potentially affect decision-making in many ways. One interpretation, following the framework of Shah et al. (2012), is that scarcity focuses attention on immediate needs and away from other economic decisions, making it more difficult to overcome behavioral bias. Another 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 activities, 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 find no significant gender difference in the degree of behavioral bias.

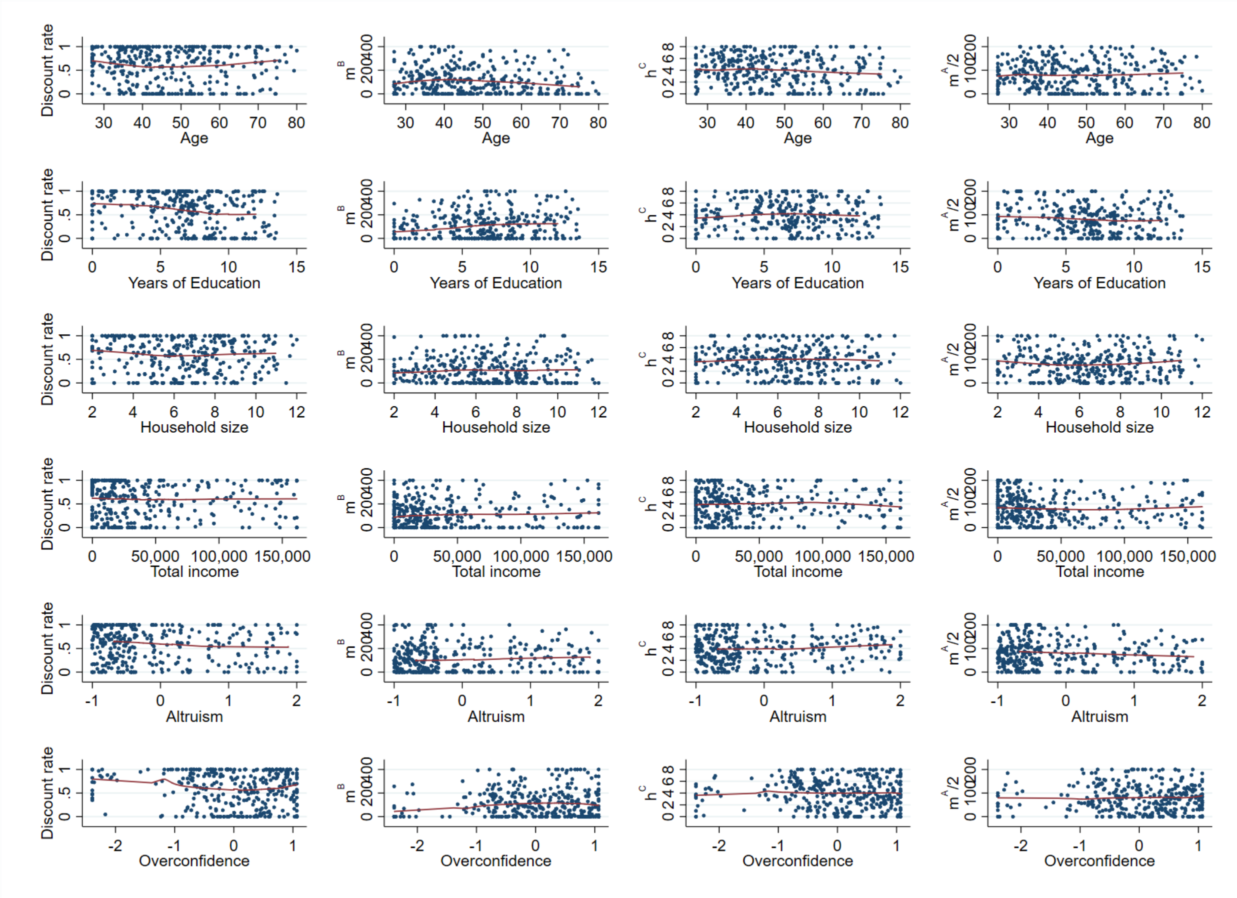
Altruism may mitigate self-serving bias (Di Tella et al., 2015). We test whether more altruistic farmers—measured using the share donated to an unspecified person in their village in a hypothetical dictator game—discount less. A one standard-deviation increase in our measure of altruism corresponds with an insignificant 0.085 reduction in the discount rate (p-val = 0.36).

Table C2: Estimates of auction outcome correlations are very similar in bivariate regressions.

| | (1)<br>Discount rate | (2)<br>Direct value of time | (3)<br>Indirect value of time | (4)<br>Cash bid | (5)<br>Time bid |
|---|---|---|---|---|---|
| Age | -0.035 | 1.3 | -3.1 | -19.9** | -0.284** |
| | (0.079) | (3.6) | (2.5) | (8.8) | (0.134) |
| Years of education | -0.299*** | -7.3* | 8.3*** | 30.2*** | 0.114 |
| | (0.085) | (4.1) | (2.6) | (8.0) | (0.147) |
| Household size | -0.140 | 0.3 | 1.5 | 7.4 | 0.023 |
| | (0.089) | (3.8) | (2.7) | (9.4) | (0.146) |
| Female = 1 | 0.263 | -5.0 | -3.3 | -18.3 | -0.406 |
| | (0.201) | (8.0) | (5.5) | (19.4) | (0.304) |
| Total income | -0.062 | 1.9 | 2.9 | 15.4 | -0.127 |
| | (0.085) | (4.4) | (2.6) | (10.5) | (0.147) |
| Considered buying pump = 1 | -0.489*** | -23.2*** | 4.3 | 48.8*** | 0.877*** |
| | (0.177) | (7.3) | (5.4) | (18.4) | (0.269) |
| Supplies casual labor = 1 | -0.295* | -20.8*** | 5.3 | 42.6** | 1.130*** |
| | (0.175) | (6.8) | (5.1) | (18.0) | (0.258) |
| Hires casual labor = 1 | -0.264 | 3.8 | 12.5** | 39.5** | 0.165 |
| | (0.170) | (6.9) | (5.0) | (17.7) | (0.265) |
| Altruism | -0.120 | -8.7*** | 0.9 | 10.9 | 0.241** |
| | (0.093) | (3.2) | (2.3) | (9.9) | (0.104) |
| Cash scarse = 1 | 0.414** | -4.3 | -10.5* | -50.3** | 0.188 |
| | (0.209) | (8.8) | (5.4) | (21.6) | (0.331) |
| Overconfidence | -0.082 | 1.5 | 4.5** | 20.1** | 0.094 |
| | (0.093) | (2.9) | (2.3) | (8.1) | (0.127) |
| Observations | 332 | 332 | 332 | 332 | 332 |
| Estimator | Tobit | Tobit | Tobit | Tobit | Tobit |

Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 Ksh). Time units are hours. Each column is estimated from a Tobit regression of an auction outcome on a single predictor variable. 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

Figure C1: Lowess regressions of experimental choices against selected predictors.




Each chart shows a lowess regression of an experimental choice on a predictor variable with 5% jitter.

# D Clustering analysis

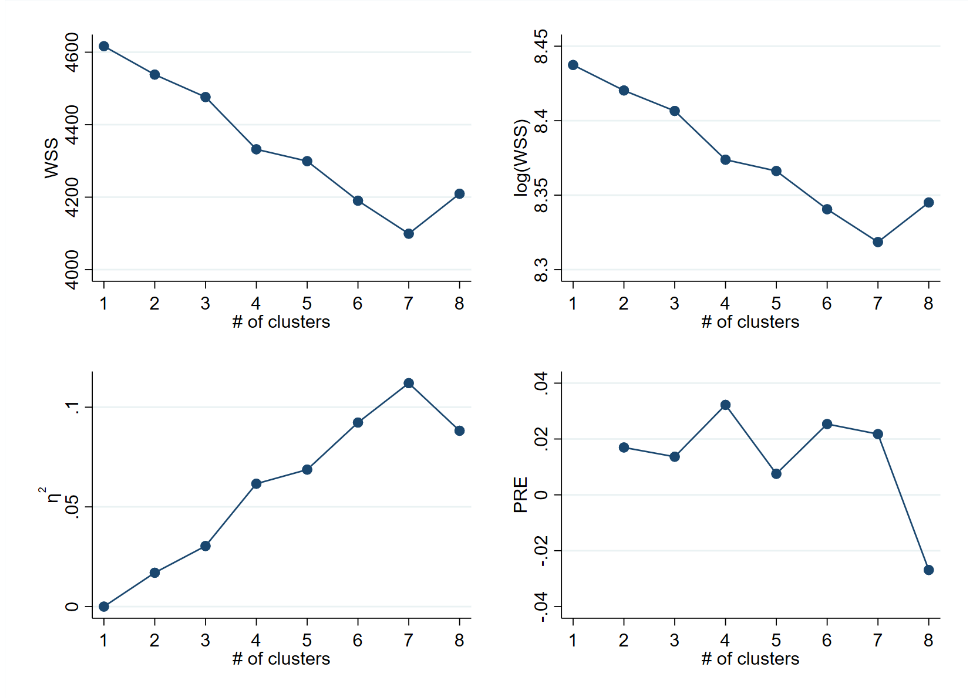
To divide our sample into groups of economically similar farmers, we conduct clustering analysis using the partition around medoids (PAM) method with dissimilarity measured by the Gower coefficient (Gower, 1971). We first solve for the optimum number of clusters by inspecting the within sum of squares function, the average silhouette width (see Rousseeuw, 1987), and the gap statistic (Tibshirani et al., 2002) for between 1 and 8 clusters. Figure D1 presents results for each of our 3 criteria. Four clusters maximizes the average silhouette width, produces a kink in the within-cluster sum of squares criterion, and is suggested by the gap statistic method. The following variables are used for clustering: age, years of education, a female dummy, a dummy for having no male head of household, household size, the number of children under 18 in the household, area of land cultivated, farming income, non-farm income, a dummy for whether the household irrigates, a measure of uncertainty aversion, measures of intra-household and intra-village altruism, a dummy for being cash constrained, two dummies for supplying or hiring casual labor, 6 occupation dummies, a measure of overconfidence, and a measure of network centrality.

# E Robustness to alternative explanations of the behavioral bias

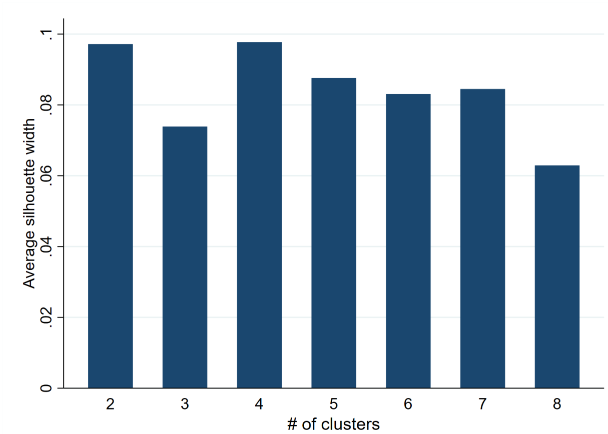
In this section we consider several alternative explanations for the large observed gap between reservation wages and the indirect value of time: differential effort or scheduling costs of work, risk aversion, order effects of the bidding activities, anchoring, non-compliance, bid censoring, and stigma surrounding low wages.

Figure D1: Three criteria suggest $n = 4$ groups for cluster analysis.

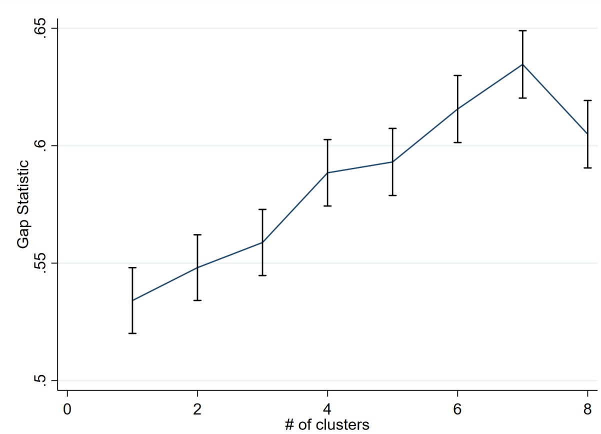
**Panel A: Elbow method**




**Panel B: Silhouette width**




**Panel C: Gap statistic**




Cluster analysis performed using partition around medoids (PAM) using the Gower dissimilarity coefficient. See Rousseeuw (1987) for a description of the silhouette method, and Tibshirani et al. (2002) for a description of the gap statistic method. "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 $PRE_k = \frac{WSS(k-1) - WSS(k)}{WSS(k-1)}$.

## E.1 Effort costs of casual work

Conceptually, the value of time is a comparison of the values of two possible activities, and thus depends on which activities are being compared. For example, if work effort is costly, farmers will require a lower payment to sit idly than they would to work for the same amount of time. Applied to interventions that affect working hours, the correct measure of the value of time is thus 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 indirect value of time and the reservation wage is that farmers 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: farmers must make room in their schedule to attend the task day. Task days for lottery tickets were scheduled on average one week out from the bidding activity; task days for a wage were scheduled on average two weeks out from the bidding activity. 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 farmers discount the value of time in the distant future more than that in the near future.

## E.2 Risk aversion

If farmers are risk averse, their bids for lottery tickets will be lower than their private expected value. Importantly, standard risk aversion does not affect the key predictions of Section 3. For risk aversion to generate a gap between our two measures of the value of time, it would be necessary for farmers to be more or less risk averse when paying in cash than when paying in time. To test for this, we elicit risk aversion in our survey instrument by directly asking respondents about their general willingness to take risks,[15] a measure that correlates well with risk-taking behavior in a paid lottery (Dohmen et al., 2011). Table E1 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 indirect value of time (coeff = 3.1 KSh/hour; p-val = 0.41) or the reservation wage (coeff = −2.5 KSh/hour; p-val = 0.68).

Table E1: We find no evidence that risk aversion, order effects, or anchoring to typical wages drives our results.

| | Discount rate | DVT | IVT | Cash bid for ticket | Time bid for ticket |
|---|---|---|---|---|---|
| Risk averse = 1 | -0.064 | -2.5 | 3.1 | -5.9 | -0.50** |
| | (0.132) | (6.1) | (3.8) | (13.5) | (0.24) |
| Cash auction appeared first = 1 | 0.146 | 0.2 | -0.1 | -10.3 | -0.31 |
| | (0.130) | (6.0) | (3.8) | (13.6) | (0.24) |
| Perceived typical wage | -0.104 | -0.0 | 2.6 | 2.7 | -0.25** |
| | (0.072) | (2.9) | (2.1) | (6.5) | (0.12) |
| Observations | 332 | 332 | 332 | 332 | 332 |
| Dep Var Mean | 0.300 | 82.75 | 29.80 | 110.8 | 4.012 |

An observation is a farmer. Currency units are Kenyan shillings (1 USD=107 KSh). Each column reports estimates from a regression of an auction choice on three predictors. "Risk averse" is a dummy = 1 if the farmer reports a willingness to take risks below the sample median. "Cash auction appeared first" is a dummy = 1 if the cash bid was elicited prior to the task bid (the order was randomized prior to the survey). "Perceived typical wage" is the wage the farmer 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.
*** p<0.01, ** p<0.05, * p<0.1

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

## E.3 Order effects

To test for order effects, we randomized the order of the cash and time activities. The wage work activity always came third. Table E1 shows the effect on bidding outcomes of the randomized order of the cash activity. We find no evidence of significant order effects.

## E.4 Anchoring

One possibility is that farmers anchor their reservation wage to what they believe to be the prevailing wage in their village, even if their true value of time is different than the prevailing wage. To test for anchoring effects, we ask farmers what the typical wage is for casual agricultural work in their village and regress bidding outcomes on their perception of the typical wage. Table E1 shows results. Although time bids are modestly lower for those who report a high typical wage, We find no evidence of significant anchoring effects on either measure of the value of time.

## E.5 Non-compliance

If farmers do not comply with the bidding 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 small down payment among cash winners, giving farmers 1–2 weeks before the full payment was due or casual work was scheduled, and stressing from the beginning that non-compliance in one activity made the farmer ineligible for the remaining activities. Overall, compliance rates were high, and we do not find evidence that non-compliance is driving our results. Among farmers 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 farmers who received a time price below their willingness to pay, 75%

completed their work on the scheduled work day. Among farmers 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 farmers' time obligations on the scheduled work day may be difficult to substitute inter-temporally in the face of unexpected shocks.

Table E2: Non-compliance cannot explain our results.

| | (1) Cash bid for ticket | (2) Time bid for ticket | (3) DVT |
|---|---|---|---|
| Complied = 1 | 48.9** | 0.16 | 0.6 |
| | (21.2) | (0.50) | (9.4) |
| Observations | 118 | 83 | 39 |
| Dep Var Mean | 184.49 | 4.76 | 46.41 |
| Compliance rate | 0.88 | 0.75 | 0.74 |

An observation is a farmer who won a ticket to be paid in cash or time, or who was eligible and randomly selected for day work. Currency units are Kenyan shillings (1 USD=107 KSh). Time bid measured in hours. 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.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The main concern for our estimates is that non-compliance is driven by inaccurate bids. To test whether compliers' bids differ systematically from those of non-compliers, we regress bid amounts on a dummy for compliance within the sample of eligible farmers.[16] Table E2 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 for which the compliance rate is lower (about 75%). The correlation between the cash bid and compliance is positive (coeff = 49 KSh on

[16]Eligible farmers are those with bids higher than the price draw in cash and task, or reservation wages lower than the wage draw and who were randomly selected for day work.

a base of 184; p-val = 0.02). The effect of this on our average measures is likely small, as compliance is 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 farmers with high predicted compliance[17] in all 3 activities. Table E3 presents results. The effect of this restriction on our estimates is generally very small.

Table E3: Value of time estimates are robust to excluding farmers with low predicted compliance. (N=298)

| | Mean | Std. Dev. | p25 | p50 | p75 |
|---|---|---|---|---|---|
| Direct value of time (DVT) | 86 | 54 | 50 | 80 | 100 |
| Indirect value of time (IVT) | 32 | 36 | 7 | 24 | 44 |
| Cash bid | 122 | 127 | 20 | 100 | 180 |
| Time bid | 4.2 | 2.1 | 3.0 | 4.0 | 5.5 |
| Behavioral discount (r) | 0.29 | 1.17 | 0.20 | 0.67 | 0.92 |

Each observation is a farmer with a predicted compliance above 50% for all three auctions. Currency units are Kenyan shillings (1 USD = 107 KSh). Cash bids, time bids, and $DVT$ elicited through BDM. $IVT$ = cash bid / time bid. Behavioral discount = $1 - IVT/DVT$. p25, p50, and p75 are the 25th, 50th, and 75th percentiles.

## E.6 Censored bid data

In our sample, 25% of farmers place a cash bid of 0 KSh, 10% place a time bid of 0 hours, and 3% express an extremely high reservation wage (more than 4x the sample median). In our main analysis we bottom-code cash and time bids at 20 KSh and 1 hour respectively, and top-code reservation wages at 250 KSh/hour (the 97th percentile). Table E4 estimates

[17] We do not observe compliance for every farmer. We only observe compliance in cash and task for those with a sufficiently high bid given the random price, and who were randomly offered a price in cash or hours of work, respectively. We only observe compliance in the reservation wage activity for those with sufficiently low reservation wages given the random wage, and whose villages 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 then re-estimate our results on the restricted sample of farmers with $\geq$ 50% predicted compliance on all three measures.

the model of Section 5 without relying on recoding: Columns (2) and (5) restrict the sample to farmers who placed at least 1 "eligible" bid (that is, a strictly positive cash or time bid, or a reservation wage not greater than 250 KSh/hour). Columns (3) and (6) restrict the sample to farmers who placed only eligible bids. This has almost no effect on the estimated value of time, which is stable at 59–60% of local wages throughout these sample restrictions.

Table E4: Estimated bias shares and value of time are robust to controls and recoding of bids.

| | (1) Full sample | (2) Participated in $\geq$ 1 bid | (3) Participated in all bids | (4) Full sample | (5) Participated in $\geq$ 1 bid | (6) Participated in all bids |
|---|---|---|---|---|---|---|
| Reservation wage bias ($\widehat{\gamma}^A$) | 0.385 | 0.384 | 0.452 | 0.385 | 0.382 | 0.45 |
| | (0.023) | (0.024) | (0.031) | (0.023) | (0.023) | (0.031) |
| Cash bid bias ($\widehat{\gamma}^B$) | 0.612 | 0.616 | 0.548 | 0.615 | 0.618 | 0.55 |
| | (0.025) | (0.026) | (0.032) | (0.025) | (0.026) | (0.031) |
| Time bid bias ($\widehat{\gamma}^C$) | 0.003 | 0.000 | 0.000 | 0.002 | 0.000 | 0.000 |
| | (0.014) | (0.012) | (0.005) | (0.013) | (0.011) | (0.005) |
| Structural value of time ($\widehat{SVT}$) | 48.8 | 48.6 | 47.0 | 48.9 | 48.7 | 47.0 |
| | (2.52) | (2.40) | (2.38) | (2.52) | (2.40) | (2.38) |
| Market Wage ($w$) | 81.6 | 81.5 | 80.0 | 81.6 | 81.5 | 80.0 |
| | (1.81) | (1.75) | (2.11) | (1.81) | (1.75) | (2.11) |
| Relative Value of Time ($\widehat{SVT}/w$) | 0.598 | 0.596 | 0.588 | 0.599 | 0.598 | 0.588 |
| | (0.032) | (0.034) | (0.034) | (0.032) | (0.034) | (0.034) |
| Observations | 332 | 329 | 231 | 332 | 329 | 231 |
| Controls? | N | N | N | Y | Y | Y |

Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 KSh). $\widehat{\gamma}^A$, $\widehat{\gamma}^B$, and $\widehat{\gamma}^C$ are the estimated share of the behavioral bias present in reservation wages, cash bids, and time bids respectively (see Section 5 for details on identifying bias shares). Structural value of time ($SVT$) is the preference parameter $b$ (see Section 4). Market wage is most recent hourly wage earned from casual work and is imputed for those who have not done casual work within the past 3 months. Column (1) shows results on the full sample, with cash and time bids bottom-coded at 20 KES and 1 hour respectively. Column (2) shows results estimated using farmers who placed eligible bids in at least 1 auction, with ineligible bids bottom-coded. Column (3) shows results estimated using farmers who placed eligible bids in all 3 auctions, with no bottom-coding. An eligible bid is a cash bid $> 0$, a time bid $> 0$, or a reservation wage below 250 Ksh/hour. Columns (4)-(6) include controls that proxy for two preference parameters—the value of time and the valuation of the lottery ticket—that determine auction choices together with the behavioral discount rate. Bootstrap standard errors in parentheses.

## E.7 Stigma surrounding low wages

If accepting low-wage work carries stigma, this could inflate our measure of DVT above SVT. For example, workers may feel ashamed of accepting low-wage work, or anticipate sanctions from other workers. Such an explanation would be consistent with the finding that workers in rural India are less likely to accept work below the prevailing wage when that decision is observed by neighbors (Breza et al., 2019).

To test whether the DVT is 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.[18] We elicited feelings of shame, anger, and pride surrounding working for low wages. We then run three regressions of the form:

$$DVT_i = \alpha_0 + \alpha_1 Emotion_i + \epsilon_i$$

where $Emotion_i \in \{0, 1\}$ is a dummy variable indicating a positive emotional response to the story. We elicit responses of shame, anger, and pride about both the worker accepting the low wage and the employer offering the low wage.

Table E5 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." Responses about the employer are similar: 72% report that the hirer should not feel ashamed "at all," 79% report that they would not feel angry at the employer

[18] The TOSCA measure of shame correlates well with psychological adjustment (Woien et al., 2003).

"at all," and 57% report feeling "very proud" of the employer. These emotional responses to low-wage work are generally uncorrelated with the DVT: the only statistically significant coefficient appears on those who report feeling proud of the low-wage worker (coeff = 11 KSh ; p-val = 0.05). We interpret this as evidence that workers do not feel that they need to inflate $m^A$ to avoid stigma.

Table E5: No evidence that low-wage stigma affects DVT

| | (1) | (2) | (3) |
|---|---|---|---|
| | Dep. Var: DVT. ($m^A/2$) | | |
| **Panel A: Reaction to low-wage worker** | | | |
| Should feel ashamed = 1 | -0.3 | | |
| | (5.9) | | |
| Angry at worker = 1 | | 0.1 | |
| | | (6.5) | |
| Proud of worker = 1 | | | 10.9** |
| | | | (5.5) |
| **Panel B: Reaction to low-wage hirer** | | | |
| Should feel ashamed = 1 | -1.9 | | |
| | (6.2) | | |
| Angry at hirer = 1 | | 6.9 | |
| | | (6.9) | |
| Proud of hirer = 1 | | | 0.8 |
| | | | (5.9) |
| Observations | 332 | 332 | 332 |
| Dep Var Mean | 82.8 | 82.8 | 82.8 |

An observation is a farmer. Currency units are Kenyan shillings (1 USD=107 KSh). Dependent variable is the farmer's DVT measured through Choice A. 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.
*** p<0.01, ** p<0.05, * p<0.1