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Abstract

People's value for their own time is a key input in evaluating public policies: evaluations should account for time taken away from work or leisure as a result of policy. 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.

JEL Classification: C93, D01, D91, J22, O12, Q12

Keywords: 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 a value of zero 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 common undervaluing of the time of the self-employed will

[1] See Section 6.2 for a survey of studies in economics. It is worth noting that, in addition to the majority that value time at zero, an additional 24% do not attempt to value time at all. Of these 24%, several note that they would like to use *some* value of time, but believe it is too difficult, in their setting, to measure one.

[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.

tend to overstate the value of technologies or interventions that increase time use, and understate 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). This is unfortunate, as more available time is associated with large improvements in mental and physical health, and economically important outcomes such as female labor force participation and education.[4] Our results can be easily applied in different ways depending on the setting, as discussed in Section 6.3, allowing researchers to ascribe more accurate valuations to time-saving interventions. 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 casual 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

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

[4] See for example Xiao et al. (2013), Albanesi and Olivetti (2016), Schilbach (2019), Bessone et al. (2021), Whillans and West (2021).

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 (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 welfare effects of these interventions requires an estimate of workers' value of time, but market wages will often be a poor proxy for this value as incomplete factor markets drive a wedge between shadow and market prices

(Benjamin, 1992, LaFave and Thomas, 2016). Difficulty assigning a value to workers' time has consequently 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.[5] 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.

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. Our approach also contributes to the small literature in structural behavioral economics: see Conlin et al. (2007), Laibson et al. (2007) and DellaVigna et al. (2012, 2016) for prominent examples.

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, Berry et al., 2020). We use BDM mechanisms over a richer choice space to identify and understand behavioral phenomena. Pinning down the relative

[5] A similar issue arises among researchers testing for labor misallocation: evaluating welfare gaps requires an estimate of the value of time gained or lost when workers transition across sectors. There is a substantial wage premium in the non-agricultural sector of most low-income countries, but non-agricultural workers also work longer hours on average (Gollin et al., 2014, Restuccia et al., 2008, Caselli, 2005). When measuring this agricultural productivity gap, Gollin et al. (2014) control for hours worked, while Pulido and Święcki (2018) do not.

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 (see Chetty 2015 and Bernheim and Taubinsky 2018 for broad perspectives).

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.[6] Figure 3 in Section 6 displays the distribution of market wages alongside values of time elicited from farmers' choices.

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

[6] 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

	Mean	Std. Dev.	N
Panel A: Demographics			
Age	47.7	14.3	328
Years of education	6.8	3.6	307
Female = 1	0.69	0.46	332
No male head in household = 1	0.14	0.35	332
Number of adults (age 18 or over) in household	2.7	1.3	324
Number of children (under 18 years) in household	4.0	2.4	324
Panel B: Household income and wealth			
Land area under cultivation (acres)	2.3	2.0	324
Household income (KSh, past year)	49,122	68,358	330
Income share from sale of crops	0.41	0.38	330
Panel C: Casual labor			
Performed or hired casual labor within past 3 months = 1	0.72	0.45	332
Performed casual labor within past 3 months = 1	0.42	0.50	332
of which, days worked in last 3 months	13.1	16.5	141
during which, hours worked per day	4.2	1.4	141
among which, hourly earnings	82	66	129
Hired casual labor within past 3 months = 1	0.46	0.50	332
of which, days hired in last 3 months	6.5	8.5	154
during which, number of workers hired	3.2	3.5	154
among which, hours hired per day	4.0	1.3	154
among which, hourly wage paid	60	33	137
Panel D: Exposure to irrigation pump			
Owns a MoneyMaker irrigation pump	0.01	0.09	332
Has used a MoneyMaker irrigation pump	0.11	0.32	332
Familiar with the MoneyMaker irrigation pump	0.99	0.09	332
Has considered buying a MoneyMaker irrigation pump	0.59	0.48	332
Self-reported valuation of pump (KSh)	4,432	3,318	303

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).

farmers fear that the pumps may be uncomfortable to operate.

2.2 Choices

Each farmer in our sample was given three choices that used the BDM design (Becker et al., 1964).[7] 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.[8]

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.[9]

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

[8] 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.

[9] 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.[10]

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 credit 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 $h \in \mathbb{R}^+$

[10] 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 credit 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

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

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	Std. Dev.	p25	p50	p75
Direct value of time ($DVT = m^{RW}/2$)	83	54	50	80	100
Indirect value of time (IVT)	30	35	3	20	40
Cash bid (m^{CB})	111	126	20	100	155
Time bid (h^{TB})	4.0	2.2	3.0	4.0	5.0
Behavioral discount ($\widehat{r}$)	0.30	1.22	0.28	0.71	0.98

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

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

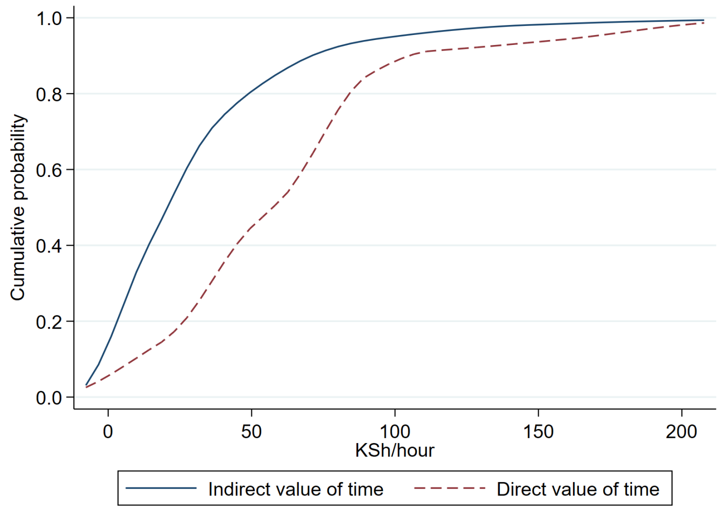
$$\widehat{r} = 1 - \frac{\text{IVT}}{\text{DVT}} \tag{4}$$

as a measure of preference intransitivity.[11] The average value of $\widehat{r}$ is 0.3, substantially higher than the benchmark prediction $\widehat{r} = 0$ (p-val<0.0001).[12]

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

[12]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.

Credit and Labor Constraints. Although our model explicitly builds in credit and labor constraints, describing why they are unlikely to be driving the wedge between IVT and DVT provides a deeper understanding of Theorem 1. The important condition underlying that result is that the choices we offer have only second-order effects on the shadow value of money or time.

If a farmer is credit constrained, then they will have a high shadow value of money, but this will be reflected in both their IVT and DVT. In particular, a higher shadow value of money will lower both a farmer's willingness to pay for a lottery ticket m^{CB}, as well as their reservation wage m^{RW}. This will lower both IVT and DVT equally, resulting in no wedge between the two. The only way that credit constraints could create such a wedge would be if the decision to buy a lottery ticket significantly tightened credit constraints, or if working for two hours significantly loosened them. We believe this is unlikely: many farmers were probably already credit constrained before facing the choices we offered. Moreover, the impact of investing in a lottery ticket is very minor compared to other investment opportunities.[13]

[13]Examples of high-return investment opportunities with low take-up rates include grain storage facilities

Thus, we interpret these failures of transitivity as an expression of behavioral phenomena, and refer to $\widehat{r}$ as a farmer's *behavioral discount rate*. 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 decision-making 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 $1 - r^{RW}$;

(Burke et al., 2018) or, outside the realm of agriculture, antimalarial bed nets (Cohen and Dupas, 2010). Similar logic applies to labor constraints.

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.[14] 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.

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

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

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).[15]

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.

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

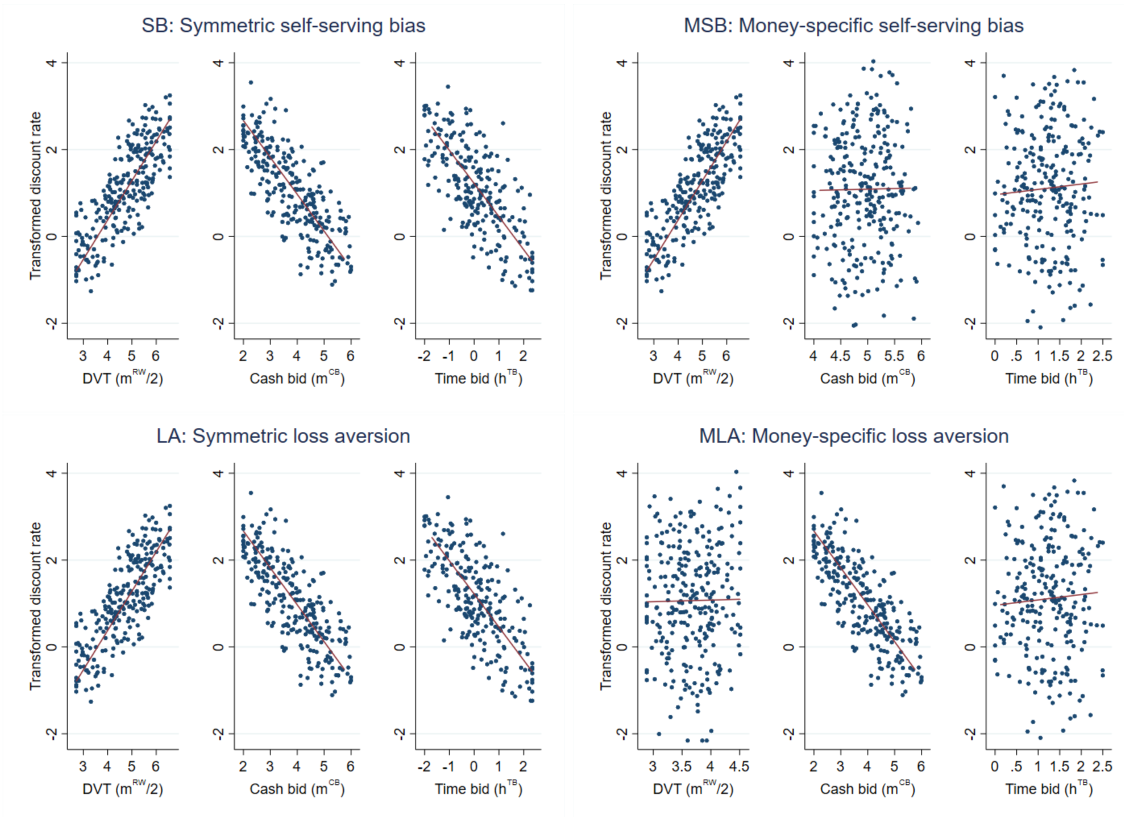
Before we turn to the model, it is useful to provide an intuitive argument for why identification of specific behavioral mechanisms may be possible. Figure 2 simulates the relationship between choice data m^{RW}, m^{CB}, h^{TB}, and the log-linearized behavioral discount rate $-\log(1-\widehat{r})$ defined 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

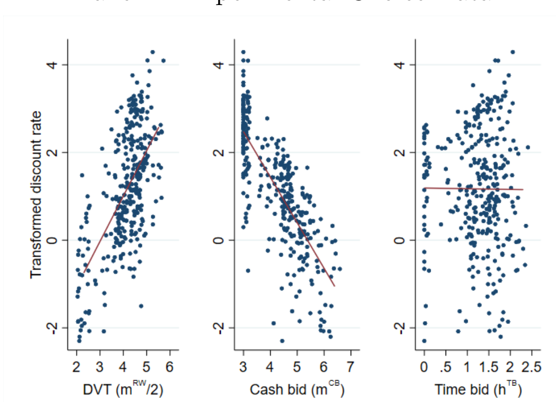
[15] Equivalently, right below a sudden kink in the value function for cash-on-hand k.

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 $= -\log(1 - \widehat{r})$. Scatterplots of raw choices show in Appendix B.

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 $V_m = -1$, 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

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

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

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

We impose two main assumptions:

Assumption 2. *Farmers vary in the their overall propensity to discount gains (ρ_i), but not in the relative intensity of each bias (γ_i^X fixed across all i for $X \in \{RW, CB, TB\}$).*

Assumption 3. *Conditional on observable characteristics, behavioral parameter ρ_i is un-*

correlated with the logarithms of preference parameters $V_{\tau,i}$*, and* $V_{h,i}$*.*[16]

With these assumptions, (7) then implies

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

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

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

Hence, it follows from (8) that

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

Note that ρ_i can only be estimated if $\gamma^{RW} + \gamma^{CB} - \gamma^{TB} \neq 0$. As $\widehat{r}_i \neq 0$ for many farmers, (9) implies this condition holds.

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:*

[16] 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).

- *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.[17] Standard errors are obtained using the bootstrap with 10,000 draws.

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 ($\widehat{\gamma}^{RW}, \widehat{\gamma}^{CB} > 0$).[18] This pattern is the same as that shown in

[17] 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.

[18] 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 Columns 1–4 of Table E.4. The estimated relative intensities $\widehat{\gamma}^{RW}, \widehat{\gamma}^{CB}, \widehat{\gamma}^{TB}$ change little across specifications, and the estimated mean structural value of time is very stable at 57–60% of the market wage.

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.[19]

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 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.[20] Despite this difference, the relative intensities γ are very similar to the full sample, and estimates of SVT in these subgroups are 63% 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 relative intensities are quite simi-

[19] 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.

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cluster breakdown				
	Full sample	Casual laborers	Considered buying pump	Low-skill self-employed	Low-skill employees	Hires casual workers	Older, low-edu households	Full sample +controls
Structural estimation								
Reservation wage relative intensity ($\widehat{\gamma}^{RW}$)	0.39	0.39	0.40	0.41	0.37	0.37	0.46	0.39
	(0.023)	(0.039)	(0.031)	(0.047)	(0.037)	(0.054)	(0.058)	(0.023)
Cash bid relative intensity ($\widehat{\gamma}^{CB}$)	0.61	0.61	0.60	0.57	0.63	0.63	0.54	0.62
	(0.025)	(0.039)	(0.032)	(0.047)	(0.044)	(0.059)	(0.070)	(0.025)
Time bid relative intensity ($\widehat{\gamma}^{TB}$)	0.003	0.000	0.000	0.024	0.000	0.000	0.006	0.000
	(0.014)	(0.007)	(0.017)	(0.007)	(0.030)	(0.019)	(0.036)	(0.013)
Structural value of time ($\widehat{SVT}$)	49	46	44	46	46	60	40	49
	(2.4)	(3.5)	(2.6)	(3.6)	(4.5)	(6.3)	(6.4)	(2.4)
Market wage (w)	82	73	82	86	75	89	81	82
	(1.8)	(3.1)	(2.4)	(3.3)	(4.0)	(3.4)	(3.4)	(1.8)
Relative value of time ($\widehat{SVT}/w$)	0.60	0.63	0.54	0.53	0.62	0.68	0.49	0.60
	(0.033)	(0.055)	(0.036)	(0.056)	(0.058)	(0.079)	(0.081)	(0.033)
Experimental choices								
Direct value of time (DVT)	83	72	73	83	67	97	95	83
	(3.0)	(3.9)	(3.2)	(6.6)	(3.3)	(7.2)	(7.7)	(3.0)
Indirect value of time (IVT)	30	31	29	31	32	36	15	30
	(1.9)	(3.1)	(2.4)	(4.4)	(3.1)	(4.5)	(2.9)	(1.9)
Cash bid	111	129	123	119	136	115	46	111
	(6.9)	(11.4)	(9.6)	(17.0)	(11.7)	(14.5)	(7.1)	(6.9)
Time bid	4.0	4.6	4.4	4.0	4.6	3.7	3.2	4.0
	(0.1)	(0.2)	(0.2)	(0.3)	(0.2)	(0.3)	(0.2)	(0.1)
Behavioral discount (r)	0.30	0.19	0.18	0.12	0.16	0.33	0.74	0.30
	(0.067)	(0.11)	(0.10)	(0.19)	(0.12)	(0.13)	(0.049)	(0.067)
Observations	332	141	189	68	123	80	61	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.

lar 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 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 the relative intensities γ are fixed across the sample. The estimated structural value of time is also stable, varying from about one-half to two-thirds of the market wage.[21] This is true despite the fact that the average behavioral discount rate $\hat{r}$ varies substantially across clusters—from 0.12 to 0.74. This provides some evidence that 60% of the market wage is a reasonable rule-of-thumb for the SVT, even across heterogeneous sub-populations.

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 $\log(-V_{h,i})$.

[21] As another way of describing the relative stability of estimates of SVT_i/w_i in our data, the standard deviation of SVT_i/w_i—0.52—is low relative to the standard deviation of DVT_i/w_i—0.92.

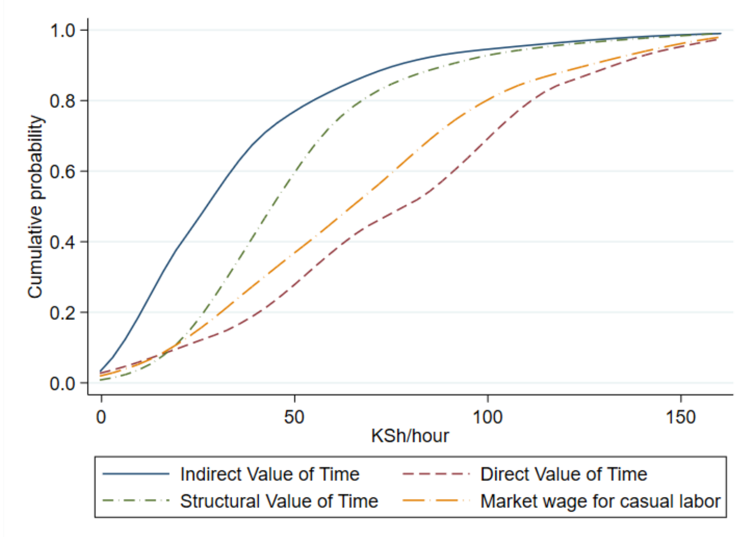
Under the premise that behavioral phenomena are exacerbated by stake size—as initially formulated by Kahneman and Tversky (1979), and later documented empirically (for example, Ert and Erev, 2013, Easton and Pinder, 2021)—unincentivized choices will be less affected by behavioral biases, but still serve 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.

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 Discussion

This paper seeks to better understand how to account for people's 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.

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) or other wage-labor constraints (Benjamin, 1992, Jones et al., 2020). 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 casual jobs.[22] 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.[23] 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 source of labor market distortions.[24]

Alternatively, if self-serving bias does not extend to most 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 shading in ex-post performance resulting from wage deviations below reference points (Hart and Moore, 2008, Fehr et al., 2011). We are able to test for this in our setting using the random variation in hourly wages paid for casual work in choices RW and TB. Specifically, we test whether the quality of work performed—as measured by field staff after work was completed—depends on the random wage paid. 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 DVT were eligible to work—eligibility is random

[22]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.

[23]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.

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

conditional on DVT. We find significant evidence of shading at lower wages, but only for wages below reference wages—the amount farmers told us they thought they could earn for casual labor—as shown in Appendix Table F.1. Moreover, shading only occurred when the farmer was working for a cash wage, as opposed to a set reward. This suggests that, when paying cash, employers may find it worthwhile to pay a higher wage to increase the average quality of work, leading to fewer jobs.

6.2 Value of Time Assumptions in the Literature

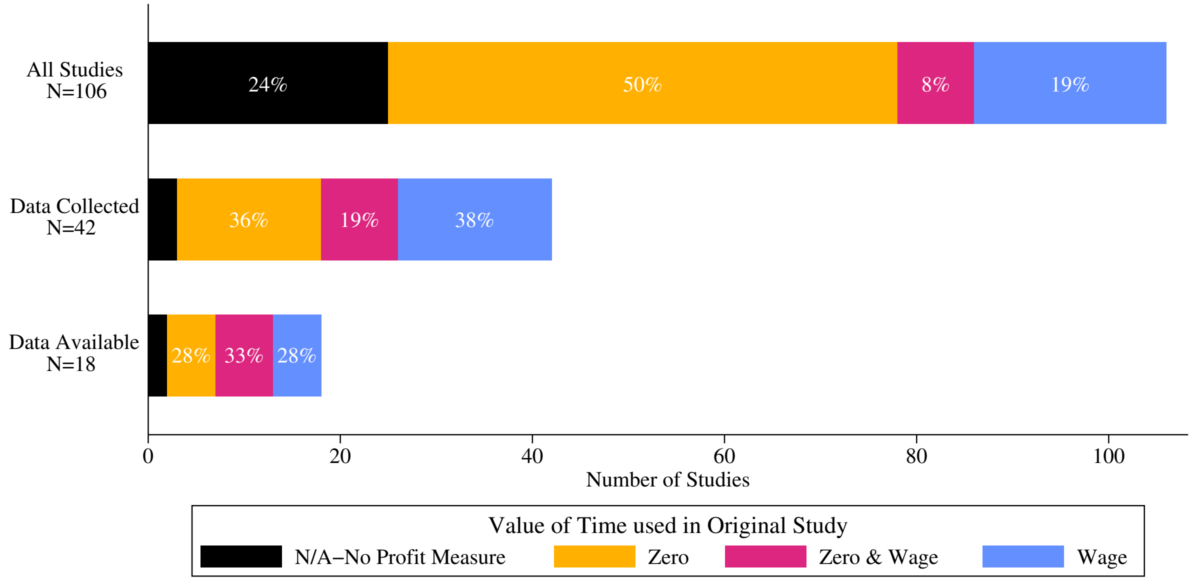
In this section we survey the extant literature to understand how it accounts for the value of time of the self-employed. We searched top economics journals for any study in the past 6 years (2016–2021) of the self-employed in a low-income country, in which revenue or profits were measured.[25] This search resulted in a total of 106 studies, of which a minority of 42 had collected enough information, in theory, for us to reinterpret their results in light of our findings.[26]

As shown in the top-left bar of Figure 4, 24% of the 106 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, 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, together, 74% of the studies considered

[25]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 G. The papers that resulted from this search were then read to find those that concerned the self-employed, and measured revenue or profits.

[26]Analyzing the sensitivity of results to assumptions about the value of time requires three pieces of information: household labor hours, the locally prevailing market wage, and revenue net of other input costs. From what we could gather, 64 of the 106 studies did not collect all necessary data. In particular, only 8 (12.5%) of these 64 studies appear to have collected data on household labor supply, and 14 (22%) on local wages.

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



cannot take a stand on welfare impacts of the intervention under evaluation. The remaining studies (23%) use the market wage to value the time of the self-employed. A subset of these (8% 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.

Studies with sufficient information that they could have, in principle, calculated profits under different values of time ($N = 42$) were more likely to value the time of the self-employed, with 57% assigning a positive value in at least some specifications, as shown in the center bar of Figure 4. For those studies where we were actually able to obtain data ($N = 18$), the percentage that values the time of the self-employed at the market wage in at least some specifications climbs to 61%.[27]

The fact that many recent studies do not measure input costs, even though they consider profits as a primary outcome, may be surprising. This may stem, in part, from the findings

[27] Of the 42 studies that collected the data needed to re-calculate profits, 6 contained sufficient information in the paper itself for us to re-evaluate their results, 12 had replication datasets with sufficient information available online, and an additional 15 studies required us to gather the source data for the paper. We received a complete replication dataset for 2 of those 15. We thank the authors who provided these data.

of De Mel et al. (2009), which suggest that asking the self-employed to self-report accounting profits is more accurate than eliciting revenues and costs, and computing profits from these quantities. However, that study does not consider the hours worked by the self-employed as a cost in their profit measure.[28] Yet, two programs that impact accounting profits equally but affect work hours for the business owner differently will clearly have different welfare impacts. Even if one were to only ask the self-employed about accounting profits, as De Mel et al. (2009) suggest, our results indicate that one should additionally ask about the hours worked by the self-employed, and use this information in calculating profits.

6.3 Practical Implications for Researchers

Overall, our findings suggest the need for more understanding of how the self-employed value their own time. However, they also suggest rules of thumbs that can be immediately applied by researchers. In this subsection we describe some rules of thumb and their limitations, and in the next, apply the simple techniques we describe 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 model or choice(s) as "correct," in line with the approach outlined in Bernheim and Rangel (2009). As we illustrate below in Figure 5, this approach 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 mar-

[28] 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]?"

ket wage for casual labor. This follows the "parametric tradition" of welfare evaluation: see Sadoff et al. (2020) for a brief summary and other examples.

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 choice experiments and associated analysis.[29] 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.

The opportunity cost of time for a given worker is likely to vary across tasks and periods of time. When benchmarking the value of time against a market wage, researchers should choose benchmarks that are comparable to the labor changes induced by their intervention. For example, workers are likely to require higher wages to work on a fixed schedule than on a flexible one: the market wage for flexible casual work would thus be too low of a benchmark for a technology that requires labor input at a specific hour every day.

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

[29] Unincentivized choices are likely to be seen as an attractive alternative, but should be used with extreme caution. In particular, unincentivized survey-based measures modeled on our choices are likely to produce unreliable results. In our sample, farmers' reservation wages elicited through an unincentivized survey question are significantly higher than the incentivized reservation wage m^{RW}—although the incentivized and unincentivized quantities are highly correlated, as described in Section 5.2.

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.

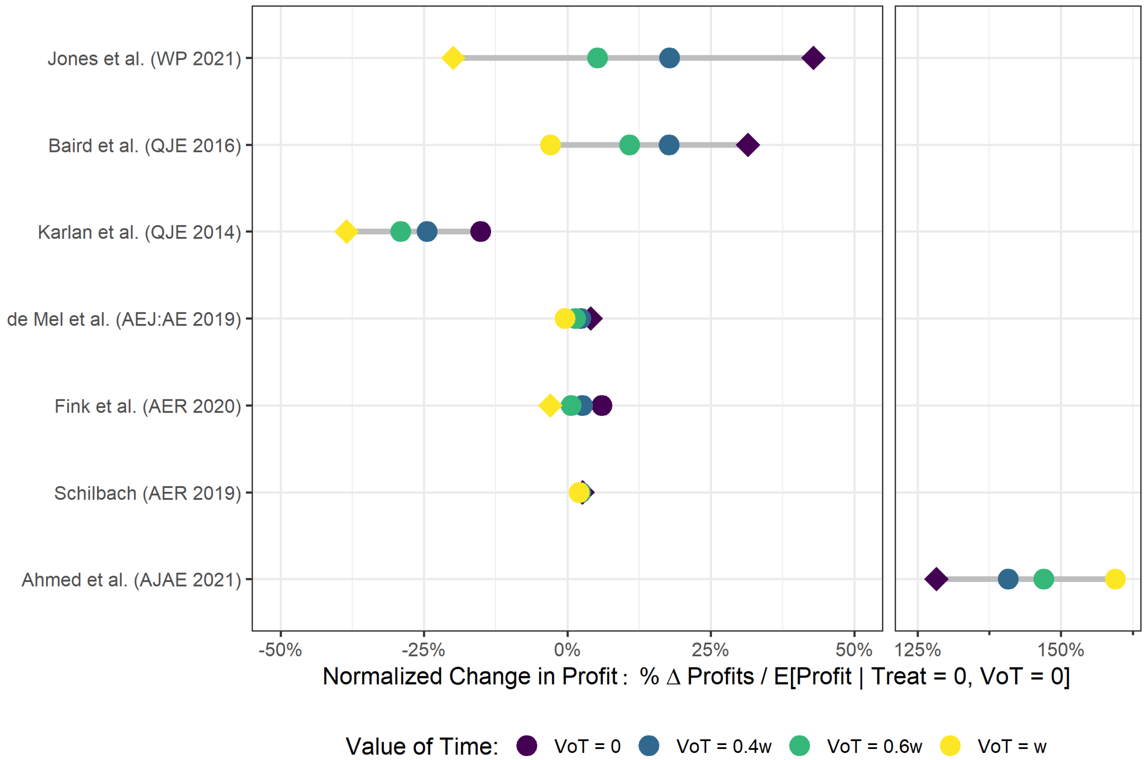
6.4 Applying Our Results to the Literature

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. Figure 5 shows results for six studies selected for their illustrative value. Results for the set of studies we could re-evaluate are shown in Table G.1. To standardize outcome measures across studies, we report treatment effects on profits normalized by mean profits in the control group. Note that most of these papers treat the value of time conservatively: valuing it at zero for time-saving interventions, and w for those that increase time usage. This is only possible because these papers all measure the market wage.

Impact assessments are most sensitive to assumptions about the value of time when the intervention significantly changes participants' labor supply. A few examples are Jones et al. (2020), which estimates the impact of irrigation by small-scale farmers, Baird et al. (2016), which finds long-run labor supply effects of de-worming, 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. A similar pattern can be seen in Baird et al. (2016). The rule-of-thumb we propose suggests that the negative profit impact scenario can likely be rejected in both cases: our recommended *lower bound* on the effect of profits (with VoT $= 0.4w$) is positive.

For interventions producing more modest changes in labor supply, the assumed value

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



Diamonds represent the value of time assumed by the authors. Note the jump in the x-axis.

of time remains important, though less dramatically so. Two examples are de Mel et al. (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.

For interventions that do not meaningfully change labor supply, the assumed value of time of the self-employed is less important when calculating treatment impacts, even when labor represents a large share of costs. For example, in Schilbach (2019), the increase in household labor associated with the sobriety incentives is small (0.4%). Consequently, the normalized change in profits varies from 2.6% when household labor is valued at zero to 2.0% when household labor is valued at the market wage.

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 for 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.

Consistent with researchers often focusing on yield or revenue maximization rather than costs, reviews of technology adoption in low-income countries indicate there has been little study of labor-saving technologies (de Janvry et al., 2017, Macours, 2019, Magruder, 2018). The failure to properly account for labor—often a primary cost—may explain adoption failures for some technologies that appear welfare-improving. Further, technologies that could improve welfare by saving users' time may appear less useful 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. There are many 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;[30] improved mental health (Whillans and West, 2021); improved cognitive capability (Bessone et al., 2021); reduced pain (Xiao et al., 2013), and reduced pain management through alcohol (Schilbach, 2019).

[30]Pinker (2018, p. 231) cites this tractor advertisement from 1921: "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 school—and let a Case Kerosene Tractor take his place in the field. You'll never regret either investment."

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