Valuing the Time of the Self-Employed*

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Abstract

People's value for their own time is a key input in evaluating public policies: evaluations should account for those policies causing people to take time away from work or leisure. Using rich choice data collected from farming households in western Kenya, we show that households exhibit non-transitive preferences consistent with behavioral features such as loss aversion and self-serving bias. As a result, neither market wages nor standard valuation techniques (such as the Becker-DeGroot-Marschak—BDM—mechanism of Becker et al., 1964) correctly measure participants' value of time. Using a structural model, we identify the mix of behavioral features driving our choice data. We find that these features distort choices when exchanging cash either for time or for goods. Our model estimates suggest that valuing the time of the self-employed at 60% of the market wage is a reasonable rule of thumb.

KEYWORDS: value of time, non-transitivity, labor rationing, loss aversion, self-serving bias

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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). Accurately measuring the value that the self-employed assign to their own time is essential for evaluating the profitability and welfare impacts of most such interventions. The majority of such evaluations ascribe no value to the time of the self-employed.[1] A minority uses the prevailing market wage, which likely overstates the value of time in the presence of the labor-market frictions endemic to developing economies (Kaur, 2019, Breza et al., 2021).[2] Directly assessing participants' value of time—by, for example, eliciting the minimum wage they would accept for comparable labor—may be unreliable, as the frictions that distort labor markets may originate in individual choices.

We create a method that pairs multiple choices with structural estimation to recover the value of time in the presence of behavioral phenomena and/or labor market failures. We elicit the preferences of self-employed farmers in western Kenya over trade-offs involving three goods: money, time, and lottery tickets for an irrigation pump. The choices over these alternatives indicate that many farmers in our study have intransitive preferences, confirming that direct trade-offs between money and time may produce unreliable results. Still, these choices bound the average value of time at 40–100% of the market wage. We then use a structural model that nests different behavioral phenomena to obtain a more precise estimate of the value of time. Our results indicate an average value of time of 60% of the market wage, and that behavioral phenomena manifest themselves, in our environment, in choices that involve money, rather than choices that only involve time and goods.

Our findings imply that the chronic undervaluing of the time of the self-employed will tend to overstate the value of technologies or interventions that increase time use, and un-

[1]See Section 6.2 for a survey of studies in economics.

[2]Putting this another way, de Janvry et al. (2017, p. 458) note, "It is well known that a large number of family farms do not seem economically viable when family labor is valued at the observed market wage rate in the casual labor market, implying that this is not the correct way to value family labor." Following the literature, we use the term *market wage* to refer to the average wage for casual laborers in our sample.

derstate the value of those that save time.[3] This may explain why some technologies that appear profitable in evaluations are not adopted, and why labor-saving interventions attract relatively less attention in the literature (Suri, 2011, de Janvry et al., 2017). Quoting Peter Drucker, "if you can't measure it, you can't improve it." Our rule-of-thumb value of time— 60% of market wages—can be applied easily, or our full method can be replicated by other researchers requiring a more precise value. Finally, our results suggest an additional explanation for the persistence of self-employment in low-income countries: the behavioral phenomena driving our results may hinder informal labor market transactions. Self-serving biases may cause workers to undervalue wages obtained through negotiation, and loss aversion may cause employers to ration jobs.

Our study augments an elicitation which directly measures participants' value of time—their reservation wage for temporary jobs—with two others that allow for an indirect assessment of the value of time, as described in Section 2. Those additional elicitations allow participants to express the value of a good—lottery tickets with a 1/10 chance of winning an irrigation pump—in both money and hours of casual labor. By dividing these two quantities, we obtain an indirect assessment of participants' value of time.

Under a standard, benchmark model that allows for labor market rigidities and credit constraints, the direct and indirect values of time should be equivalent, but, in our choice data, they are not, as described in Section 3. The value of time measured directly is roughly the same as the prevailing market wage, while the same value measured indirectly is only 40% of the market wage, on average. This difference is caused by a large proportion of our participants—and the data overall—exhibiting preference intransitivities in the three choices we gave them. Despite these intransitivities, our two measures are enough to bound the average value of time between 40–100% of the market wage.

In order to rationalize our results, we turn to four possible models of two well-known behavioral phenomena—self-serving bias and loss aversion—as shown in Section 4. Self-serving bias is the tendency to undervalue goods or money obtained through in-person transactions

[3] Valuing time using the market wage would tend to have the opposite effect.

(Babcock et al., 1995), while loss aversion refers to the tendency to overvalue the goods or money one parts with in a transaction (Kahneman and Tversky, 1979). We model two variants of each phenomenon—a version that overvalues or undervalues any object, and a version where the overvaluation or undervaluation applies only to money. All four of these models can rationalize the gap between direct and indirect values of time observed with the data. However, they have distinct implications for the welfare-relevant value of time.

We use a structural model, in Section 5, to recover an average value of time of 60% of the market wage. In essence, the structural model uses data from all three elicitations to identify—under certain assumptions for which we provide supporting evidence—the extent to which the trade-off between money and time is affected by behavioral phenomena. Once identified, the impact of behavioral phenomena can be removed—if needed—to produce estimates of the value of time. As this model nests the benchmark model, and all four of its behavioral extensions, this estimate is robust to a broad class of behavioral features, in addition to market failures such as credit constraints or labor rigidities. The model estimation shows that both self-serving bias and loss aversion are at play, but only affect monetary expenditures or monetary compensation. Neither affects compensation in terms of goods, or labor expenditure to obtain goods.

Our results inform a broad literature that evaluates the welfare impacts of interventions. 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' value of time, but the absence of credible measures of the value of time 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. As self-serving bias and loss aversion are common in high-income contexts (see, for example, Babcock et al., 1995, Babcock and Loewenstein, 1997, Goette et al., 2020), the market wage and other standard valuation techniques may also produce unreliable estimates of the value of time in high-income economies. Mas and Pallais (2019) offer the first experimental estimates of the value of time among job-seekers in the U.S., but do not consider behavioral phenomena. Instead, they use estimates obtained by simply offering a choice between time and money, a choice that we show produces unreliable estimates.

Measuring the value of time is also central to the literature on labor misallocation. 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), but non-agricultural workers also work longer hours on average, with longer working hours explaining about one-fifth of the non-agricultural earnings premium (Pulido and Święcki, 2018). There is again no consensus on how to value workers' time when testing for misallocation: Gollin et al. (2014), in their measure of the agricultural productivity gap, control for hours worked, while Pulido and Święcki (2018) do not. Individuals' value of time is also a key parameter in the literature on business cycles (Hornstein et al., 2011, Shimer, 2005, Hagedorn and Manovskii, 2011). Our results demonstrate that ignoring workers' value of time will tend to overstate sectoral gaps and the welfare impact of business cycles.

Our paper also contributes to an emerging literature that uses the tools of behavioral economics to understand the persistence of poverty. Several studies find that the lack of material resources—or *scarcity*—directly affects decision-making capabilities (see Mullainathan and Shafir, 2013, for a review) and the formation of human capital (see Dean et al., 2017, for a review). We describe how the behavioral features behind our results may distort labor markets and slow down the transition away from self-employment.

Finally, our paper also contributes to the literature on preference elicitation using mechanisms procedurally similar to the BDM mechanism (Crockett and Oprea, 2012, Holt and Smith, 2016, Azrieli et al., 2018). We use BDM mechanisms over a richer choice space to identify and understand behavioral phenomena. Pinning down the relative importance of different sources of bias allows us to take a stand on the correct welfare interpretation of our measures of the 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 conclude, in Section 6, with a discussion of the broader implications of our results. We methodically review the economic literature from the last six years, and show that the extant literature uses crude estimates for the value of time. We then describe how researchers who are evaluating policies and interventions can best make use of our results, and we apply our results to some prior studies to illustrate when more reliable estimates for the value of time are likely to affect program evaluations.

2 Study Design and Choice Data

Our analysis exploits data from three choices. We elicit choices that trade off: (i) money and time; (ii) money and a good (a lottery ticket for an irrigation pump); and (iii) time and the same good. This allows us to recover two measures of each farmer's value of time: a direct measure from a choice between money and time; and an indirect measure that combines one choice over money and the good and another choice over time and the good.

In this section we describe our study setting, before turning to a more detailed description of the choices offered to farmers.

2.1 Setting

The study took place in rural western Kenya in April and May, 2019. Households in our study all did at least some agricultural work and had land suitable for manual irrigation. Nearly all households (99%) sold part of their harvest. Most households also engaged in micro-entrepreneurship or provided casual labor on neighbors' farms. Each household selected a single adult member to participate in the study. Table 1 displays sample summary statistics. The average participant was 47.7 years old and had 6.8 years of education. Women comprised

69% of our sample. The average household in our study earned about 50,000 KSh ($461) per year, of which 41% came from the sale of crops.

The jobs we offered—weeding and preparing land—were designed to mimic casual paid labor that most households engage in. Casual labor is, by far, the second most common source of income, after farming, for our participants, with 42% of participants having performed casual labor—and 46% of households having hired casual laborers—within the past 3 months. Those who had engaged in casual labor had worked an average of 13 days in the prior 3 months, with an average workday of 4.2 hours. Average wages were 82 KSh (about $0.77) per hour.[4]

Our analysis in Section 3.1 relies on the good in our choices having a relatively small value compared to the farmers' overall budgets. A small surplus of unused irrigation pumps, made by KickStart International, was available to us. As the pump is expensive given farmers' budgets we decided to use lottery tickets offering a 1-in-10 chance of winning a pump. As we expected, these tickets had a relatively small average subjective value of 111 KSh, representing roughly what the average participant could earn from 1.4 hours of casual labor.

The manually-powered irrigation pumps we used (branded as "MoneyMaker" by KickStart) 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 and increase both their food and income security (Sijali and Mwago, 2011). However, at baseline, only 11% of farmers in our study had tried a KickStart pump themselves. The main reasons given for this low uptake are that the pumps are expensive (they retail for 9,500 KSh, or about $89), and farmers fear that the pumps may be uncomfortable to operate.

[4]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 employers ration jobs. Section 6.1 discusses how our data improve the understanding of labor markets in developing countries.

Table 1: Summary statistics

Panel A: Demographics
Age
Years of education
Female = 1
No male head in household = 1
Number of adults (age 18 or over) in household
Number of children (under 18 years) in household
Panel B: Household income and wealth
Land area under cultivation (acres)
Household income (KSh, past year)
Income share from sale of crops
Panel C: Casual labor
Performed or hired casual labor within past 3 months = 1
Performed casual labor within past 3 months = 1
of which, days worked in last 3 months
during which, hours worked per day
among which, hourly earnings
Hired casual labor within past 3 months = 1
of which, days hired in last 3 months
during which, number of workers hired
among which, hours hired per day
among which, hourly wage paid
Panel D: Exposure to irrigation pump
Owns a MoneyMaker irrigation pump
Has used a MoneyMaker irrigation pump
Familiar with the MoneyMaker irrigation pump
Has considered buying a MoneyMaker irrigation pump
Self-reported valuation of pump (KSh)

Note: Each observation is a single farmer. Data are taken from multiple rounds of household surveys between 2014–2019. Values are coded as missing if the farmer was not surveyed when the relevant information was collected, when answering "Don't Know" to the question, or if the question is not applicable. All monetary units are expressed in 2019 Kenyan shillings (KSh).

2.2 Choices

Each farmer in our sample was given three choices that used the BDM design (Becker et al., 1964).[5] These choices ask participants to state their preferences for some object, for example a lottery ticket for a pump, in some unit of payment, for example, hours of labor. After stating their preferences, a random price is drawn, and if their stated value is higher than the price, that is what they pay for the object. If their value is lower than the price, no transaction occurs.[6]

Choice RW: Reservation Wage. In the *reservation wage* (RW) choice, 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 they would be willing to accept the job at 120 KSh per hour. If they answered "no," we asked about their reservation wage directly. If they answered "yes," we asked whether they would accept the job at incrementally lower wages until they changed their answer to "no."

The lowest amount of money the farmer was willing to accept for the job is denoted by m^{RW}.

Choice CB: Cash Bid. In the *cash bid* (CB) choice, 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.[7]

[5]In particular, the design of each choice was similar to those in Crockett and Oprea (2012).

[6]Thus, the BDM design is like a second-price auction with a single participant and a random reserve price. Like a second-price auction, the BDM design is incentive compatible, and revelation of true values is a dominant strategy. Complete implementation details are provided in Appendix B.

[7]We chose descending wages in RW and ascending prices in CB and TB so that the utility of the bid was decreasing through each sequence of questions.

The maximum amount of money the farmer was willing to pay for the lottery ticket is denoted by m^{CB}.

Choice TB: Time Bid. In the *time bid* (TB) choice, farmers were offered the option to obtain a lottery ticket for the MoneyMaker pump in exchange for casual labor.

We explained to each farmer that we were offering lottery tickets with 1-in-10 odds of winning a MoneyMaker pump. We collected time bids 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 amounts of time, until the farmer declined the offer.

The maximum amount of time the farmer was willing to work for the lottery ticket is denoted by h^{TB}.

Offer Revelation and Payment. Choices CB and TB occurred at the beginning of a survey, in random order. Choice RW 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.

We implemented the random draws such that farmers could be sure that their bids did not influence the drawn prices. Before the experiment, we assigned each farmer a random ticket price in either cash or time (but not both), and a random cash wage. 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 choices, the envelope was opened and the ticket price, payment denomination (cash or time), and wage were revealed.

Cash winners—farmers who drew a cash price weakly lower than m^{CB}—were asked to make a down payment of 20 KSh (\$0.19) at the end of the experiment, and were given about one week to collect the remaining money to pay for the ticket. Time winners—farmers who drew a time price weakly lower than h^{TB}—were scheduled for casual work approximately one week from the date of the experiment. Casual jobs for eligible wage workers—farmers who drew an hourly cash wage weakly greater than $m^{RW}/2$—were scheduled approximately two weeks from the date of the experiment.[8]

Direct and Indirect Value of Time. Our design lets us compute two measures of each farmer's value of time: an hourly *Direct Value of Time* (DVT)—$m^{RW}/2$—obtained from the RW choice: preferences over direct trade-offs between time and money; and an hourly *Indirect Value of Time* (IVT)— m^{CB}/h^{TB}—combining information from choices CB and TB: trade-offs between money and the lottery, and time and the lottery.

In the next section, we show that under our benchmark model, these two different values of time should be approximately equal.

3 The Benchmark Model and Evidence Against It

We model farmers' choices in a framework that allows for credit constraints and *labor rationing*. Labor rationing implies that a farmer's reservation wage may be strictly less than the market wage. The literature discusses a number of mechanisms that may result in workers being off their labor supply curve, for example, downward wage rigidity resulting from social norms or effort retaliation (Kaur, 2019), or workers acting as a cartel to withhold work from the market and increase wages (Breza et al., 2019). While the model allows for any source of mismatch between supply and demand, without taking a stand on its cause, in Section 6.1 we discuss possible interpretations of this mismatch that are consistent with our data. We model borrowing constraints by assigning a direct utility to cash-on-hand. This captures credit constraints that are either binding now, or may be binding in the future.

Specifically, a farmer makes decisions over bundles (τ, h, m) corresponding to

- obtaining or not the lottery ticket $\tau \in \{0, 1\}$
- time spent on work $h \in \mathbb{R}^+$

[8] Compliance was imperfect but high: 88% for cash payments and 75% for casual labor tasks. We discuss implications of non-compliance in Section E.5.

- a monetary transfer m that can be sent ($m > 0$ for symmetry with h) or received ($m < 0$)

Preferences are represented by the indirect utility function

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

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 of 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 τ in $(0, 1)$ using the right-hand side of (1), capturing scaled-down returns $\tau\theta$ to owning a pump. Without loss of generality, we normalize $V(0, 0, 0) = 0$ and make the following assumption:

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

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

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

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

with

$$V_\tau = v'_0 \mathbb{E}[\theta], \quad V_h = u_{l|0}, \quad \textit{and} \quad V_m = -k'_0 - v'_0.$$

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 observations from this Theorem are that the first-order approximation holds, and that the derivative V_h is continuous with respect to bundle (τ, h, m). That is, small changes in optimization problem (1) have a small impact on the shadow value of labor provision. Note that it is sometimes useful to normalize $V_m = -1$—implying that receiving 1 KSh increases indirect utility by 1 unit, as this puts the marginal value of hours worked V_h—or of the lottery ticket V_τ—in terms of the numeraire KSh.

3.1 Testable Implication of the Benchmark Model

Importantly, we believe that the choices in our study satisfy the requirements of Theorem 1: farmers are making decisions over bundles with values that are small compared to the total value of their overall optimization problem. Choice RW (reservation wage) involved 2 hours of work. The average cash bid m^{CB} for lottery tickets in choice CB was 111 KSh (equivalent to about 1.4 times the hourly market wage). The average time bid h^{TB} for lottery tickets in choice TB was 4 hours. As a result, the remainder of this section attempts to interpret choice data using linearized preferences (2). We show that this leads to a contradiction.

Direct Value of Time. A farmer's optimal choice m^{RW} corresponds to the amount of money for which the farmer is indifferent between performing two hours of work for an amount m^{RW}, and the status quo:

$$V(\tau = 0, h = 2, m = -m^{RW}) = V(\tau = 0, h = 0, m = 0).$$

Using first order approximation (2), this implies that $2V_h - m^{RW}V_m = 0$. Thus, the Direct Value of Time (DVT), defined as $\text{DVT} \equiv \frac{m^{RW}}{2}$, satisfies

$$\text{DVT} \equiv \frac{m^{RW}}{2} = \frac{V_h}{V_m}.$$

Indirect Value of Time. The indirect value of time (IVT), defined as $\text{IVT} \equiv \frac{m^{CB}}{h^{TB}}$, can also be interpreted using (2). A farmer's optimal choices m^{CB} and h^{TB} satisfy

$$V(\tau = 1, h = 0, m = m^{CB}) = V(0,0,0) \quad \text{and} \quad V(\tau = 1, h = h^{TB}, m = 0) = V(0,0,0),$$

respectively. Theorem 1 implies that

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

Hence,

$$\text{IVT} = \frac{m^{CB}}{h^{TB}} = \frac{V_h}{V_m} = \text{DVT}. \tag{3}$$

Thus, under our benchmark model, the direct and indirect measures for the marginal value of time should be equal. The next subsection shows that, in our choice data, they are not.

3.2 Evidence of Preference Intransitivity

The data clearly reject the benchmark model, as shown in Table 2. The average direct value of time DVT, elicited through choice RW, 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 choices CB and TB, is 30 KSh/hour, substantially below the mean DVT (diff = 53 KSh/hour; p-val< 0.0001). Moreover, the distribution of DVT first-order stochastically dominates the distribution of IVT, as shown in Figure 1.

At the individual level, these data suggest that a majority of farmers have cyclical, non-

Table 2: Experimental choice data (N=332 farmers)

	Mean
Direct value of time ($DVT = m^{RW}/2$)	83
Indirect value of time (IVT)	30
Cash bid (m^{CB})	111
Time bid (h^{TB})	4.0
Behavioral discount ($\widehat{r}$)	0.30

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.

transitive preferences. For instance, one of the farmers in our study, from the village of Turumba A, expressed $m^{RW}/2 = 80$ KSh, $m^{CB} = 100$ KSh, and $h^{TB} = 4$ hours (which matches the average values of these choices). This farmer would then exhibit the following choice behavior:

- 150 KSh $\prec$ 3 hours (as $m^{RW}/2 = 80$),
- $\tau = 1 \prec 150$ KSh (as $m^{CB} = 100 < 150$), and
- 3 hours labor $\prec \tau = 1$ (as $h^{TB} = 4$),

Examining these choices in the reverse order reveals a cycle: 3 hours $\prec \tau = 1 \prec 150$ KSh $\prec$ 3 hours.

For each farmer, we define

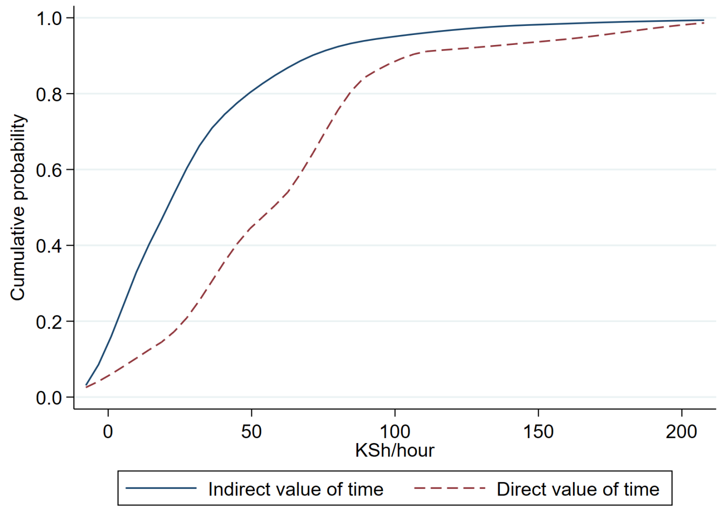
$$\widehat{r} = 1 - \frac{\text{IVT}}{\text{DVT}} \tag{4}$$

as a measure of preference intransitivity.[9] The average value of $\widehat{r}$ is 0.3, substantially higher than the benchmark prediction $\widehat{r} = 0$ (p-val<0.0001).[10]

[9] The hat emphasizes that $\widehat{r}$ is empirically observable from choice data.

[10] Note that the median value of $\widehat{r}$, 0.71, is much larger than the mean of 0.3. This is due to a long left tail in the distribution, with 17% of farmers exhibiting a $\widehat{r} < 0$. A potential explanation of this long tail is that second-order effects are significant for farmers with a high willingness to pay for the lottery ticket in cash, m^{CB}: the mean of m^{CB} for farmers with $\widehat{r} \geq 0$ is 77 KSh; for farmers with $\widehat{r} < 0$ it is 274 KSh. For a given value of $\widehat{r}$, a high m^{CB} is rationalized by a high number of working hours in the task activity, h^{TB}. As the marginal disutility of labor is likely to be very high at high values of h, these second-order effects will bring down h^{TB} and $\widehat{r}$. Our results are robust to truncating these negative values (see Table E.4).

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



Kernel-smoothed cumulative distribution functions (Van Kerm, 2012) estimated on all farmers.

We interpret these failures of transitivity as an expression of behavioral phenomena, and refer to $\widehat{r}$ as a farmer's *behavioral discount rate*. Note that, to a first order, Theorem 1 implies this wedge between DVT and IVT cannot be explained by credit or labor-supply constraints, as these are explicitly accounted for in the model, and do not generate systematic kinks in indifference curves at status quo consumption. In the next section, we use models from behavioral economics to investigate the possible causes of this discount rate, and, eventually, to obtain a structural estimate of the value of time of the self-employed.

4 Behavioral Models and Other Explanations

In this section, we delineate different models of behavioral decisionmaking that can potentially explain the wedge between DVT and IVT. We then explore alternative (and, in our view, implausible) non-behavioral explanations. Finally, we highlight how different models result in different interpretations of the data. Section 5 estimates a general structural model that nests the behavioral factors discussed here.

4.1 Behavioral Explanations

The wedge between DVT and IVT can be explained by two types of behavioral phenomena—both of which are the topics of an extensive literature—*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 from other parties, and *loss-aversion* (Kahneman et al., 1991, Kahneman and Tversky, 1979) in which a farmer inflates the cost of losses. While these phenomena both generate kinks in preferences, they are distinct: self-serving biases are relevant during social interactions, while loss aversion potentially applies to all losses. We distinguish two variants of each phenomenon: a version that treats all goods symmetrically, and a version that applies specifically to monetary transactions.

Our model nests these various phenomena in a single framework by applying a different discount to the benefits received by the agent in each of the three choice problems: under reservation wage choice RW, the size of monetary benefit is reduced by a factor $1 - r^{RW}$; under cash bid CB, the returns θ to owning the pump are scaled down by a factor $1 - r^{CB}$; under time bid, the returns θ to owning the pump are scaled down by a factor $1 - r^{TB}$. This means that choices RW, CB, and TB are characterized by the indifference conditions

$$\begin{aligned} V(0, 2, -(1 - r^{RW})m^{RW}) &= 0 \\ V(1 - r^{CB}, m^{CB}, 0) &= 0 \\ V(1 - r^{TB}, 0, h^{TB}) &= 0 \end{aligned} \quad \Rightarrow \quad \begin{aligned} 2V_h - (1 - r^{RW})V_m m^{RW} &= 0, \\ (1 - r^{CB})V_\tau + V_m m^{CB} &= 0, \\ (1 - r^{TB})V_\tau + V_h h^{TB} &= 0. \end{aligned} \tag{5}$$

Where the equations on the right-hand-side follow from linearizing using (2).

Note that there is a symmetry between shrinking the value of one object of choice, and inflating the value of the other object: for example, shrinking the value of the monetary payment in Choice RW (reservation wage) by an amount $1 - r^{RW}$ is equivalent to inflating the value of the number of hours worked in that choice by $1/(1 - r^{RW})$. Using this structure, we can solve for m^{RW}, m^{CB}, and h^{TB} in the three choices and obtain:

$$\text{DVT} \equiv \frac{m^{RW}}{2} = \frac{V_h}{(1-r^{RW})V_m} \quad \text{and} \quad \text{IVT} \equiv \frac{m^{CB}}{h^{TB}} = \frac{(1-r^{CB})V_h}{(1-r^{TB})V_m},$$

leading to an empirically observable behavioral discount rate $\widehat{r}$ defined as

$$\widehat{r} \equiv 1 - \frac{\text{IVT}}{\text{DVT}} = 1 - \frac{(1-r^{RW})(1-r^{CB})}{(1-r^{TB})}. \tag{6}$$

We now clarify how this model nests the different behavioral biases described above:

Model SB: 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 that party by an amount $1-r^{SB}$. This applies to the monetary amount received in choice RW, and the lottery ticket received in choices CB and TB. That is, $r^{RW} = r^{CB} = r^{TB} = r^{SB}$, and plugging into (6), $\widehat{r} = r^{SB}$. Thus, under this model, we can interpret the measured behavioral discount as self-serving parameter r^{SB}.

Model MSB: Money-specific Self-serving Bias. Under money-specific self-serving bias, the farmer discounts the value of money they receive from other parties by a factor $1 - r^{MSB}$, but does not discount other benefits. Thus, the farmer discounts wage offer m^{RW}, but not the lottery ticket received in choices CB and TB. As such, $r^{RW} = r^{MSB}$, while $r^{CB} = r^{TB} = 0$. Plugging into (6), we obtain $\widehat{r} = r^{MSB}$.

Model LA: Symmetric Loss Aversion. We now turn to models of loss aversion (Kahneman et al., 1991, Kahneman and Tversky, 1979). We assume that the farmer inflates the cost of losses by a factor $1/(1-r^{LA})$. That is, for example, a farmer perceives the cost of the two hours of labor in choice RW as $-2V_h/(1-r^{LA})$. As in Model SB, this affects all three choices, and as in that model, $r^{RW} = r^{CB} = r^{TB} = r^{LA}$, and $\widehat{r} = r^{LA}$.

Model MLA: Money-specific Loss Aversion. Under money-specific loss aversion, the farmer inflates the cost of unexpected monetary losses with a factor $1/(1 - r^{MLA})$. This only applies to choice CB; other losses are non-monetary, and therefore undiscounted. Thus, $r^{CB} = r^{MLA}$, and $r^{RW} = r^{TB} = 0$. Plugging into (6), we obtain $\widehat{r} = r^{MLA}$.

Note that while the $\widehat{r}$ we observe from a given set of choices is rationalized by any of these models, the preference parameters—V_h and V_τ—underlying those choices vary across models. As a result, different models lead to different implications for the value of time. In the structural model of Section 5, we use the fact that different models do not predict the same patterns of correlation across choices m^{RW}, m^{CB}, and h^{TB} to identify, under some assumptions, the distribution of preference parameters r^{RW}, r^{CB}, and r^{TB} in the population.

4.2 Interpretation

The models above can lead to different estimates for the value of time V_h in (2), which, after normalizing $V_m = -1$, we refer to as the *Structural Value of Time* (SVT). Whether the correct measure of the SVT is the DVT, IVT, or something in between, depends on the behavioral phenomena expressed in the various choices.[11] Under models SB, MSB, and LA (both self-serving biases, and symmetric loss aversion), the structural value of time coincides with the indirect value of time: SVT = IVT. In contrast, under model MLA (money-specific loss aversion), the structural value of time is equal to the direct value of time: SVT = DVT. For interior values of discount rates r^{RW} and r^{CB}, r^{TB}, the SVT will be a function of the DVT and/or the IVT, involving the unknown discount rates.

These different models lead to a range of possible values for farmers' structural value of time. The lower bound, corresponding to models SB, MSB, and LA, is 30 KSh/hour, or about 40% of the market wage, as shown in Table 2. The upper bound, corresponding to model MLA, is 83 KSh/hour, roughly equal to the market wage.

[11]This final statement requires $r^{CB} \geq r^{TB}$, which is true in all four models, as well as our estimation results.

As we show in Section 6 by re-examining the conclusions of prior evaluations, knowing that the value of time is somewhere in this broad range may be sufficient to draw conclusions about whether or not a particular intervention is beneficial. However, there are also interventions where more precise estimates are necessary. Section 5 refines this range using a structural model that nests all four behavioral explanations.

4.3 Non-Behavioral Alternatives

Explaining the wedge between DVT and IVT requires a steep change, or kink, in the indirect utility function (1). In the behavioral explanations above, this kink comes from discounting goods one receives from another party relative to those one sends to another party (self-serving bias) or weighing losses more heavily than gains of equivalent size (loss aversion).

Although implausible to us, a kink coming from second-order effects of credit and labor constraints is possible. To illustrate both how such an explanation would work, and its implausibility, we provide an example: 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 RW). They find the lottery ticket potentially very attractive, so they are willing to supply a relatively large amount of labor for it (Choice TB). However, even though farmers find the lottery ticket an attractive proposition, they are only willing to pay a relatively small amount for it because the cost pushes them into a binding credit constraint (Choice CB).[12]

We believe this is implausible. Farmers operate in an environment that includes many opportunities for useful investment, and are likely already credit constrained when we offer them our choices. Furthermore, as the valuations expressed by the farmers reflect, the acquisition of a lottery ticket constitutes a relatively small change to their economic environment, worth at most a few hours of labor. Thus, we do not believe the choices farmers made as part of our study radically changed their shadow cost of capital.

[12]Equivalently, right below a sudden kink in the value function for cash-on-hand k.

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 RW and Choice TB, risk aversion, order effects of the bidding activities, anchoring, non-compliance, bid censoring, and stigma surrounding low wages.

5 Structural Estimation

Before we turn to the model, it is useful to provide an intuitive argument for why identification of specific behavioral mechanisms may be possible. Figure 2 simulates the relationship between choice data m^{RW}, m^{CB}, h^{TB}, and the log-linearized behavioral discount rate $-\log(1-\widehat{r})$ defined in (4), under the four models in Section 4. Simulated choices assume that parameters r—as specified in the definitions of models SB, MSB, LA, and MLA—V_τ, and V_h are drawn independently across farmers, according to log-normal distributions with parameters chosen to match our experimental data.

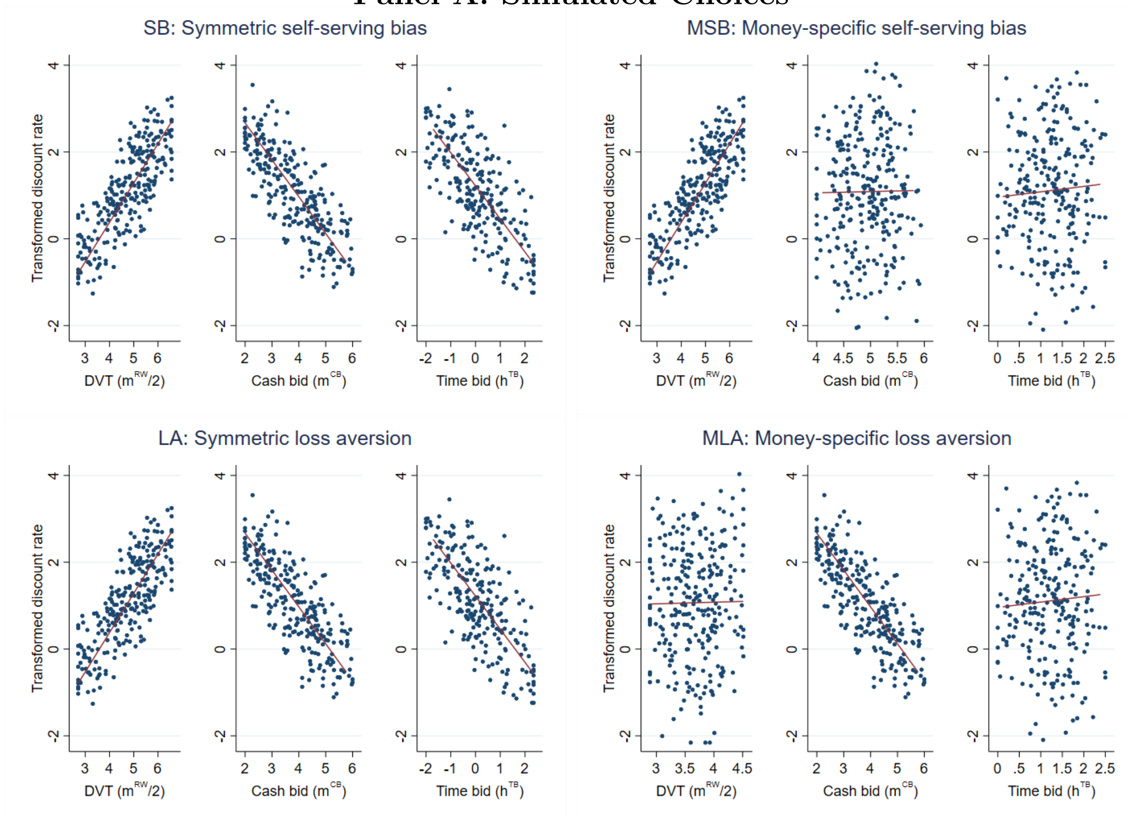
In our data, farmers' time bids h^{TB} (labor bid for a lottery ticket) are uncorrelated with the behavioral discount rate $\widehat{r}$. Our behavioral models exhibit either negative correlation between h^{TB} and $\widehat{r}$ (models SB and LA) or zero correlation (models MSB and MLA). Additionally, in our data, $\widehat{r}$ is positively correlated with m^{RW} (reservation wage), and negatively correlated with choice m^{CB} (cash bid for a lottery ticket). Taken together, these correlations can only be explained by a mixture putting weight on both models MSB (money-specific self-serving bias) and MLA (money-specific loss aversion). In the next subsection, we formalize this intuitive argument.

5.1 Framework and Data-generating Process

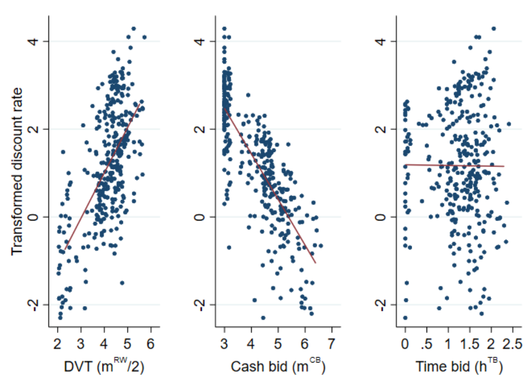
We return to the general model in (5), which contains (potentially independent) parameters r^{RW}, r^{CB}, and r^{TB} that can affect each choice in a distinct way. We use this model to specify variation in preferences across farmers. We index farmers by $i \in \{1, \cdots, N\}$, normalize

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

Panel A: Simulated Choices



Panel B: Experimental Choice Data



Panel A shows the relationships between choices m^{RW}, m^{CB}, m^{TB}, and the behavioral discount rate r that would arise under each of our behavioral models using simulated data. **Panel B** shows the same relationships observed between choices in our experimental data. Each observation is a farmer with a 3% jitter. OLS line in red. All variables are log transformed. Transformed discount rate $= -\log(1 - \widehat{r})$.

$V_m = -1$, and allow for farmer-level heterogeneity so that (5) takes the form

$$2V_{h,i} + (1 - r_i^{RW})m_i^{RW} = 0, \quad (1 - r_i^{CB})V_{\tau,i} - m_i^{CB} = 0, \quad (1 - r_i^{TB})V_{\tau,i} - V_{h,i}h_i^{TB} = 0. \quad (7)$$

It is convenient to re-express farmer i's discount rates r_i^{RW}, r_i^{CB}, and r_i^{TB} as

$$1 - r_i^{RW} = \exp(-\rho_i \gamma^{RW}), \qquad 1 - r_i^{CB} = \exp(-\rho_i \gamma^{CB}), \qquad 1 - r_i^{TB} = \exp(-\rho_i \gamma^{TB})$$

with γ parameters such that $\gamma^{RW} + \gamma^{CB} + \gamma^{TB} = 1$.

Thus, parameter ρ_i is an aggregate index of farmer i's propensity to discount gains, while parameters γ^{RW}, γ^{CB}, and γ^{TB} capture the relative intensity with which gains are discounted across choice problems.

We impose two main assumptions:

Assumption 2. *Farmers vary in the degree of behavioral biases they exhibit (ρ_i), but not in the relative importance of each bias (γ^X fixed across all i for $X \in \{RW, CB, TB\}$).*

Assumption 3. *Conditional on observable characteristics, behavioral parameter ρ_i is uncorrelated with the logarithms of preference parameters $V_{\tau,i}$, and $V_{h,i}$.*[13]

With these assumptions, (7) then implies

$$\begin{aligned} \log(m_i^{RW}/2) &= \log(-V_{h,i}) + \rho_i \gamma^{RW} \\ \log m_i^{CB} &= \log V_{\tau,i} - \rho_i \gamma^{CB} \\ \log h_i^{TB} &= \log V_{\tau,i} - \log(-V_{h,i}) - \rho_i \gamma^{TB}. \end{aligned} \quad (8)$$

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

$$1 - \widehat{r}_i = \frac{\mathrm{IVT_i}}{\mathrm{DVT_i}} = \frac{2m_i^{CB}}{m_i^{RW} h_i^{TB}}.$$

[13] An alternative model—in which farmers are randomly affected by a single discount rate, and the relative probabilities of being affected by each are constant—is also identified, and leads to almost exactly the same estimate of the mean of log(SVT).

Hence, it follows from (8) that

$$\log \frac{1}{1-\widehat{r}_i} = \log(m_i^{RW}/2) - \log(m_i^{CB}) + \log(h_i^{TB}) = \rho_i(\gamma_A + \gamma_B - \gamma_C). \tag{9}$$

Note that $\widehat{r}_i \neq 0$ for many farmers, implying $\gamma^{RW} + \gamma^{CB} - \gamma^{TB} \neq 0$, which is needed for estimation.

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

$$\begin{aligned} \log(m_i^{RW}/2) &= c_A + \widehat{\delta}^{RW} \log \frac{1}{1-\widehat{r}_i} + \epsilon_i^{RW} \\ \log m_i^{CB} &= c_B - \widehat{\delta}^{CB} \log \frac{1}{1-\widehat{r}_i} + \epsilon_i^{CB} \\ \log h_i^{TB} &= c_C - \widehat{\delta}^{TB} \log \frac{1}{1-\widehat{r}_i} + \epsilon_i^{TB}. \end{aligned} \tag{10}$$

Theorem 2 (identification)**.** *With probability one as the sample size N gets large:*

- *For all $X \in \{RW, CB, TB\}$,*

$$\widehat{\gamma}^X \equiv \frac{\widehat{\delta}^X}{\widehat{\delta}^{RW} + \widehat{\delta}^{CB} + \widehat{\delta}^{TB}} \to \gamma^X;$$

- *For all $i \in \{1, \cdots, N\}$,*

$$\widehat{\rho}_i \equiv (\widehat{\delta}^{RW} + \widehat{\delta}^{CB} + \widehat{\delta}^{TB}) \log \frac{1}{1-\widehat{r}_i} \to \rho_i.$$

Simulations show that these estimators perform well for sample sizes similar to that of our data.[14] Standard errors are obtained using bootstrap methods with 10,000 draws.

[14]That is, across a large number of simulations, estimating the model (10) on data simulated from the two symmetric models (SB & LA), produces estimates of $\widehat{\gamma}^{RW}$, $\widehat{\gamma}^{CB}$, and $\widehat{\gamma}^{TB}$ very close to 0.33. Estimations on data generated using the money-specific self-serving bias model (MSB) produces estimates of $\widehat{\gamma}^{RW}$ very close to 1. Finally, estimations on data generated from the money-specific loss aversion model (MLA), produces estimates of $\widehat{\gamma}^{CB}$ very close to 1. [XXX this seems unnecessary + we will be asked to provide code for this; also, do we actually run simulations for sample sizes similar to our data?]

Theorem 2 allows for consistent estimates of the structural value of time of farmer i, $\widehat{SVT}_i$, which can be recovered using (8), given estimates $(\widehat{\gamma}^{RW}, \widehat{\gamma}^{CB}, \widehat{\gamma}^{TB})$ and $\widehat{\rho}_i$:

$$\widehat{SVT}_i = -\widehat{V}_{h,i} \equiv \frac{m_i^{RW}}{2} \exp(-\widehat{\rho}_i \widehat{\gamma}^{RW}). \tag{11}$$

Note that this formula represents the process described intuitively in the introduction: data from all three choices are used to estimate the extent to which choice RW is impacted by behavioral phenomena $(\widehat{\rho}_i \widehat{\gamma}^{RW})$, and then to remove that effect.

5.2 Estimation Results and Robustness

Across the specifications and sub-populations in Table 3, all estimated using Theorem 2, choice TB shows no evidence of distortions $(\widehat{\gamma}^{TB} = 0)$, while those choices that involve cash are the source of distortions $(\widehat{\gamma}^{RW}, \widehat{\gamma}^{CB} > 0)$.[15] This pattern is the same as that shown in Figure 2: distortions are consistent only with models MSB and MLA—each of which posits that participants treat choices involving cash differently.

These results suggest that, in most cases, the estimated Structural Value of Time is the appropriate value of time to use in evaluating interventions. This is because most interventions involve trade-offs between time and a good—such as working longer for improved farm yields—rather than between time and cash, and our choice data suggest no distortion in these trade-offs.[16]

Fitting data from the full sample, in Column 1, results in a mean structural value of time 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

[15] As 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 DVT above 250 KSh/hour, we test for sensitivity to recoding in Table E.4. The estimated shares $\widehat{\gamma}^{RW}, \widehat{\gamma}^{CB}, \widehat{\gamma}^{TB}$ change little across specifications, and the estimated mean structural value of time is very stable at 59–60% of the market wage.

[16] Additionally, interventions typically affect choices—such as working hours on a family farm—that do not involve transactions with other people, and are well-integrated into reference expectations.

Table 3: Behavioral bias appears only in transactions over cash—cash bids and DVT—across several subgroups.

	(1)
	Full sample
Structural estimation	
Reservation wage share ($\widehat{\gamma}^{RW}$)	0.39
	(0.023)
Cash bid share ($\widehat{\gamma}^{CB}$)	0.61
	(0.026)
Time bid share ($\widehat{\gamma}^{TB}$)	0.003
	(0.015)
Structural value of time ($\widehat{SVT}$)	49
	(2.5)
Market wage (w)	82
	(1.8)
Relative value of time ($\widehat{SVT}/w$)	0.60
	(0.034)
Experimental choices	
Direct value of time (DVT)	83
	(3.0)
Indirect value of time (IVT)	30
	(1.9)
Cash bid	111
	(6.9)
Time bid	4.0
	(0.1)
Behavioral discount (r)	0.30
	(0.067)
Observations	332

Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 KSh). See Section 5 for details on the structural model. 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). Column (8) controls for unincentivized proxies of the value of time and the valuation of the lottery ticket. Cash and time bids bottom-coded at 20 KES and 1 hour respectively. Bootstrap standard errors in parentheses.

100% of the market wage). The rest of this subsection describes the results from performing the same estimation on various subgroups, or with additional controls, which allows us to provide support for the identifying Assumptions 2 and 3.

Behavioral Phenomena across Sub-populations. Both theoretical and empirical analyses suggest that behavioral phenomena will be less pronounced when individuals are experienced with specific choices (List, 2003, Feng and Seasholes, 2005, Kőszegi and Rabin, 2006, Carney et al., 2019). Column 2 of Table 3 shows data for those who have performed casual labor within the past three months, while Column 3 shows individuals who self-report that they have considered purchasing a MoneyMaker pump. We find that both subgroups exhibit less severe behavioral discounting: both groups have behavioral discount rates $\widehat{r}$ slightly less than 0.2, compared with 0.3 for the full sample.[17] Despite this difference, the shares γ are very similar to the full sample, and estimates of SVT in these subgroups are 62% and 54% of the market wage: close to the 60% estimated in the full sample. This finding provides initial support for Assumption 2, as the shares are quite similar in both subgroups, despite other differences. These results also provide support for the rule-of-thumb approximation of SVT as 60% of market wages.

Check of Assumption 2. To investigate both 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. 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 $V_{\tau,i}$ and $V_{h,i}$ is more likely to hold. We form 4 groups using partition around medoids (PAM) cluster analysis, which is described in Appendix D. We characterize these four clusters—sorted from lowest to highest average behavioral discount rate $\widehat{r}$—as consisting of the low-skill self-employed, low-skill employees, hirers of casual labor, and older, low-education households that do not hire or provide casual

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

labor. These characterizations are based on the strongest predictors of membership in each group, as shown in Table D.1.

Estimated parameters γ^{RW}, γ^{CB}, and γ^{TB} are very stable across clusters, as shown in Columns 4–7 of Table 3. This supports Assumption 2: that shares γ are fixed across the sample. The estimated value of time is also stable, with most of the variation driven by differences in the market wage or DVT. This is true despite the fact that the overall magnitude of the behavioral discount rate $\hat{r}$ varies substantially across clusters—from 0.12 to 0.74.

Check of Assumption 3. We can evaluate the plausibility of Assumption 3—that farmers' discount rates ρ_i are uncorrelated with $\log(V_{\tau,i})$ and $\log(-V_{h,i})$—by examining the estimates of $\widehat{\rho}_i$ conditional on the log of proxies of $V_{\tau,i}$ and $-V_{h,i}$ that are not themselves influenced by behavioral phenomena. If the estimates of $\widehat{\rho}_i$ are unaffected by including the log of such proxies, this implies that ρ_i is uncorrelated with $\log(V_{\tau,i})$ and $\log(-V_{h,i})$.

Under the premise that behavioral phenomena are exacerbated by stake size—as initially formulated by Kahneman and Tversky (1979), and later documented empirically (for example, Ert and Erev, 2013, Easton and Pinder, 2021)—unincentivized choices will be less affected by behavioral biases, but still serve as proxies for preference parameters. We investigate whether this is the case for unincentivized survey responses. We have two such unincentivized proxies. First, we use stated willingness to work—in hours—for a lottery ticket for an irrigation pump (collected as part of a baseline survey conducted five years earlier, in 2014) as a proxy for $V_{\tau,i}$. Second, we use the stated minimum amount of money for which the respondent would be willing to travel one hour (collected during our main 2019 survey) as a proxy for $V_{h,i}$.

We find that these unincentivized proxies are uncorrelated with the behavioral phenomena, but strongly correlated with bids. The p-value from the bivariate regression of $-\log(1-\widehat{r}_i)$ on the logarithm of the unincentivized willingness to work for the ticket is 0.50, and on the logarithm of the unincentivized reservation payment for traveling one hour it is

0.29. The p-values from bivariate regressions of $\log(m_i^{CB})$ and $\log(h_i^{TB})$ 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 $\log(m_i^{RW}/2)$ on the logarithm of the unincentivized reservation payment for traveling 1 hour is 0.01.

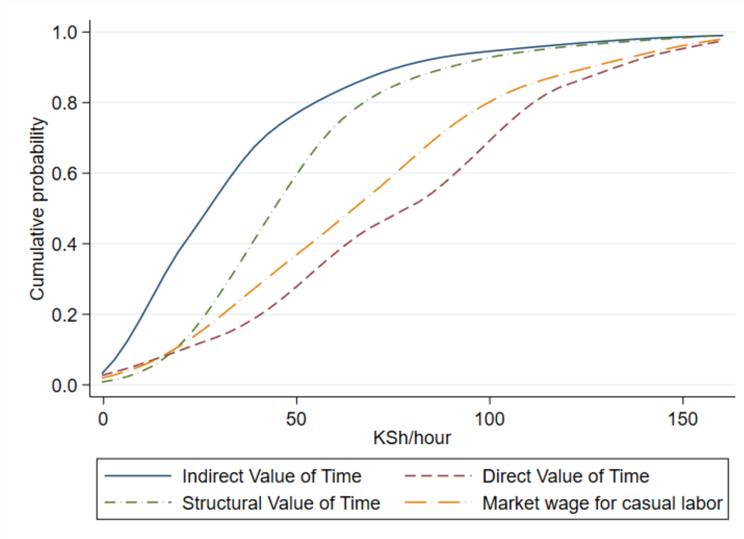
Controlling for the log of the unincentivized proxies of $V_{\tau,i}$ and $-V_{h,i}$, in Column 8 of Table 3, has very little effect on our estimates. In particular, $\widehat{\rho}_i$ changes very little between Columns 1 and 8—from an average of 1.18 to 1.17. This suggests that, indeed, $\log(V_{\tau,i})$ and $\log(-V_{h,i})$ are uncorrelated with ρ_i, which is exactly Assumption 3.

Additionally, if preference parameters are uncorrelated with ρ_i, then the DVT among farmers exhibiting no behavioral phenomena 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 market wage. This is close to the average SVT of 49 KSh/hour in the full sample.

6 Discussion

This paper seeks to better understand how to account for peoples' value of time in policy evaluations. We show that a direct, incentivized, BDM-based approach in which participants perform casual labor for money may not produce reliable results due to behavioral phenomena. In particular, participants seem to overvalue their time when exchanging it for cash. Using a design involving choices between time, money, and a third good, we are able to identify the effects of behavioral phenomena and recover a welfare-relevant structural value of time. This value of time is roughly 60% of both the value elicited through a direct BDM mechanism and the market wage for casual labor. Figure 3 displays these facts visually for the entire distribution of participants. Market wages and reservation wages elicited through a direct BDM mechanism are fairly similar. However the structural value of time is unquestionably much lower than either the market wage or the BDM elicitation.

Figure 3: The Structural Value of Time is lower than wages and the Direct Value of Time.



Kernel-smoothed cumulative distribution functions (Van Kerm, 2012) estimated on all farmers. All variables top coded at 150 KSh/hour.

6.1 Implications for Labor Markets

The majority of employment in Africa is self-employment in the informal sector (O'Higgins et al., 2020). Self-employment may be disguised excess labor supply (Breza et al., 2021) generated by frictions such as wage rigidity (Kaur, 2019). Our results suggest an additional factor contributing to high self-employment levels: self-serving bias. As this bias can cause an impasse in negotiations even when information is complete (Babcock and Loewenstein, 1997), it may lead workers to opt for self-employment over higher-paying informal jobs.[18] Specifically, a self-serving bias may lead workers to turn down job offers that would be welfare improving absent the bias, thereby driving self-employment levels above the neo-classical equilibrium.[19] Note that the presence of self-serving bias may make maintaining norms of not accepting lower wage jobs easier, which Breza et al. (2019) identifies as a key

[18]The other cause of behavioral phenomena in our data—money-specific loss aversion—could cause those who hire casual labor to undervalue it relative to cash during negotiations. Unfortunately, we do not observe willingness to pay for labor in any of our activities.

[19]Note that this analysis does not imply that behavioral phenomena are welfare reducing in equilibrium, even for a given individual. In strategic contexts like wage bargaining, behavioral phenomena can influence the behavior of other parties, helping individuals to obtain better terms.

Table 4: Evidence of shirking at lower wages

Random wage (× 10-KSh / hour)	0.062
	(0.036)
2-sided p-value	0.10
Observations	29
Sample	Wage workers
Control for predicted compliance?	No

An observation is a farmer who showed up to the task day to perform work for wages ("Wage workers") or for a lottery ticket ("Task workers"). The dependent variable is a dummy = 1 if the monitor judged the worker to have performed work quality at or above the sample median. "Random wage" for wage workers is the wage drawn in the RW BDM; for task workers it is the estimated average ticket valuation V_τ divided by the number of work hours drawn in the TB BDM. Wage units are in 10-KSh increments. Regressions on wage workers control for the reservation wage elicited through BDM (DVT); regressions on task workers control for the maximum working hours elicited through BDM (h^{TB}). All regressions control for DVT and a work-site fixed effect (each village was assigned one work site). Robust standard errors in parentheses.

source of labor rationing.[20]

Alternatively, if self-serving bias does not extend to labor market negotiations, then the finding that market wages for casual labor first-order stochastically dominate the Structural Value of Time suggests that wages are higher than the market-clearing rate, and that casual jobs are rationed. Job rationing may be a response to workers' shirking due to imperfect monitoring (Shapiro and Stiglitz, 1984). We are able to test for this in our setting using the random variation in effective hourly wage paid for casual work within choices RW and TB. Specifically, we test whether the quality of work performed—as measured by our field staff after work was completed—depends on the random wage paid.[21] For example, in the RW choice, the wage paid for day work is random, and—because only those who drew a wage higher than their reservation wages were eligible to work—eligibility is random conditional

[20]We also test for norms preventing workers from accepting low-wage work, as in Breza et al. (2019). These norms do not appear strong in our context, and do not predict variation in DVT; see Appendix Table E.7.

[21]We do not distinguish between shirking—which occurs because of imperfect monitoring and can lead employers to pay higher wages (Shapiro and Stiglitz, 1984)—and shading—which occurs because of deviations from reference points (Fehr et al., 2011, Hart and Moore, 2008).

on DVT.

There is evidence of shirking at lower wages, but not when more work is being performed for a set reward. We regress a binary measure indicating whether the quality of work was above the median rating in our distribution on the random effective wage, controlling for the DVT and a worksite fixed effect.[22] Because the random wage may affect the decision to show up for work, we add controls for predicted compliance (see Section E.5).[23] There is significant evidence of shirking when working for a wage: Table 4 shows that each 10-KSh increase in the hourly wage increases the chance of performing high-quality work by seven percentage points (p-value = 0.08). There is no significant evidence of shirking for farmers performing casual work for the lottery ticket: the point estimate on the effect of a 10-KSh increase in the implied hourly wage is 2 percentage points and is not statistically different from zero. This suggests that, when paying cash, it may be worthwhile to pay a higher wage to increase the average quality of work, leading to fewer jobs at higher wages.

6.2 Value of Time Assumptions in the Literature

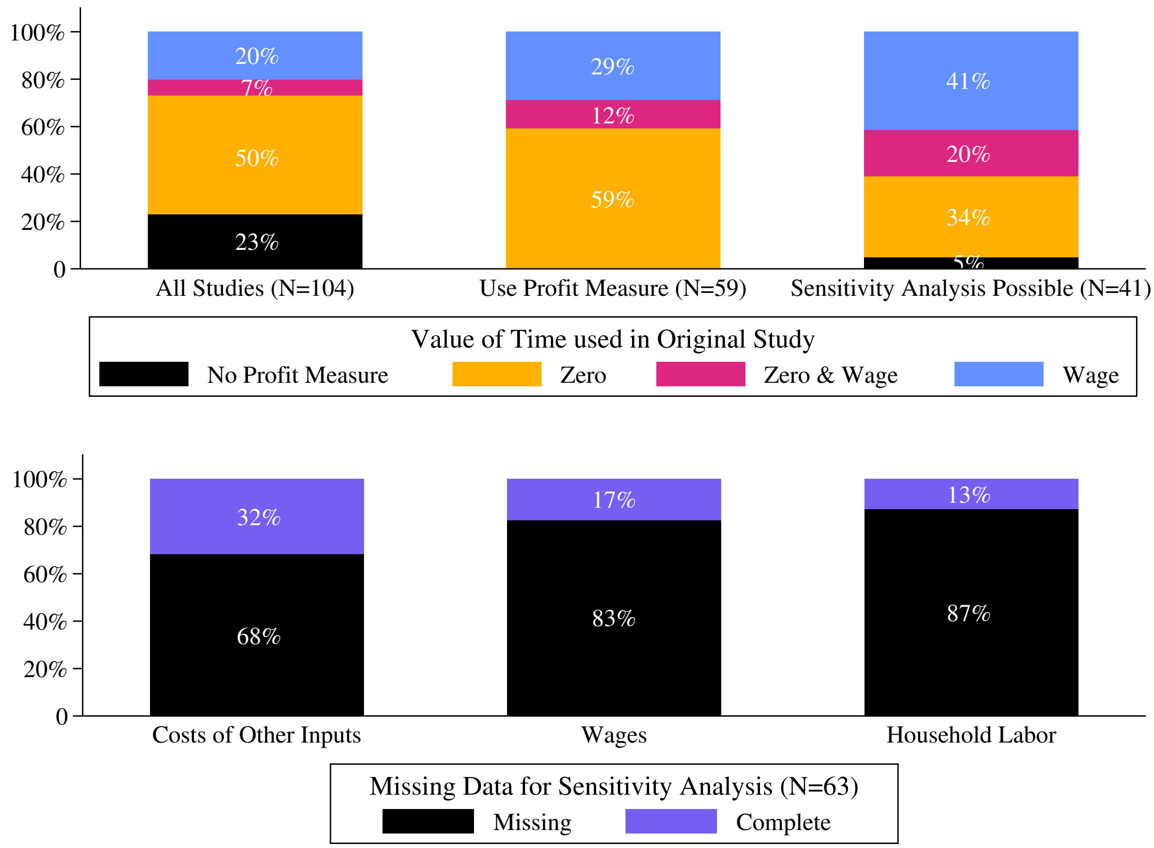
In this section we survey the extant literature to understand how it accounts for the value of time of the self-employed. We searched top economics journals for any study in the past 6 years (2015-2021) of the self-employed in a developing country, in which revenue or profits were measured.[24] This search resulted in a total of 104 studies, of which a minority of 41

[22]Average wages paid in the RW choice were 70 KSh/hr; the average effective wage—defined as the average ticket valuation divided by the required number of work hours—in the TB choice was 57 KSh/hr. Work quality was measured on a 5-point scale. The median quality report was a 4.

[23]Work days took place 1–2 weeks after farmers made their choices, so the decision to show up on the work day may be affected by the random wage draw. We see no evidence of this: regressing a dummy for showing up to work on the random wage draw—controlling for the reservation wage and a worksite fixed effect—yields small, insignificant coefficients: 3 percentage point per 10-KSh increase for wage workers, p-val = 0.47; -1 percentage point per 10-KSh increase for task workers, p-val = 0.73.

[24]In particular, we searched Top-5 journals, plus top applied journals (*Journal of Development Economics* and *American Economic Journal: Applied Economics*), and top ag-econ journals (*American Journal of Agricultural Economics* and *European Review of Agricultural Economics*) for papers with 45 *JEL* codes during the years 2016–2021. The reviewed *JEL* codes can be found in Appendix F. The papers that resulted from this search were then read to find those that concerned the self-employed, and measured revenue or profits.

Figure 4: Value of time used in prior literature on the self-employed



contained enough information, in theory, for us to reinterpret their results in light of our findings.[25] Of those, we were only able to obtain the data for XXX studies that allowed us to re-interpret their results.

As shown in the top-left bar of Figure 4, 23% of these 104 studies do not attempt to use profit as an outcome, instead only reporting output-oriented measures that do not account for changing costs. Many of these papers justify their focus on output with the fact that it is difficult to measure the value of time for the self-employed (see, for example, Suri, 2011,

[25]Analyzing the sensitivity of results to assumptions about the value of time requires three pieces of information: household labor, the locally prevailing market wage, and revenue net of other input costs.

Beaman et al., 2021, Ahmed et al., 2021). An additional 50% of the studies compute profit estimates using zero as the value of time. That is, 73% of the studies we found do not base their evaluation on a welfare-relevant measure. The remaining studies (27%) use the market wage to value the time of the self-employed. A subset of these (7% of all studies) use both zero and the market wage to bound profit estimates under a range of values of time, similar to our first simple strategy above—although we recommend a lower bound of 40% of the market wage.

Among studies that made use of an outcome measure described as "profit" or "net revenues" (N=59), a full 60% use a value of time of zero, as shown in the middle-top bar of Figure 4. Studies with sufficient information for us to re-evaluate their results (N=41) were more likely to impute value to the time of the self-employed, with 61% assigning a positive value, as shown in the top-right bar.[26] We were not able to re-evaluate 63 of the 104 studies because many were missing important cost data, as shown in the bottom panel of Figure 4. The most common missing data were on household labor supply or market wages, although many of these studies were also missing the costs of other inputs, such as seed and fertilizer.

The fact that many recent studies do not measure input costs even though they consider profits as a primary outcome may be surprising. It may stem from a 2009 study concluding that one may not need to "ask how the sausage is made": De Mel et al. (2009) estimate that simply asking the self-employed to report their profits provides a better measure than computing profits based on detailed questions on revenues and costs—because the self-employed under-report revenue but not costs. That study does not consider own hours worked as a cost, however, de facto valuing the time of the self-employed at zero.[27] Yet two programs that impact profits equally, but affect work hours for the business owner differently, can hardly be thought of as having the same welfare impact.

[26]Of these 41 studies, 7 contained sufficient information in the paper itself for us to re-evaluate their results, while an additional 34 studies required us to gather the source data for the paper. We received data for XX of the 34. We thank the authors who provided these data.

[27]When eliciting profits directly, they ask: "What was the total income the business earned during the month of [March] after paying all expenses including the wages of employees, *but not including any income you paid yourself.* That is, what were the profits of your business during [March]?

6.3 Practical Implications for Researchers

Finally, we describe practical lessons that researchers interested in accounting for participants' value of time can draw from our research, and, in the next subsection, apply the simple techniques we describe here to a few prior studies in order to illustrate their potential usefulness.

How might one evaluate the value of time of the self-employed? We begin with two simple strategies:

Use a range of 40–100% of the market wage. This does not require committing to a particular behavioral model, and, as we illustrate below in Figure 5, is often sufficient for evaluating whether a particular intervention is beneficial or not. However, for some applications, a point estimate may be necessary, in which case we suggest that researchers:

Use 60% of market wage. Researchers evaluating interventions in similar contexts as ours could opt to rely on our estimate that the value of time is close to 60% of the market wage for casual labor.

The main limitation of these approaches is external validity: factors that keep wages above the value of time 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. (2021), or that the importance of behavioral phenomena varies across seasons and/or populations.

A more complex strategy, but one that might be useful for large-scale studies that need a precise value of time, would be to replicate our choices and analysis. Interventions that are likely to substantially increase or decrease family labor supply are the most likely to meet this criterion. If the study is large enough, adding a replication of our method may have a relatively low marginal cost. This does present some challenges—it requires scheduling workdays and transporting workers to and from work sites—so conducting this exercise within a representative subset of participants may be optimal.

Regardless of the strategy used to estimate the value of time, researchers will need to take a stand on how to incorporate behavioral parameters into welfare evaluations. Our results suggest that the behavioral features observed in this study are specific to transactions involving cash. The Structural Value of Time, V_h, is appropriate for an intervention in which participants are exchanging time for a good—for example, irrigating longer to increase yields. The Direct Value of Time, m^{RW}, is appropriate for an intervention involving time exchanged for cash—for example, one that increases the supply of casual labor.

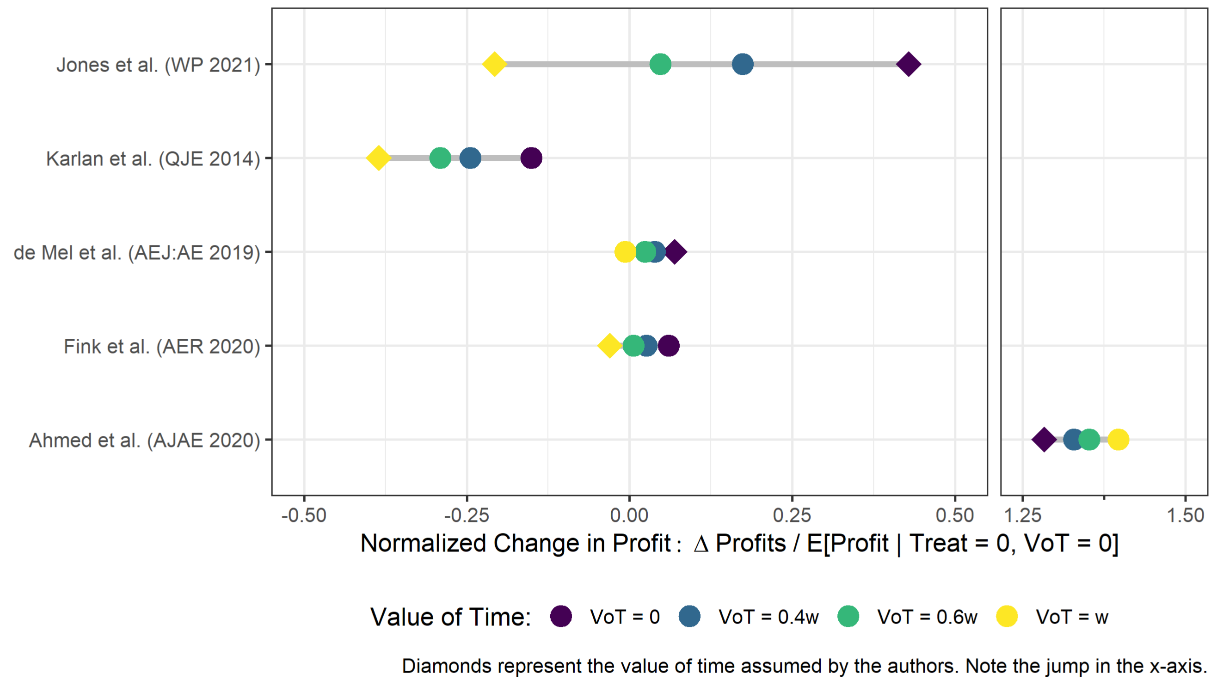
6.4 Applying Our Results to the Literature

Finally, we apply our bounding and rule-of-thumb strategies to prior studies. We calculate treatment impacts under four assumptions about the value of time of the self-employed: zero, and 40%, 60%, and 100% of the market wage. Results from five selected studies are shown in Figure 5. To standardize outcome measures across studies, we report treatment effects on profits normalized by mean profits in the control group.

Impact assessments are most sensitive to assumptions about the value of time when the intervention significantly changes participants' labor supply. Two examples are Jones et al. (2020), which estimates the impact of irrigation by small-scale farmers, and Karlan et al. (2014), which studies the introduction of rainfall index insurance. In each of these cases, treatment effect estimates vary dramatically depending on the assumed value of time. In particular, for Jones et al. (2020), as the authors themselves point out, impacts are negative when valuing time at the market wage, but very large when the labor is valued at zero. The rule-of-thumb we propose suggests that the negative profit impact scenario can likely be rejected: our recommended lower bound on the effect of profits ($0.4w$) is positive.

For interventions producing more modest changes in labor supply, the assumed value of time remains important, though less dramatically so. Two examples are de Mel et al.

Figure 5: Sensitivity of estimated profit impacts to the assumed value of time



(2019), which subsidizes paid employees of micro-enterprises and finds small treatment effects on family labor, and Fink et al. (2020), which subsidizes loans to farmers during the lean season. In each of these studies, estimated treatment effects are positive when valuing time using our rule-of-thumb of 60% of the market wage, but negative when valuing time at the market wage. For de Mel et al. (2019), estimated treatment effects are statistically significant under the authors' assumed value of time of 0, but statistically insignificant under our rule-of-thumb assumption.

Finally, for labor saving technologies, using a more reliable value of time can increase their apparent efficacy. For example, Ahmed et al. (2021) studies the introduction of genetically-modified eggplant in Bangladesh, which reduces the amount of time farmers spend on weeding and applying pesticides. Note that, in Figure 5, for this study profit estimates are in reverse order—highest when time is most highly valued. In particular, valuing time at zero leads to an estimate that is too low, as it fails to account the saved farmer labor. This highlights a general point: relative to more appropriate assumptions about the value of time, valuing participants' time at zero overestimates the efficacy of interventions that increase participants' time use, and underestimates the efficacy of those that save time.

Reviews of technology adoption in developing economies indicate that relatively few labor-saving technologies have been evaluated, consistent with researchers focusing on yield or revenue-maximization, while ignoring costs (de Janvry et al., 2017, Macours, 2019, Magruder, 2018). As the self-employed likely prioritize profit—not revenue—maximization, failure to properly account for labor, which is often a primary cost, may explain why some technologies that appear welfare-improving when the value of participants' time is ignored are not adopted. It also suggests that technologies that could improve welfare by saving users' time may not appear welfare-improving in evaluations, and thus may not be deployed by development agencies. Under the principle that we only value what we measure, accounting for the labor of self-employed workers may help redirect efforts to improve the lives of the poor in novel and useful ways. It is not difficult to imagine several channels by which labor saving technologies can improve welfare: increased leisure (Devoto et al., 2012); increased female labor participation (Albanesi and Olivetti, 2016); increased school participation;[28] improved mental health, and cognitive capability (Bessone et al., 2021); reduced pain (Xiao et al., 2013), and pain management through alcohol (Schilbach, 2019), and so on.

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." We believe our method and estimates mark a substantial advance in answering this important question.

[28] Pinker (2018) cites this tractor advertisement from 1921 (p.231): By investing in a Case Tractor and Ground Detour Plow and Harrow outfit now, your boy can get his schooling without interruption, and the Spring work will not suffer by his absence. Keep the boy in schooland let a Case Kerosene Tractor take his place in the field. Youll never regret either investment.

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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, Δz, 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

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

with

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

The fact that

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

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

Proof of Theorem 2. Equations (8) and (9) imply that

$$\begin{aligned}
\log(m_i^{RW}/2) &= \log(-V_{h,i}) + \frac{\gamma^{RW}}{\gamma^{RW}+\gamma^{CB}-\gamma^{TB}} \log \frac{1}{1-\widehat{r}_i} \\
\log m_i^{CB} &= \log V_{\tau,i} - \frac{\gamma^{CB}}{\gamma^{RW}+\gamma^{CB}-\gamma^{TB}} \log \frac{1}{1-\widehat{r}_i} \\
\log h_i^{TB} &= \log V_{\tau,i} - \log(-V_{h,i}) - \frac{\gamma^{TB}}{\gamma^{RW}+\gamma^{CB}-\gamma^{TB}} \log \frac{1}{1-\widehat{r}_i}.
\end{aligned}$$

Under the assumption that ρ_i—and thus also $-\log(1-\widehat{r}_i)$, a linear transformation of ρ_i—is uncorrelated with $\log(V_{\tau,i})$ and $\log(-V_{h,i})$, it follows that for all $X \in \{RW, CB, TB\}$, OLS coefficient $\widehat{\delta}^X$ consistently estimates $\gamma^X/(\gamma^{RW}+\gamma^{CB}-\gamma^{TB})$. In turn, the assumption that $\gamma^{RW}+\gamma^{CB}+\gamma^{TB}=1$ implies that $\widehat{\delta}^{RW}+\widehat{\delta}^{CB}+\widehat{\delta}^{TB}=1/(\gamma^{RW}+\gamma^{CB}-\gamma^{TB})$.

This implies that for all $X \in \{RW, CB, TB\}$, $\widehat{\delta}^X/(\widehat{\delta}^{RW}+\widehat{\delta}^{CB}+\widehat{\delta}^{TB})$ is a consistent estimator of γ^X. ■

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.[29]

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 CB and TB occurred at the beginning of the survey, in random order. Choice RW 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 RW (Reservation Wage): Time vs. Money. Each farmer was asked whether they 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 their reservation wage in a single question. Once their reservation wage was determined, it was explained once more that if the wage drawn were 10 KSh lower than their stated reservation wage, they would be unable

[29]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.

to take the job. At this point, they were given the option to revise their answer.[30]

Choice CB (Cash Bid): Money vs. Lottery Ticket. Each farmer was asked whether they 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 their maximum willingness to pay (WTP) in a single question. Farmers were not aware that there was a price ceiling during the elicitation. Once their WTP was determined, it was explained once more that if the price drawn were 20 KSh higher than their stated WTP, they would be unable to purchase the ticket. At this point, they were given the option to revise their answer.

Choice TB (Time Bid): Time vs. Lottery Ticket. Each farmer was asked whether they 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 their maximum WTP (in hours) in a single question. Farmers were not aware that there was an hours ceiling during the elicitation. Once their WTP was determined, it was explained once more that if the price drawn were 30 minutes greater than their stated WTP, they would be unable to purchase the ticket. At this point, they were given the option to revise their 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

[30] 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.[31]

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),

[31]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^{CB}—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^{TB}—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 $m^{RW}/2$—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 Correlates of Bias

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

$$y_i = \alpha + X_i'\Gamma + \epsilon_i, \tag{12}$$

where y_i is an experimental choice such as the behavioral discount rate $\widehat{r}$, X_i is a vector of predictor variables, and ϵ_i is an error term. To account for censoring in bids, we estimate (12) using Tobit models. Table C.1 shows results. Table C.2 displays bivariate estimates of (12). Results are overall very similar across these two specifications.

The characteristics we analyze are not randomly assigned, and so estimates of Γ 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 (12) as informative of the characteristics of farmers that exhibit a more severe behavioral bias.

The literature on self-serving bias and loss aversion motivates our selection of behavioral

Table C.1: 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
Age	-0.157*
	(0.093)
Years of education	-0.286***
	(0.093)
Household size	-0.130
	(0.084)
Female = 1	0.007
	(0.196)
Total income	0.105
	(0.093)
Considered buying pump = 1	-0.333*
	(0.185)
Supplies casual labor = 1	-0.371**
	(0.170)
Hires casual labor = 1	-0.154
	(0.165)
Altruism	-0.085
	(0.092)
Cash scarce = 1	0.387*
	(0.216)
Overconfidence	-0.037
	(0.092)
Observations	332
Estimator	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

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 C.1 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 by 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 choices, 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 they do not 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. Persistent scarcity—or poverty—may also influence the formation of human capital (see Dean et al., 2017, for a review). Another possibility is that scarcity increases present bias (Schofield, 2014). We do not believe that our results are driven by changes in present bias. 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.

Scarcity may also mitigate behavioral responses by increasing decision stakes. Fehr et al.

(2020) randomize which of two equally-valued items was given to households as compensation for their time. The authors find evidence of exchange asymmetries: when households are offered the opportunity to trade the endowed item for the alternative item at the end of the survey, only 35% of households (far fewer than the 50% predicted by neoclassical theory) trade the endowed item. These asymmetries are reduced by scarcity, consistent with a decision-stakes effect. The contrast of this result with our finding that cash-scarce farmers exhibit a greater behavioral response suggests that the mechanism matters: BDM may interact with scarcity in a way that simpler trades do not.

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.

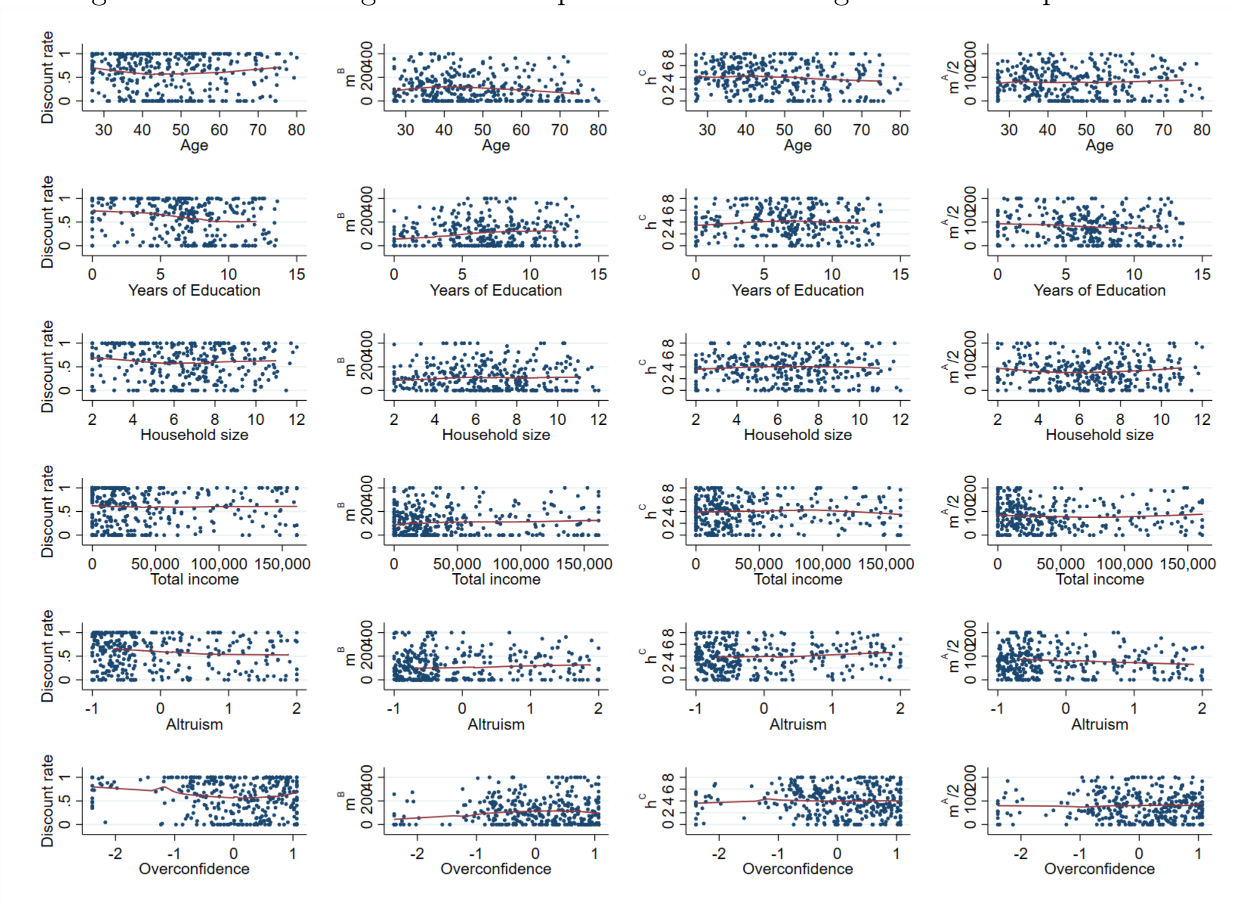
Altruism may mitigate self-serving bias (Di Tella et al., 2015). We test whether more altruistic farmers—measured using the share donated to an unspecified person in their village in a hypothetical dictator game—discount less. A one standard-deviation increase in our measure of altruism corresponds with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

Table C.2: Estimates of auction outcome correlations are very similar in bivariate regressions.

	(1) Discount rate
Age	-0.035
	(0.079)
Years of education	-0.299***
	(0.085)
Household size	-0.140
	(0.089)
Female = 1	0.263
	(0.201)
Total income	-0.062
	(0.085)
Considered buying pump = 1	-0.489***
	(0.177)
Supplies casual labor = 1	-0.295*
	(0.175)
Hires casual labor = 1	-0.264
	(0.170)
Altruism	-0.120
	(0.093)
Cash scarce = 1	0.414**
	(0.209)
Overconfidence	-0.082
	(0.093)
Observations	332
Estimator	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 C.1: Lowess regressions of experimental choices against selected predictors.



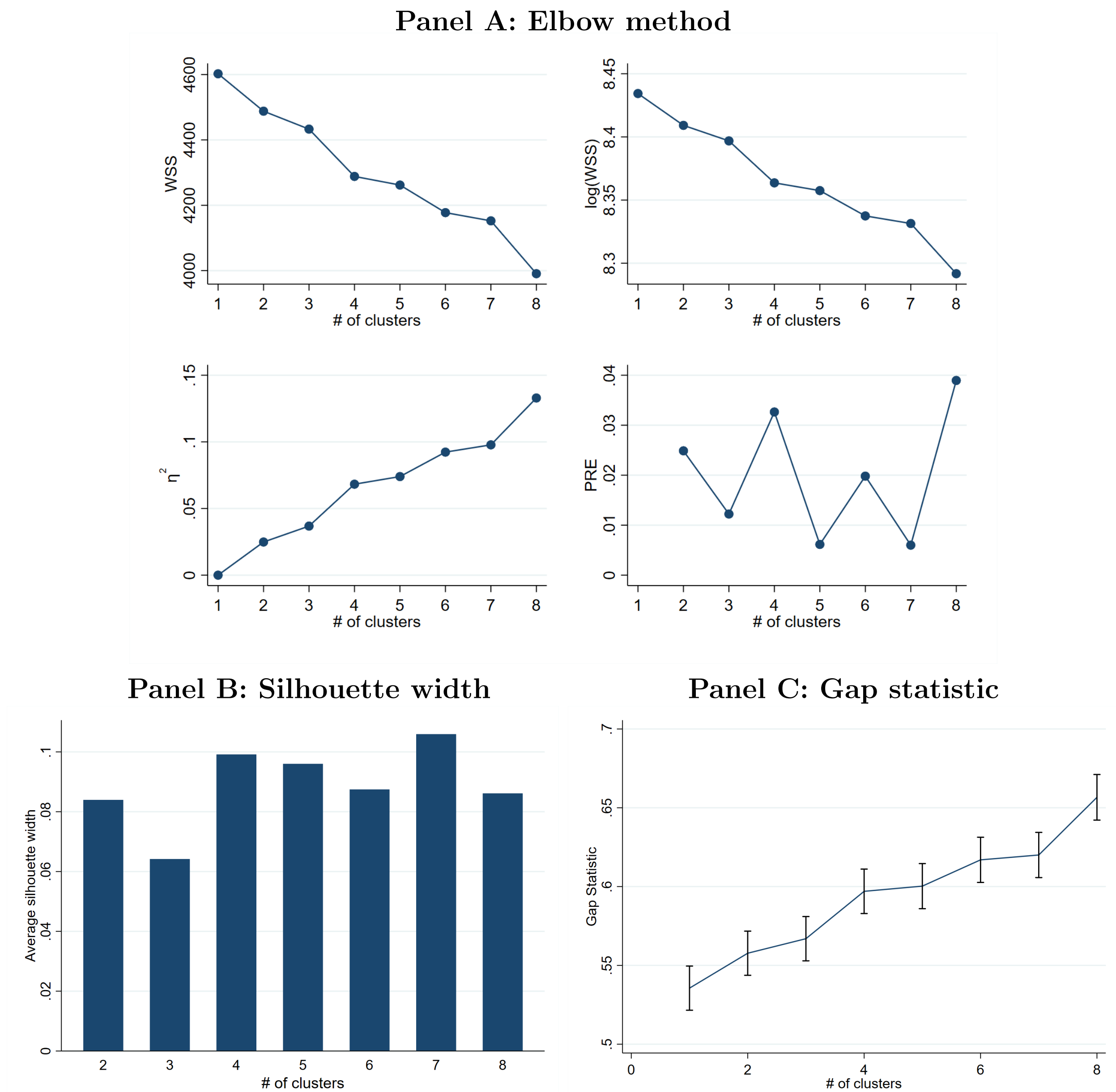
Each chart shows a lowess regression of an experimental choice on a predictor variable with 5% jitter.

D Clustering Analysis

To divide our sample into groups of economically similar farmers, we conduct clustering analysis using the partition around medoids (PAM) method implemented by the Stata command *clpam* (part of package *clutils*, 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., 2001) for between 1 and 8 clusters. Figure D.1 presents results for each of our 3 criteria. Four clusters is a local maximum of 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 cash-scarcity dummy, two dummies for supplying or hiring casual labor, 6 occupation dummies, a measure of overconfidence, and a measure of network centrality.

To describe these clusters in the text, we characterize each cluster using post-LASSO OLS regressions (Belloni and Chernozhukov, 2013, Tibshirani, 1996) of membership in the cluster on the set of control variables used to construct the clusters above. The results are shown in Table D.1. We also show results from the same process for the the two subgroups of interest in Table 3.

Figure D.1: Three criteria suggest $n = 4$ groups for cluster analysis.



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. (2001) 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 $PRE_k = \frac{WSS(k-1) - WSS(k)}{WSS(k-1)}$.

Table D.1: Characteristics of farmer subgroups

Farmer characteristics
Years of education
Age
No male head in household
Farm income
Performs casual labor
Hires casual labor
Irrigates
Agricultural employee
Low-skill self-employed
Network centrality
Observations

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). 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.

E Robustness to Alternative Explanations of the Behavioral Bias

In this section we consider several alternative explanations for the large observed gap between the direct and indirect values 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.

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 direct and indirect values of time 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,[32] a measure that correlates well with risk-taking behavior in a paid lottery (Dohmen et al., 2011). Table E.1 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 IVT (coeff = 3.1 KSh/hour; p-val = 0.41) or the DVT (coeff = −2.5 KSh/hour; p-val = 0.68).

Table E.1: We find no evidence that risk aversion, order effects, or anchoring to typical wages drive our results.

	Discount rate
Risk averse = 1	-0.064
	(0.132)
Cash auction appeared first = 1	0.146
	(0.130)
Perceived typical wage	-0.104
	(0.072)
Observations	332
Dep Var Mean	0.300

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

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 E.1 shows the effect on choices of the randomized

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

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 E.1 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 E.2: Non-compliance cannot explain our results.

	(1) Cash bid for ticket
Complied = 1	48.9**
	(21.2)
Observations	118
Dep Var Mean	184.49
Compliance rate	0.88

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.[33] Table E.2 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 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

[33]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.

farmers with high predicted compliance in all 3 activities.[34] Table E.3 presents results. The effect of this restriction on our estimates is generally very small.

Table E.3: Value of time estimates are robust to excluding farmers with low predicted compliance.

	Mean
Direct value of time (DVT)	86
Indirect value of time (IVT)	32
Cash bid	122
Time bid	4.2
Behavioral discount (r)	0.29

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 Censoring

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 10x 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). Our estimates are not sensitive to this recoding, as shown in Table E.4, which shows estimates of our structural model under various recoding strategies. Our estimates of the SVT vary from 46–49 KSh (or 57–60% of the market wage). Further restricting our estimation sample to farmers with non-negative discount rates yields an estimated SVT of 54 KSh (or 70% of the market wage).

[34] 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 regression of compliance on the three choices m^{RW}, m^{CB}, h^{TB} 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.

Table E.4: Value of time estimates are not sensitive to recoding of choices.

	(1)
	Full sample
Reservation wage share ($\widehat{\gamma}^{RW}$)	0.39
	(0.023)
Cash bid share ($\widehat{\gamma}^{CB}$)	0.61
	(0.026)
Time bid share ($\widehat{\gamma}^{TB}$)	0.003
	(0.015)
Structural value of time ($\widehat{SVT}$)	49
	(2.5)
Market wage (w)	82
	(1.8)
Relative value of time ($\widehat{SVT}/w$)	0.60
	(0.034)
Observations	332

Each observation is a farmer. Currency units are Kenyan shillings (1 USD=107 KSh). See Section 5 for details on the structural model. This table shows sensitivity of our results to recoding of lottery choices, with increasing strictness moving from left to right. Column (5) shows results among farmers with non-negative discount rates and no recoding of bids. Column (4) adds farmers with negative discount rates. Column (3) adds farmers with stated DVT greater than 120 KSh/hour. Column (2) bottom-codes cash and time bids and 20 KSh and 1 hour respectively, restricting to the set of farmers who placed at least 1 eligible bid (defined as a positive cash or time bid, or a DVT less than or equal to 120 KSh/hour) across the three lotteries. Column (1) recodes bids for all farmers. All regressions include controls for unincentivized proxies of the value of time and the valuation of the lottery ticket. 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.[35] 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 E.5 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

[35] 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 reservation wages to avoid stigma.

Table E.5: No evidence that low-wage stigma affects DVT

	(1)
Reaction to low-wage worker	
Should feel ashamed = 1	-0.3
	(5.9)
Angry at worker = 1	
Proud of worker = 1	
Reaction to low-wage hirer	
Should feel ashamed = 1	-1.9
	(6.2)
Angry at hirer = 1	
Proud of hirer = 1	
Observations	332
Dep. Var. Mean	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 RW. 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

F Literature Review Details

To relate our work to the existing literature, we reviewed all papers published between 2016 and Spring 2021 in the *American Economic Review, Quarterly Journal of Economics, Econometrica, Review of Economic Studies, Journal of Political Economy, Journal of Development Economics, American Economic Journal: Applied Economics, American Journal of Agricultural Economics* and the *European Review of Agricultural Economics* which were listed under the following 45 *JEL* codes:

C91, C93, C99, D00, D01, D10, D13, D60, D90, I00, I15, I30, I31, I32, I38, I39, J00, J01, J20, J22, J30, J38, J40, J43, J46, O00, O01, O12, O13, O14, O15, O17, O22, O30, Q00, Q01, Q10, Q11, Q12, Q13, Q14, Q16, Q18, Q19.