

Informal Redistribution Through Work

Elisa Macchi*, Jeremia Stalder †‡

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Abstract

We investigate work as informal redistribution, leveraging field experiments and firm-level survey data from Kampala, Uganda. Employers and workers consistently choose work redistribution over cash transfers, revealing a willingness to pay for work. By randomizing work tasks—some designed to have zero marginal product—we find that production value does not explain these choices: employers pay for zero value work. These patterns are also inconsistent with other relational benefits, such as signaling or networking. Instead, motivations are normative. Experimental evidence reveals a norm for work redistribution rooted in incentive arguments on the demand side—as employers stop requiring work when recipients have verifiable emergencies—and in reciprocity and dignity from earning on the supply side. This norm shapes both the organization and measurement of production: failing to account for work redistribution makes firms appear significantly larger and less productive than they are.

*Macchi: Department of Economics, Brown University (email: elisa_macchi@brown.edu)

†Stalder: Department of Economics, University of St. Gallen (email: jeremia.stalder@unisg.ch)

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1 Introduction

“In over-populated countries [...] it becomes good form for each person to offer as much employment as he can. The line between employees and dependents is very thinly drawn.”

— A. Lewis, 1954

Economic theory posits that firms hire workers until wages equal the marginal product of labor and that workers supply labor in response to prevailing wages. However, labor markets in poor countries often deviate from this benchmark. Classic explanations emphasize frictions, while a literature grounded in sociology and psychology emphasizes that work has value beyond production and consumption. These perspectives suggest that employment may also serve purposes other than profit maximization, including—as hypothesized as early as [Lewis \(1954\)](#)—redistribution motives.

Employment is a salient channel of informal redistribution in poor countries.¹ However, rigorous evidence that redistribution motives drive hiring—and, in particular, that employers pay above the marginal product of labor—remains limited.² Observational tests face a fundamental endogeneity problem: the production technology itself responds to social preferences or pressures, making it difficult to distinguish productive from non-productive labor demand. Moreover, employers in a frictional labor market may have many reasons for hiring more workers than necessary. For example, idle workers could reflect a non-smooth demand or contracting frictions (the [Schultz critique](#)).

In this paper, we address these identification challenges using field experiments that vary the terms of redistribution on both sides of the labor market, working with over 400 small and medium grain-processing enterprises in Kampala, Uganda.³ The experiments introduce exogenous variation in how redistribution can occur—including randomized variation in the value of work tasks, some designed to have zero marginal

¹This relationship between employment and redistribution has been documented descriptively by comparing firms owned by locals and non-locals in sub-Saharan Africa ([Alby, Auriol, and Nguimkeu, 2020](#)), theorized in [Ferguson \(2013\)](#) and [Ferguson \(2015\)](#), and observed in political contexts as “white elephant” projects ([Robinson and Torvik, 2005](#)).

²At the extreme, this reflects [Lewis \(1954\)](#)’s surplus-labor assumption that workers may be employed even when their marginal product is near zero.

³This sector ranks among the largest in labor demand ([Uganda Bureau of Statistics, 2011](#)) and features clear employer-employee relationships, meaning that workers have a primary employer and are paid wages or salaries by the employer ([Bassi, Lee, Peter, Porzio, Sen, and Tugume, 2023](#)).

1 product—allowing us to separate redistributive motives from productivity considera-
2 tions, relational benefits, and other confounds. We find that work serves as a channel for
3 informal redistribution, with norms promoting redistribution via work leading employers
4 to pay for non-productive labor and workers preferring work over cash transfers.

5 We first implement an incentive-compatible experiment where employers choose be-
6 tween giving work or cash transfers to workers, and workers separately choose between
7 receiving work or cash, with both parties making decisions across varying wage and
8 transfer levels.⁴ Choices are private. Anonymity and geographic separation between
9 participants further reduce relational and reputational concerns ex ante. We find stark
10 preferences for work over cash redistribution. Employers choose to give work 86.5% of
11 the time, while workers choose to receive work 87.8% of the time. Strikingly, these pref-
12 erences exhibit minimal elasticity to offered wages and transfers: 79.7% of employers
13 hire at UGX 10,000—over three times the market wage—while 57% of workers accept
14 work for UGX 500, nearly free, over a UGX 3,000 cash transfer. This inelasticity is
15 inconsistent with payoff-maximization, but also generosity, or inequality aversion. For
16 example, most employers choose to hire when the wage is lower than the transfer.

17 One possibility is that the value of work explains these preferences. While employers
18 have willingness to pay for work even at wages above the market wage, this premium
19 could reflect frictions rather than redistributive motives. We test this using task ran-
20 domization. If work production value drove choices, employers and workers should be
21 less likely to choose work and pay lower wages for lower-value tasks. We compare stan-
22 dard tasks and two low-value tasks: “busywork” (loading and immediately unloading
23 sacks, zero production value but potential screening or skill-building value) and sweeping
24 (minimal value on all dimensions). We find that work preferences remain unchanged.
25 In particular, employers are equally likely to hire for zero-value work and are willing to
26 pay the same premium.

27 Could relational benefits or image concerns explain work redistribution preferences?
28 While our design limits these channels, we implement additional robustness checks tar-
29 geting three plausible confounds: signaling (by making work unobservable to third par-
30 ties), networking (by having cash recipients also meet employers in person), and inat-
31 tention (by very explicitly highlighting the anonymity and privacy of all choices). We
32 leverage a multi-scenario replication of the main experiment on the full sample of firms,

⁴As is typical in this spot labor market, “work” entails a 30-minute task at the employer’s firm.

1 conducted in July 2024. Our findings are robust: work redistribution preferences remain
2 substantially unchanged across all scenarios for both employers and workers.⁵

3 Qualitative responses reveal the normative nature of these preferences. Both employ-
4 ers and workers consistently invoke the principle that “people must work” and should
5 not receive “free money” when motivating their experimental decisions, regardless of
6 whether deciding for themselves or others. Combined with the price inelasticity, which
7 implies costly choices despite privacy, these patterns satisfy [Bicchieri \(2016\)](#)’s diagnos-
8 tic criteria for internalized norms rather than mere habits or customs. We therefore
9 interpret the results as evidence of an internalized norm for informal redistribution via
10 work.⁶

11 We hypothesize that the norm for work redistribution is sustained by its incentive
12 properties for receivers, which mirror formal workfare. In the theory of workfare, work
13 requirements improve targeting when need is unobservable and encourage productive be-
14 havior when poverty is not purely due to bad luck ([Nichols and Zeckhauser, 1982](#); [Besley
15 and Coate, 1992](#)). We test this hypothesis by experimentally varying the information
16 employers receive about workers’ verifiable emergency need. If workfare incentives drove
17 the internalized norm for work redistribution, employers should relax work requirements
18 for recipients observably in need.⁷ We also test for alternative determinants, such as
19 reciprocity, screening for moral character, and dignity.

20 We find that when receivers have verified emergencies, only 27.4% of employers
21 choose to give work when wages equal transfers, compared to 82.7% without this in-
22 formation. Thus, employers’ perspective resembles that of the government providing
23 formal workfare: work requirements are relaxed when need is verifiable and clearly ex-
24 ogenous. In contrast, we rule out several alternative explanations for workers’ persistent
25 work preferences. Workers with verifiable emergencies do not reduce their willingness to

⁵Workers show a small but significant reduction (4.5%) in willingness to pay for work when we highlight anonymity and privacy, suggesting either minor image concerns or expectations of lower social taxation of earnings relative to cash transfers.

⁶Given our results, the underlying norm may be moral or social. This distinction depends on whether compliance is driven by internal convictions or by beliefs about others’ expectations. For a comprehensive discussion, see [Bicchieri \(2016\)](#), who highlights that the boundary between moral and social norms can be fuzzy. While distinguishing between moral and social norms is beyond the scope of this study, the normative component we identify aligns with [Lewis \(1954\)](#)’s concept of a “code of ethical behavior” and, as reformulated by [Ranis and Fei \(1961\)](#), the notion of “institutional or non-market forces” driving work redistribution.

⁷We again leverage the multi-scenario replication of the main experiment, designing one scenario in which the worker is pre-screened to have a verifiable emergency (but can still work).

1 work, suggesting they value work beyond signaling their type to employers. Reciprocity
2 explains approximately 10% of their willingness to pay for work. More tellingly, when
3 we provide workers with “moral wiggle room” à la Dana, Weber, and Kuang (2007)
4 by framing cash transfers as payment for work done for us (rather than charity), their
5 willingness to work declines by 6.2% (p -value < 0.001). This sensitivity to framing, com-
6 bined with the stability of work preferences across other scenarios and the motivations,
7 is consistent with workers valuing the dignity of earning through labor.

8 We validate experimental findings using employer-reported survey data on self-reported
9 giving patterns and firm characteristics. First, employers who give more via work in the
10 experiment hire more workers in their firms yet produce similar output, implying ob-
11 servably lower labor productivity, as reflected in lower revenues, profits, and sales per
12 work hour. Second, work redistribution is substantial: among the 46.2% of firms whose
13 employers report giving work to help others, hours given as assistance account for 11.3%
14 of total work hours and 9.8% of profits. Even when we restrict to hours given explicitly
15 defined by employers as symbolic or idle work, these figures remain sizable at 6% and
16 5.2%, respectively.

17 Accounting for work redistribution has measurement implications for firm size and
18 productivity. Intuitively, failing to account for work hours given as redistribution makes
19 firms appear larger and less productive. We therefore implement a bounding exercise to
20 estimate the magnitude of the effects. Total redistribution work hours (i.e., hours given
21 to help out, as reported by the employer) define the upper bound, while explicitly defined
22 symbolic or idle redistribution work hours define the lower bound.⁸ Across all firms in
23 our sample—including those that do not redistribute—standard measures overstate firm
24 size by 4.3%–10%. This mechanically deflates standard productivity measures such
25 as output per work hour. Specifically, this measure understates effective productivity
26 (revenue per effective hour worked) by 2.8% to 5.1%, depending on whether we consider
27 all hours given or only those identified as symbolic or idle.⁹

28 This paper makes three main contributions. First, it contributes to a long-standing
29 literature dating back to Lewis (1954) and Schultz (1964) investigating the functioning

⁸Non-symbolic and non-idle redistribution hours could be productive but also redundant, for ex-
ample, extra workers hired to perform tasks that could have been performed by existing workers.

⁹These statistics are the mean of ratios of revenue to adjusted hours calculated at the firm level.
All bounds are significant at the 1% significance level. The p -values are reported in Online Appendix
Table H.3, Panel A.

1 of labor markets in poor countries (see Breza and Kaur, 2025 and Rosenzweig, 1988 for
2 reviews). We show that both labor supply and demand are driven by motivations un-
3 related to production and consumption, echoing work in sociology on the non-economic
4 value of work (Morse and Weiss, 1955; Jahoda, 1981). Recent experimental evidence
5 shows that social motives and norms affect worker effort and labor supply (Bandiera,
6 Barankay, and Rasul, 2005; Ashraf and Bandiera, 2018; Breza, Kaur, and Shamdasani,
7 2018; Breza, Kaur, and Krishnaswamy, 2019; Oh, 2023). We extend these results in two
8 ways. First, we show that social preferences also drive labor demand: employers hire
9 for redistributive purposes, independent of productivity. This is critical as employers
10 typically set wages. Second, we document workers' intrinsic demand for work indepen-
11 dent of consumption value, extending Hussam, Kelley, Lane, and Zahra (2022)'s findings
12 from displaced Rohingya refugees to non-displaced urban workers.¹⁰

13 Second, we identify work as a preferred yet understudied channel of informal redistri-
14 bution. While sharing networks in poor countries are well-established (Fafchamps, 1992;
15 Townsend, 1994; Foster and Rosenzweig, 2001; De Weerd and Dercon, 2006), existing
16 research either examines aggregate welfare without specifying channels or investigates
17 pressures while assuming cash transfers (Jakiela and Ozier, 2016; Boltz et al., 2019). Our
18 results highlight new channels through which informal redistribution can affect produc-
19 tive decisions, beyond disincentivizing investment (Squires, 2024), and without requiring
20 social pressure (Carranza, Donald, Grosset, and Kaur, 2022; Swanson, 2024).

21 Finally, we show that employers' social preferences can lead to unproductive hiring,
22 contributing to the nascent behavioral firm literature (DellaVigna and Gentzkow, 2019;
23 Kremer, Rao, and Schilbach, 2019). Prior work documented large productivity gaps
24 between firms in high- and low-income countries (Hsieh and Klenow, 2009; McKenzie and
25 Woodruff, 2017) and emphasized the role of frictions in contracting, finance, and market
26 access (see, for example, De Mel, McKenzie, and Woodruff, 2008; Atkin, Khandelwal,
27 and Osman, 2017b; Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen, 2017a;
28 Bassi, Muoio, Porzio, Sen, and Tugume, 2022). Yet, alleviating these frictions often fails
29 to generate large productivity gains (Atkin, Donaldson, Rasul, Teachout, Verhoogen,

¹⁰Our findings also relate to Hussam et al. (2022) in that both papers highlight an understudied dimension of redistribution in poor countries: preferences for how redistribution occurs, especially on the receiver side. Literature on redistribution preferences typically focuses on formal redistribution in high-income countries from givers' (voters') perspectives (Alesina and Giuliano, 2011; Fehr and Charness, 2025).

1 and Woodruff, 2019). Our results provide a behavioral explanation for this puzzle,
2 suggesting that firms are not purely profit-maximizing entities and employers in poor
3 countries may at times choose labor-intensive or inefficient organizational structures.

4 **2 Setting and Informal Redistribution Patterns**

5 Our setting is the grain-processing sector in Kampala, Uganda. This sector is character-
6 ized by highly heterogeneous firms, both in terms of size and main activity, from larger
7 grain-milling firms that produce human food to simpler feed resellers.

8 We focus on this industry due to its economic relevance, ranking among the largest
9 (top four in the manufacturing sector) in terms of labor demand according to Uganda
10 Bureau of Statistics (2011), and because it features a clear employer-employee relation-
11 ship. As per Bassi, Lee, Peter, Porzio, Sen, and Tugume (2023)’s definition, workers
12 typically hold an ongoing primary job with a single firm and are paid wages or salaries
13 by employers. In our sample, on average, workers spend 83.5% of their time working
14 for their primary employer, and 69.1% earn more than two-thirds of their earnings from
15 that employer.

16 **2.1 Sampling and Data**

17 Given that most grain-processing firms are informal, in September 2022 we conducted
18 a listing exercise to identify them in the Greater Kampala area, resulting in 491 firms
19 within a 30-km radius of the city center.¹¹ Our population of interest includes only
20 firms where the owner or manager reports employing at least two workers. The main
21 experimental sample comprises 399 employers (190 owners and 209 managers) from 427
22 firms, where the owner consented to participate in the study, and 449 workers from 406
23 firms, where employers allowed us to interview the workers.¹²

24 In March 2023, we conducted follow-up phone interviews with a random subset of
25 99 employers. In July 2024, we conducted a final round of in-person follow-up data

¹¹As shown in Online Appendix Figure G.1, grain-processing firms are clustered geographically. Therefore, in the listing we identified major clusters in the city center through focus groups and then moved outward along the main roads leading to the countryside.

¹²We exclude 28 employers due to a programming error that resulted in missing task assignments for some respondents. These observations are balanced on observables, and including them does not affect the results.

1 collection with the entire employer sample, interviewing 405 employers and 652 workers
2 currently employed at these firms. Because at each visit we interviewed the employer on
3 site (owner or manager) and up to two workers currently employed there, we construct
4 a panel at the firm level. Of these, 77.3% are perfect follow-ups, meaning that the same
5 employer was interviewed and the firm was located in the same geographic area. In
6 the first wave (2022), we required diversity across worker types—one permanent and
7 one casual worker per firm. When no casual or no permanent workers were employed,
8 only one worker was interviewed. Since we found no systematic differences by worker
9 type, this restriction was lifted in 2024, allowing two workers of the same type to be
10 interviewed per firm. This explains the larger worker sample in July 2024.

11 We also collected employer-level survey data on firm outcomes as well as giving pat-
12 terns and redistribution preferences across three waves. In September 2022, we captured
13 firm characteristics, task characteristics, and the extensive margin of informal redistri-
14 bution. In March 2023, we re-measured the extensive margin of redistribution, and in
15 July 2024 we collected firm characteristics and refined our measurement by eliciting the
16 intensive margin of work redistribution (hours and amount given). A worker-task roster
17 in this final wave enabled us to construct task-level estimates of work redistribution and
18 to gather information on characteristics of redistribution workers.

19 **2.2 Descriptives**

20 Table 1 summarizes firm, employer, and worker characteristics. As mentioned, the grain-
21 processing sector is heterogeneous. Based on their main production activity, firms can
22 be classified into three groups: those dealing in grain milling for human food, those
23 using maize milling by-products to produce animal feed, and those focusing on animal
24 feed processing and/or trading with non-maize products. About 31.1% of firms belong
25 to the first group, mostly producing maize flour. Of the remaining 68.9%, most deal in
26 maize grain processing, where the most common tasks include loading, milling, weighing,
27 sealing/packing, and sweeping. Firms in our sample employ an average of five to six
28 workers during the peak season (September 2022) and about three to four workers during
29 the moderate/lean season (July 2024).

30 Among the surveyed employers, 47.6% are owners (the remaining 52.4% are man-
31 agers); 31.1% of managers are the owners' family members. Most employers (70.4%) are
32 men, and all but two are Ugandans. The worker sample also primarily comprises men

	Summary statistics				Covariates balance									
	September 2022		July 2024		Individual tasks					Average	Value t. vs. busywork		Value t. vs. sweeping	
	Mean	Median	Mean	Median	Loading	Sealing	Weighing	Sweeping	Busywork	Value tasks	Difference	p-value	Difference	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A: Firms														
Workers (on day of interview)	5.94	3	3.90	3	7.17	5.80	4.13	6.69	3.50	6.10	-1.31	0.562	0.70	0.555
Workers (on standard day)	5.40	3	3.70	2.50	6.39	5.73	3.83	5.76	3.16	5.65	-1.35	0.270	0.29	0.802
Revenue (monthly, thousand UGX)	32,223	10,000	8,863	5,000	39,405	32,266	37,094	28,991	12,351	36,435	-13,358	0.190	-6,619	0.456
Profit (monthly, thousand UGX)	3,541	1,500	2,260	1,000	3,939	4,169	3,319	3,236	2,026	3,902	-964.4	0.085	-574.5	0.379
Establishment (years)	6.14	5	7.93	6	6.57	6.22	5.94	5.67	5.89	6.33	0.12	0.911	-0.66	0.300
Main product (share)	0.69	0.70	0.69	0.70	0.71	0.67	0.69	0.68	0.66	0.69	-0.01	0.261	-0.02	0.405
Sales (monthly, tonnes)	21.53	5	22.98	6	28.54	27.81	12.98	17.68	7.38	25.10	-11	0.069	-6.69	0.340
Management score (0-17)	9.74	10	9.91	10	9.88	10.49	8.93	9.48	9.24	9.90	-0.35	0.093	-0.58	0.460
Workers' time at the firm (hours)			9.89	10										
Workers' idle time (hours)			1.86	2										
Panel B: Employers														
Gender: male	70.43%		68.4%		0.74	0.72	0.63	0.70	0.66	0.71	0	0.707	-0.01	0.746
Age (years)	33.22	32	35.30	34	33.34	32.47	34.67	32.86	33.35	33.31	0.02	0.654	-0.36	0.765
Education (years)	8.85	6	6.77	4	8.94	7.99	9.81	8.73	9.43	8.80	0.57	0.424	-0.11	0.832
Role: owner	47.62%		41.05%		0.46	0.42	0.56	0.49	0.52	0.46	0.02	0.208	0.02	0.713
Panel C: Workers														
Gender: male	95.55%		91.85%		0.94	0.96	0.96	0.96	0.98	0.95	0.03	0.383	0	0.998
Age (years)	26.02	25	27.62	26	26.68	26.74	25.89	25.44	24.91	26.47	-1.18	0.083	-0.90	0.366
Is permanent worker	49.22%		57.3%		0.51	0.69	0.35	0.61	0.34	0.51	-0.15	0.221	0.09	0.782
Education (years)	7.33	6			7.10	8.36	6.85	6.90	7.73	7.31	0.61	0.892	-0.27	0.687
Tenure firm (years)	1.93	1	3.89	3	2.04	2.49	1.76	2	1.37	2.06	-0.57	0.144	0.01	0.952
Hours worked (on standard day)	10.43	11	9.95	10	10.64	10.56	10.40	10.72	9.76	10.55	-0.53	0.417	-0.08	0.877
Days worked (in standard week)	6	6	5.88	6	5.88	6.13	5.96	6.19	5.99	5.96	0.07	0.114	0.17	0.314
Income (monthly, thousand UGX)	293.2	265.7	436.2	320	307.9	325.9	258.0	297.7	274.6	297.5	-2.21	0.379	1.85	0.923
Has written contract	10.96%				0.10	0.04	0.23	0.05	0.21	0.11	0.11	0.605	-0.04	0.430
Pay type: piece-rate only	67.71%				0.71	0.64	0.66	0.68	0.66	0.68	0	0.870	0.02	0.697
Pay type: piece-rate and salary	20.04%				0.15	0.24	0.26	0.22	0.18	0.20	-0.04	0.554	0	0.991
Has emergency			23.57%											
Panel D: Task characteristics														
Tenure (days)					7.90	3.70	3.87	0.83	7.66	5.05	-2.61	0.290	4.23	0.000
Effort (1-4)					3.96	2.03	2.85	1.02	3.95	2.95	-1.01	0.000	1.92	0.000
Piece rate (employers, thousand UGX)					0.74	0.49	0.17	n/a	0.75	0.42	-0.33	0.000	n/a	n/a
Piece rate (workers, thousand UGX)					0.87	0.52	0.11	n/a	0.81	0.48	-0.33	0.000	n/a	n/a

Table 1: Summary statistics and covariate balance. *Note:* Data from employer and worker surveys in September 2022 (N = 399 employers; N = 449 workers) and July 2024 (N = 405 employers; N = 652 workers). Firm characteristics: self-reported by employers. Task characteristics: reported by employers of firms where each task is routinely performed; median-imputed for others. Busywork task characteristics: imputed from Loading. Sweeping piece rate: N/A. Difference columns: mean differences. *P*-value columns: randomization inference *p*-values. Currency: UGX. Management score: based on McKenzie and Woodruff (2017); details are in Online Appendix E. Workers, Revenue, Profit, Sales, and Age trimmed at 99th percentile.

1 (95.6%). All worker respondents report being employed full time, with a roughly equal
2 representation of permanent and casual workers. The average worker works six days per
3 week for 10.4 hours per day. Around 20%–30% of this work time is spent idle, depending
4 on the season and whether this question is asked to the employer or the worker. Salary
5 and piece-rate payments are both common. Piece rate is most common among casual
6 workers (90.7%), while permanent workers are relatively more likely to be paid a salary
7 or a mix of salary and piece rate.

8 Consistent with the view that becoming an entrepreneur marks economic success
9 in sub-Saharan Africa (Alby et al., 2020), employers—owners especially—are wealthier
10 than both the workers in our sample and the average Ugandan, as shown in Appendix
11 Figure A1. The average firm profit, an estimate of the owners’ household income, is
12 5.3 times the median household income in Kampala (UGX 667,000). The self-reported
13 average monthly wage for workers is UGX 293,211 (USD 77.16) per month, in line with
14 the median monthly wage income in urban Uganda.¹³

15 **2.3 Patterns of Informal Redistribution**

16 Employers in our sample are embedded in informal redistribution networks: 96% report
17 sharing earnings to help someone in the past month. Among givers, the average donation
18 amounts to 28.9% of monthly income, consistent with Carranza et al. (2022) in Côte
19 d’Ivoire. Contrary to the common view that sharing is purely kin-based, and potentially
20 because of the urban setting, employers report giving as often to friends and family
21 (81.8%) as to acquaintances or strangers (83.8%), perhaps reflecting the urban setting.
22 Motivating our focus, work emerges as the most salient channel of redistribution, with
23 over 90% of employers and workers citing it (Figure 1, Panel A).¹⁴

24 About half of employers self-report giving work “to help out” in the past month.
25 As shown in Panel B, the prevalence is remarkably stable across seasons: 46.4% in
26 September 2022 (peak), 46.5% in March 2023, and 46.2% in July 2024. This consistent
27 likelihood of giving work across seasons suggests that work redistribution is a sustained
28 practice. According to the self-reports, the work given is not always necessary for the
29 firm’s operations. When asked explicitly, many employers assign tasks “even if they did

¹³Numbers reported in the 2019/2020 Uganda National Household Survey (Uganda Bureau of Statistics, 2021).

¹⁴This question used pre-coded options during the pilot phase. In the March 2023 phone survey, responses remained consistent when asked in open-ended form.

1 not need the work [task],” which they describe as “symbolic.” We adopt this terminology
2 throughout. Symbolic giving is more common in the peak season (38.4%) than in lean
3 season (28.3%), consistent with employers giving more when resources are abundant.

4 The most common redistribution tasks are loading, milling, packing/sealing, and
5 mixing; 38% of these are defined as symbolic, as shown in Panel C. These tasks are ob-
6 servationally indistinguishable from regular production activities and are also among the
7 most common in firms’ everyday operations. This illustrates the fundamental difficulty
8 of identifying unproductive redistribution work in observational firm data and motivates
9 our experimental approach.

10 **3 Work-Versus-Cash Experiment**

11 We use a field experiment to overcome the identification challenges inherent in the ob-
12 servational data. Our design elicits real-world redistribution decisions in a controlled
13 environment, isolating work redistribution preferences from other distributional prefer-
14 ences, as well as confounds such as productivity and relational considerations.

15 **3.1 Experimental Flow, Outcomes, and Incentives**

16 Our goal is to identify preferences for the channel of giving: work or cash. We elicit
17 choices from employers (givers) and workers (receivers) to understand preferences on
18 both sides of the labor market. Respondents choose between giving/receiving an uncon-
19 ditional cash transfer or hiring/working at varying wages within an incentive-compatible
20 framework.

21 We anonymously match employers and workers from different firm clusters across
22 the city. Each pair enters a lottery for a UGX 16,000 (USD 4.21) payoff as part of their
23 survey compensation. The payoff is split unevenly: person A (the employer) receives
24 UGX 15,000, while person B (the worker) receives UGX 1,000, creating inequality within
25 the pair that motivates redistribution. Participants are informed that these initial payoffs
26 are not final, as one person for each pair—the randomly selected dictator—will decide
27 how to redistribute a portion through either an unconditional cash transfer or payment
28 for work. Choices are made privately before the lottery draw.

29 Work in the experiment consists of a task that person B performs at person A’s firm.
30 Before eliciting redistribution decisions, employers (person A) and workers (person B)

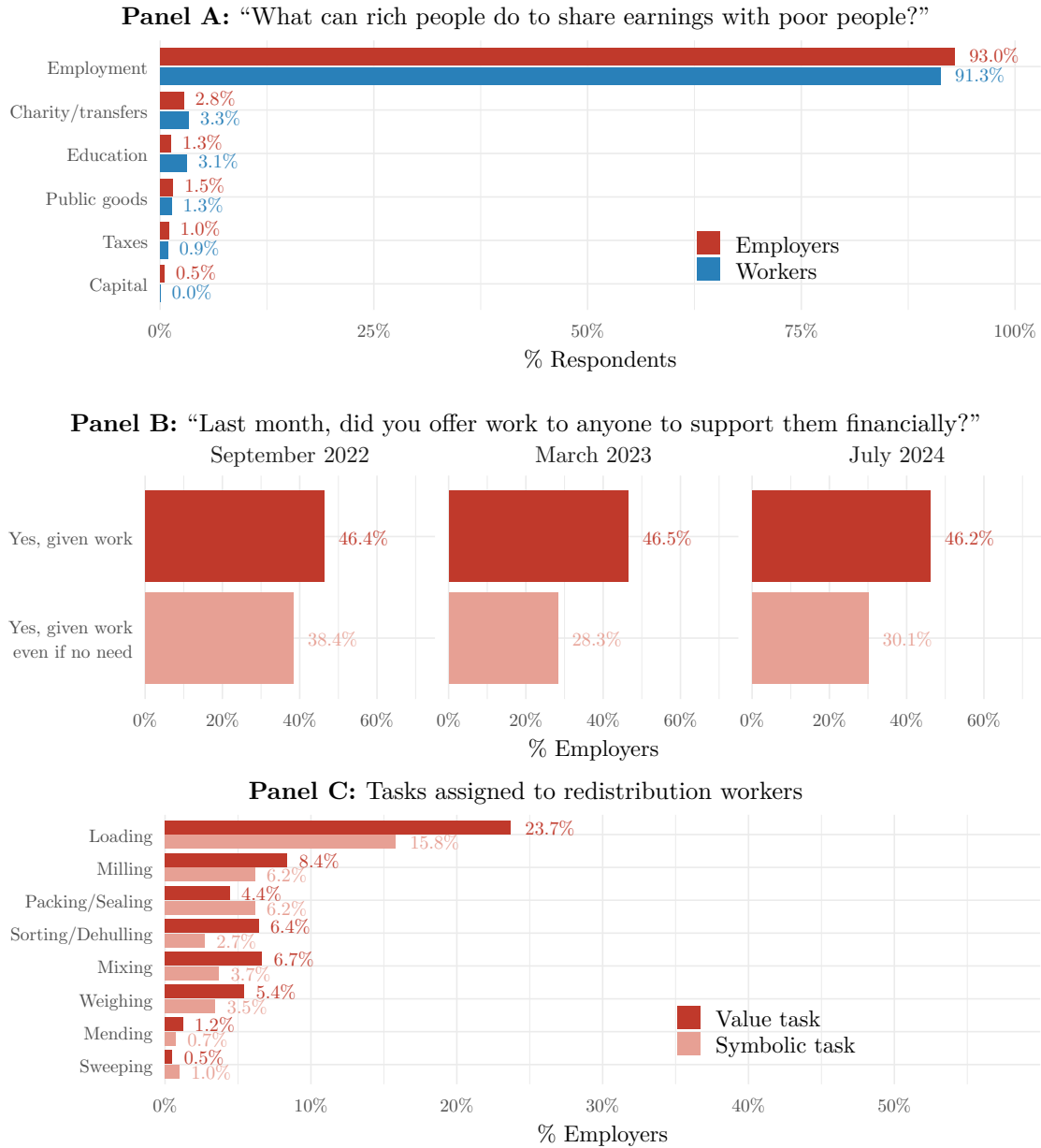


Figure 1: Self-reported redistribution preferences and informal redistribution via work. *Note:* Data: September 2022 (N = 399 employers, N = 449 workers; Panels A–B), March 2023 (N = 99; Panel B), and July 2024 (N = 405; Panel C) surveys. Panel C: Employers reporting work redistribution were asked which tasks redistribution workers performed (open-ended) and whether each task was needed or symbolic. Only the first task mentioned is shown, and tasks with fewer than six mentions are not displayed.

1 are explained the task that person B will have to carry out if work redistribution is
 2 chosen. Tasks are drawn from common grain-processing activities—sealing, loading,

1 weighing, and mending—and are calibrated to last about 30 minutes. For example,
2 sealing involves “sealing 10 sacks,” while loading is defined as “loading 3 sacks.” Short-
3 term hiring is very common in this setting: over 50% of workers in our sample are hired
4 temporarily, and 70.6% of employers report hiring workers for less than an hour in the
5 past month. The short tasks also ensure that workers can carry them out even when
6 employed nearly full time given the slack in their work schedule.¹⁵

7 Employers are asked, “Do you want to hire person B to perform task i at your firm
8 for wage w , or do you want to give a cash transfer t ?” Workers answer the symmetric
9 question about whether to receive work or cash transfers at the same wage and transfer
10 combinations.¹⁶

11 We use a double multiple-price list to elicit decisions, presenting up to 22 questions
12 with varying wage or transfer amounts. We begin with the wage and transfer set at UGX
13 3,000, the market wage for a standard 30-minute task in September 2022 (the midpoint
14 choice). In later choices, either the wage or the transfer is adjusted to be above or below
15 the market wage:

- 16 • Block 1—High wage: The wage varies from UGX 3,500 to UGX 10,000, and the
17 transfer is fixed at UGX 3,000.
- 18 • Block 2—Low wage: The wage varies from UGX 500 to UGX 2,500, and the
19 transfer is fixed at UGX 3,000.
- 20 • Block 3—Low transfer: The wage is fixed at UGX 3,000, and the transfer varies
21 from UGX 500 to UGX 2,500.
- 22 • Block 4—High transfer: The wage is fixed at UGX 3,000, and the transfer varies
23 from UGX 3,500 to UGX 6,500.

24 Each multiple-price list is iterative: once a respondent switches from work to cash
25 (or vice versa), we assume they maintain that preference for all higher amounts. We
26 employ binary search, starting with extreme values and narrowing to the switching
27 point. When respondents consistently choose the same option at the boundary prices

¹⁵As noted in Section 2.2, workers in our sample are substantially underemployed, reporting 20%–30% slack time during their workday. When we ask directly in the July 2024 worker follow-up survey, workers report having capacity for an average of 2.5 additional hours of work per day, confirming considerable available time for experimental tasks.

¹⁶See Online Appendix B for the experimental script.

1 and the midpoint choice, we impute all intermediate choices to match the boundary
2 choice (staircase method).¹⁷

3 Notably, to measure willingness to pay for work redistribution, it would have been suf-
4 ficient to fix either the transfer and vary the wage, or vice versa. Our design implements
5 both approaches sequentially (hence the double multiple-price list). The wage-varying
6 blocks form the main focus of the analysis, allowing us to estimate the elasticity of work
7 choices with respect to the wage. The transfer-varying choices provide complementary
8 tests *ex ante*. The low-transfer region serves as a useful sanity check that choices for
9 work are not simply driven by the experimental requirement to share, as it allows us
10 to observe whether employers continue to give via work when the alternative transfer
11 is very small. The high-transfer region, compared with the low-wage region, allows us
12 to separate generosity from aversion to paying below the market wage—in both cases
13 giving cash is costly, but only the latter violates potential market wage norms (Breza
14 *et al.*, 2019).

15 We measure two outcomes: binary choices and willingness to pay. Binary choices are
16 whether the respondent chooses work or cash at each wage-transfer combination, and
17 willingness to pay is the maximum amount by which the wage exceeds the transfer (or
18 transfer exceeds the wage) at which the respondent still chooses work.

19 Choices are incentive-compatible with meaningful stakes. Five percent of pairs are
20 randomly selected to receive their experimental payoffs, with one randomly chosen de-
21 cision implemented. The maximum wage (UGX 10,000) approximates average daily
22 giving (UGX 6,241) and equals 83.2% of a permanent worker’s daily wage. Participants
23 must complete any chosen work arrangement or forfeit winnings. For winning pairs, we
24 arranged fast transportation from the worker’s location to the firm to minimize time
25 costs. We also monitored task completion and distributed payments.

26 **3.2 Task Randomization**

27 Tasks are randomly assigned to employer-worker pairs, and both parties learn about the
28 task before work or cash redistribution choices are made. This randomization allows
29 us to separate work redistribution preferences from production value considerations.
30 Specifically, if the production value of work drives preferences for work redistribution,

¹⁷As in other studies using this method (e.g., Bursztyn and Coffman, 2012), question order is not randomized but follows an intuitive sequence. Piloting confirmed ordering did not affect choices.

1 we would expect respondents to choose work redistribution less frequently (and show
2 lower willingness to pay for work) when randomly assigned a lower-value task.

3 Beyond the four standard grain-processing tasks (sealing, loading, weighing, mend-
4 ing), we include two low-value tasks: busywork and sweeping. Busywork involves loading
5 and immediately unloading three sacks, with zero production value. A concern is that
6 it may still serve a screening or training function. This is why we include the second
7 low-value task: sweeping the firm’s floor for 30 minutes—a task with minimal productive
8 value and no screening or training benefits, given that it has the lowest skill requirements
9 among all tasks (Table 1). Importantly, the hourly wage for sweeping is also significantly
10 lower, around UGX 700 per 30 minutes compared to UGX 3,000 for standard tasks.

11 Our main identification test compares choices for these deliberately low-value tasks
12 against standard tasks. Because standard tasks vary in firm-specific value and are
13 multidimensional—differing in piece rates, effort requirements, and tenure requirements
14 (Table 1)—there is no clearly defined comparative static. The ad-hoc low-value tasks
15 provide cleaner identification: if production, screening, or training considerations pri-
16 marily drive work redistribution choices, preferences for work should fall substantially
17 among respondents randomly assigned to sweeping or busywork.

18 **3.3 Other Design Features**

19 **Anonymity and distance.** Choices and payments are private and anonymous, iso-
20 lating intrinsic preferences from social pressure or image concerns (Bursztyn and Jensen,
21 2017). In particular, employers face no risk of future requests, and workers need not
22 worry about signals from accepting handouts.¹⁸ Matching between employers and work-
23 ers is implemented across clusters 15.6 km apart on average, limiting post-experimental
24 encounters and the networking value of work.

25 In real life, work redistribution choices are observable and social ties stronger, both
26 factors that should increase the likelihood that redistribution occurs via work outside our
27 experimental setting. Additionally, since employers face monitoring constraints (Heath,
28 2018), anonymity makes work redistribution costlier in our experiment.

¹⁸Experimenter demand effects are unlikely given that surveys were brief, respondents met enumer-
ators only once, and the experiment occurred at the interview’s start before rapport developed.

1 **Windfall payoffs.** Experimental payoffs come from a lottery rather than earned in-
2 come. While windfall gains may increase generosity overall, they should reduce work
3 redistribution specifically: employers should be less willing to ask workers to work to
4 share windfall money, and workers should be less willing to work for windfall transfers.

5 **Minimum redistribution.** The experiment places respondents in a position where
6 they must give and cannot fully escape redistribution (minimum transfer of UGX 500).
7 This design choice reflects reality in our setting, where social pressure makes declining
8 assistance requests difficult or impossible.¹⁹ The benefit of this feature is that we can
9 measure preferences for redistribution via work or cash across all employers, not just
10 those who voluntarily give in the experiment. Importantly, we can test if the minimum
11 transfer induced artificial choices as we would expect responsiveness to price: employers
12 should switch to cash when this choice minimizes giving. To validate this, the July 2024
13 replication includes zero as a transfer option (see Section 3.4 below).

14 **3.4 Robustness Experiments**

15 We conduct three robustness experiments to address potential confounds and test gen-
16 eralizability.

17 **Spectator design (September 2022).** To distinguish self-interest from prescriptive
18 norms, we implement a spectator version. Respondents make work-versus-cash choices
19 on behalf of anonymous employer-worker pairs. The chosen allocation is implemented for
20 actual participants, making choices consequential, but spectators have no personal stake
21 in the outcome. If work redistribution reflects pure self-interest, choices with stakes and
22 spectator choices should not align, especially when costly for the respondent. Details
23 are provided in Online Appendix B and C.

24 **Food versus cash (March 2023).** Work preferences in our main experiment could
25 reflect aversion to giving cash rather than preferences for work per se. We test this

¹⁹In most African settings, sharing is viewed as a moral duty, and personal accumulation is frowned upon. For a review of the evidence on such forced mutual help, see [Alby et al. \(2020\)](#) or [Carranza et al. \(2022\)](#). In our sample, 96% of employers gave to kin, acquaintances, or strangers in the past month. Most report feeling compelled to give and that requests affect business growth (Online Appendix Figure G.2).

1 with 99 employers who choose between giving food (a meal or snack) or cash at vary-
2 ing amounts, using the same experimental structure. Details are provided in Online
3 Appendix B and D.

4 **Replication (July 2024).** We replicate the work-versus-cash experiment with several
5 design enhancements in a multi-scenario version of the work-versus-cash experiment.
6 The replication coincides with the off-peak season (versus the peak season in September
7 2022), providing evidence of robustness across economic conditions. First, in a baseline
8 scenario, we test boundary conditions: (i) the wage ceiling increases to UGX 15,000,
9 allowing us to measure higher willingness to pay, and (ii) the minimum transfer is zero,
10 testing whether work preferences persist when employers have the option to give nothing.

11 We next leverage a set of scenarios to test for robustness to alternative explanations
12 for work redistribution preferences as well as drivers. Using the strategy method, re-
13 spondents make choices across varying scenarios. Three scenarios are designed to rule
14 out confounds: (i) anonymity emphasis (explicit reminders that choices are private with
15 no future contact), (ii) cash delivered in person (equalizing networking opportunities
16 across work and cash), and (iii) work observability (task performed at the worker’s loca-
17 tion, eliminating signaling value). Additional scenarios test for drivers, such as workfare
18 incentives, reciprocity, screening for character, and dignity. Participants decide across
19 all scenarios before outcomes are revealed. For lottery winners, one scenario and one
20 choice are randomly implemented. We discuss the details and results in Sections 4.3 and
21 4.4.²⁰

22 3.5 Benchmarks

23 Our design remains agnostic about motives, but thanks to the price variations, it allows
24 us to distinguish work redistribution preferences from other distributional preferences
25 or self-interest through choice patterns. To interpret the results, we derive how choices
26 should vary with wages and transfers under three benchmarks: payoff maximization,
27 generosity or altruism, and inequality aversion. The formal derivations are provided
28 in Online Appendix A. The key assumption we make is that work is valued at the
29 prevailing market wage of UGX 3,000 for both employers (production value) and workers

²⁰The scripts are provided in Online Appendix B.2.

1 (opportunity cost of time). We consider this assumption conservative: employers face
2 monitoring costs when hiring unknown workers, while workers incur transport time.

3 **Payoff maximization.** Under the assumed value of work, a weakly payoff-maximizing
4 employer will weakly prefer hiring at any wage $w \leq 6,000$ and at any transfer $t > 0$. A
5 payoff-maximizing worker will weakly prefer a $\bar{t} = 3,000$ cash transfer over work at any
6 $w \leq 6,000$. Given the outside option of $\bar{w} = 3,000$, workers should choose cash to work
7 for all $t > 0$.

8 **Generosity or altruism.** Under generosity or altruism, givers maximize receivers'
9 payoffs. This implies hiring only when the wage $w \geq 6,000$ given an outside option
10 of $w = 3,000$. An altruistic employer should never hire at any transfer $t > 0$ given a
11 $\bar{w} = 3,000$. Altruistic receivers, who maximize the giver's payoff, should weakly prefer
12 work at any $w \leq 6,000$ and choose to work for any $t > 0$.

13 **Inequality aversion.** Under inequality aversion, both employers and workers aim for
14 a 50-50 equal split of the total payoff. Both givers and receivers should weakly prefer
15 work to cash only when the wage $w \geq 6,000$ given the usual outside options. For
16 robustness, we also consider a benchmark where respondents target a 65-35 split, which
17 is closer to respondents' non-incentivized dictator game preferences with the same initial
18 endowments. Under this benchmark, respondents should weakly prefer work only when
19 the wage lies between 6,000 and 9,000.

20 4 Preferences for Work Redistribution

21 In this section, we present results from the main work-versus-cash experiment, exam-
22 ining whether employers and workers prefer work to cash transfers. We then use task
23 randomization in the main experiment to rule out production value as the driver of
24 work choices. Next, we report results from the multi-scenario replication of the main
25 experiment that exclude relational benefits or default behavior. Finally, we explore the
26 motivations behind work redistribution preferences and describe the results from the
27 multi-scenario replication that test for normative motivations.

4.1 Redistribution Choices: Work-Versus-Cash Experiment

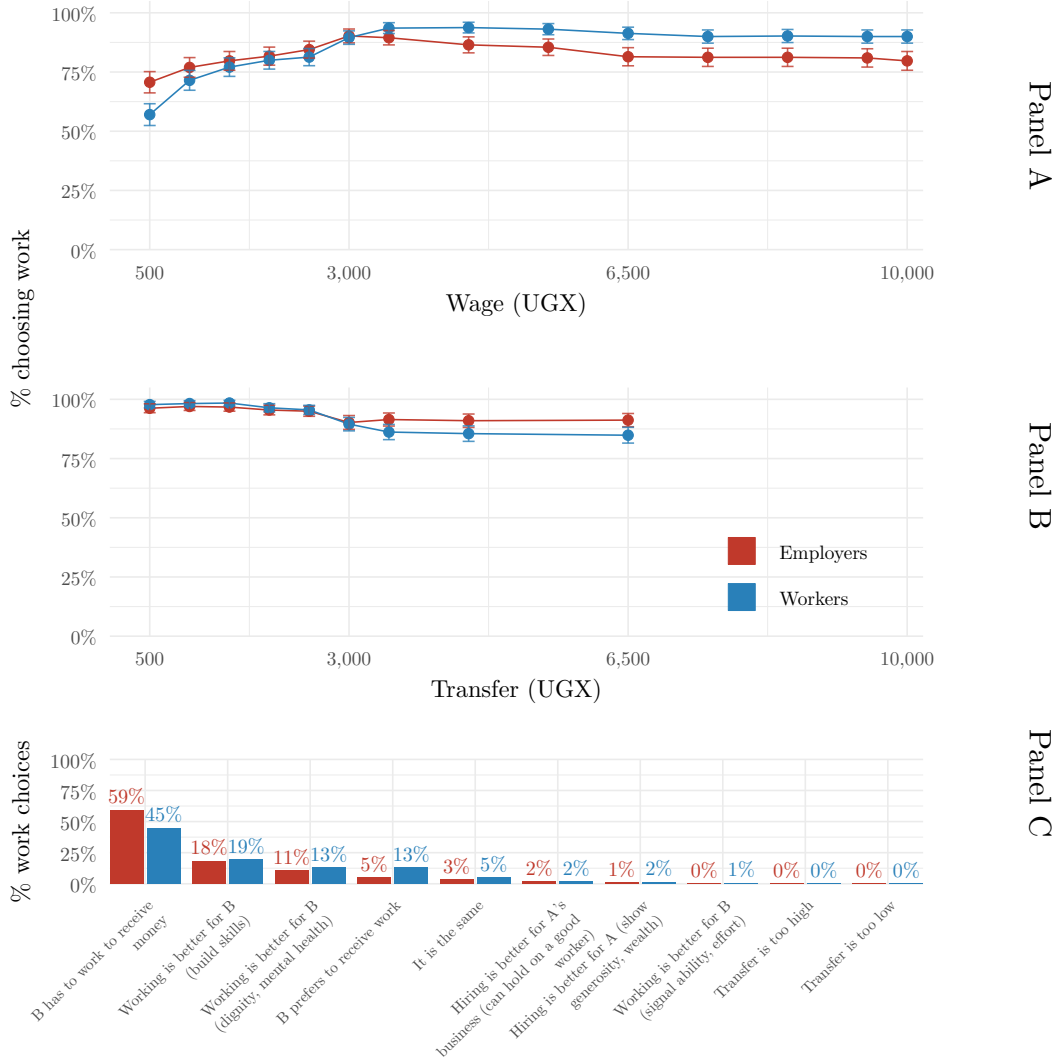


Figure 2: Work redistribution choices and motivations. *Note:* Data are from the main experiment (September 2022; N employers = 399, N workers = 449). In Panel A, the outside option is to give a UGX 3,000 cash transfer, while in Panel B it is hiring at a UGX 3,000 wage. Employers make up to 22 decisions, each about giving, and workers make up to 22 decisions, each about receiving. Confidence intervals: 95% level. Panel C plots the self-reported motivations as coded by field officers. We focus on reasons for work choices at the “Wage UGX 3,000 – Transfer UGX 3,000” choice. The ranking is unaffected when looking across all choices. “A” denotes the anonymous giver, and “B” denotes the anonymous receiver.

We begin by examining choices in the main work-versus-cash experiment. Figure 2 shows work redistribution choices across all wage and transfer levels. Employers choose to give work over cash in 86.5% of decisions (range: 70.7%–97%). When the experimental

1 wage equals the transfer as well as the market wage of UGX 3,000, 90.2% of employers
2 choose to hire. This pattern holds at the wage extremes: 79.7% hire at UGX 10,000
3 versus a UGX 3,000 transfer, and 70.7% hire at UGX 500 versus a UGX 3,000 transfer.
4 When the alternative is the highest transfer (UGX 6,500), 91.2% still choose to give
5 work, yet 96.2% of employers choose to hire at the market wage when the alternative is
6 a much lower transfer (UGX 500).²¹

7 Employers' choices are inconsistent with payoff maximization, which predicts hir-
8 ing only at wages below UGX 6,000 (Online Appendix A, Benchmark 1). Less than
9 4% of employers switch from work to cash from UGX 5,500 to UGX 6,500 (the payoff-
10 maximizing threshold). When the option to give nothing is available (July 2024 repli-
11 cation), 88.6% still hire at the market wage.²² Indeed, work choices imply a meaningful
12 willingness to pay for work: 97.7% of employers are willing to pay for work, and 81.7%
13 are willing to pay above the market wage. The average willingness to pay for work is
14 about twice the market wage (UGX 6,085), 40.6% of employers' initial payoff.

15 The patterns are also inconsistent with generosity or inequality aversion. Generous
16 employers maximizing worker payoffs should hire only at wages above UGX 6,000 given
17 workers' UGX 3,000 opportunity cost of working (Online Appendix A, Benchmark 2).
18 Inequality-averse employers targeting equal splits should also avoid hiring at low wages.
19 Additionally, employers' preferences for work redistribution cannot be explained by a
20 broader aversion to giving cash or concerns about workers misusing the money. In the
21 food-versus-cash experiment, employers prefer giving cash over food 79.8% of the time
22 (Online Appendix Figure G.4).

23 Workers' choices mirror employers' decisions. Workers choose work over cash in
24 87.8% of decisions, a share statistically indistinguishable from employers' 86.5% (p -value
25 0.388).²³ Workers' choices are also inconsistent with payoff maximization. Accounting
26 for the opportunity cost of their time, a worker should choose to receive work only at
27 wages above UGX 6,000, yet 93.1% choose to work when the wage equals UGX 5,500.
28 At the lowest wage, UGX 500, 57% opt to work rather than accept a UGX 3,000 cash

²¹Fewer employers hire at UGX 500 than at UGX 3,000, producing a locally upward-sloping demand curve. This may reflect aversion to paying wages below market rates.

²²See Online Appendix Figure G.3 for a comparison between the work-versus-cash experiment in September 2022 and the replication in July 2024.

²³ p -value from a pooled regression of Work, an indicator variable for choosing work over cash at a given wage/cash combination, on an indicator variable for whether the respondent is a worker, including wage (log) and transfer (log) controls, and standard errors clustered at the respondent level.

1 transfer, and 84.9% choose to work for the market wage of UGX 3,000 instead of receiving
 2 a transfer over twice as large. The average willingness to pay is UGX 3,004, about 26%
 3 of the daily earnings of a permanent worker (UGX 12,021). Workers’ willingness to
 4 accept work at wages lower than the transfer is incompatible not only with generosity
 5 (Online Appendix A, Benchmark 2) but also with the more realistic benchmark of an
 6 equal split of the total payoff (Online Appendix A, Benchmark 3).

7 We complement the descriptive evidence with regression analysis estimating the price
 8 elasticities of work choices, leveraging the following model:

$$Work_{ij} = \beta_1 \log(Wage_j) + \beta_2 \log(Transfer_j) + \lambda_i + \epsilon_{ij}, \quad (1)$$

9 where i indexes the respondent, j indexes a wage-transfer combination, and λ_i are
 10 respondent-level fixed effects. Standard errors are clustered at the respondent level,
 11 and separate regressions are estimated for employers and workers.

12 The regression results are summarized in Table 2, columns 1 and 10 (employers and
 13 workers, respectively). In line with the descriptive results, both employers’ and workers’
 14 work choices display very limited price sensitivity. The semi-elasticity of employers’ work
 15 choices with respect to the wage is small, positive (0.017), and statistically insignificant.
 16 The semi-elasticity with respect to the transfer is also significant but negative: a 1%
 17 transfer increase reduces employer work choices by 0.064 percentage points. Workers’
 18 price sensitivity is somewhat larger and in the standard direction but remains modest:
 19 a 1% wage increase raises work choices by 0.099 percentage points, while a 1% transfer
 20 increase reduces work choices by 0.087 percentage points.²⁴ The results hold when
 21 splitting the decisions by whether the wage or the transfer are below or above the
 22 market wage (Online Appendix Table H.1). Finally, demographic characteristics do not
 23 predict work choices (Online Appendix Table H.2).

24 Several factors argue against experimenter demand as a primary explanation for the
 25 observed preference for work redistribution. First, the experimental environment was
 26 deliberately low pressure: surveys were brief (typically under an hour), respondents
 27 met enumerators only once, and the redistribution experiment was administered at the
 28 interview’s start before any rapport could develop. Second, comparative evidence from
 29 similar contexts shows that privacy alone suffices to reveal genuine preferences that

²⁴Using the staircase method, interior choices are imputed when the boundary choice equals the midpoint. Restricting the sample to directly observed choices leaves results unchanged.

1 deviate from social norms. For example, in an experiment with similar privacy levels
2 in Kenya, [Jakiela and Ozier \(2016\)](#) detect meaningful departures from socially desirable
3 choices. Third, in the food-versus-cash experiment conducted in March 2023 using
4 an identical set-up, most respondents chose cash over in-kind transfers. Since neither
5 the work-versus-cash nor the food-versus-cash experiment signaled what the “right”
6 choice should be, respondents should have consistently selected non-cash options in
7 both contexts if experimenter demand were systematically driving behavior.

8 Our experimental estimates likely represent a lower bound on the preference for
9 work redistribution in practice. The alignment of preferences between employers and
10 workers—both privately preferring work over cash—indicates that work arrangements
11 are mutually agreeable and likely to be fulfilled. Since our experiment imposes anonymity,
12 the likelihood of choosing work redistribution could have been substantially greater in
13 more real-world settings where choices are publicly observable and workers can exert
14 social pressure on employers, a dynamic similar to that documented in [Breza et al.](#)
15 [\(2019\)](#).

16 **4.2 The Role of Production Value in Work Choices**

17 Random task assignment, particularly of the busywork and sweeping tasks, allows us to
18 test whether production value drives work choices. If so, lower-value tasks should reduce
19 work choices and willingness to pay to work.

20 Figure 3 displays work choices by task, with Panel A showing employers’ choices
21 and Panel B showing workers’ choices. The share of employers choosing work is observ-
22 ably identical irrespective of whether the pair is assigned to busywork (zero production
23 value), sweeping (minimal production value, no screening), or standard (productive)
24 tasks. Workers exhibit the same pattern: both the binary decision to choose work and
25 the willingness to pay remain constant across task types. These results are inconsistent
26 with the production value of work driving redistribution preferences on both sides of the
27 labor market.



Figure 3: Work redistribution choices by value and no-value tasks. *Note:* Data: main experiment (September 2022; $N = 399$ employers, $N = 449$ workers). Choices displayed: wage-varying choices (500–10,000 UGX) with alternative UGX 3,000 cash transfer; transfer-varying choices are in Online Appendix Figure G.6, Panel A. Value tasks: choices of respondents randomly assigned to loading, weighing, or sealing. Busywork and Sweeping: binary indicators for respondents assigned to these tasks. Confidence intervals: 95% level. p -values: from regressions following Table 2’s specification (equation 2) and adjusted for multiple-hypothesis testing (Holm method).

	Employers									Workers								
	Work					WTP				Work				WTP				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Wage (log)	0.017 (0.010)	0.017 (0.010)	0.033 (0.011)	0.017 (0.010)	-0.009 (0.007)					0.099 (0.010)	0.099 (0.010)	0.109 (0.010)	0.099 (0.010)	0.135 (0.006)				
Transfer (log)	-0.064 (0.008)	-0.064 (0.008)	-0.061 (0.009)	-0.064 (0.008)	0.002 (0.004)					-0.087 (0.008)	-0.087 (0.008)	-0.083 (0.008)	-0.087 (0.008)	-0.088 (0.005)				
No value tasks		-0.010 (0.024)	0.014 (0.037)			-0.178 (0.207)	0.276 (0.292)				-0.017 (0.019)	0.030 (0.023)			0.033 (0.119)	0.211 (0.139)		
Effort			-0.021 (0.019)				-0.050 (0.156)					-0.013 (0.043)				0.209 (0.229)		
Piece rate			0.007 (0.013)				-0.026 (0.111)					-0.015 (0.013)				-0.182 (0.091)		
Tenure requirement			0.002 (0.019)				-0.031 (0.140)					-0.012 (0.049)				-0.060 (0.208)		
Unfamiliar task			-0.061 (0.052)				-0.527 (0.428)					-0.068 (0.022)				-0.343 (0.144)		
Sealing				0.033 (0.031)				0.059 (0.259)					0.017 (0.027)					-0.280 (0.197)
Weighing				0.026 (0.038)				0.077 (0.321)					0.048 (0.024)					0.185 (0.146)
Busywork				0.021 (0.037)				0.278 (0.290)					0.041 (0.023)					0.283 (0.137)
Sweeping				-0.001 (0.034)				-0.358 (0.285)					-0.047 (0.031)					-0.286 (0.201)
No rule of thumb					-0.006 (0.012)				-0.108 (0.097)					-0.028 (0.010)				-0.102 (0.043)
Cash in person					0.015 (0.012)				0.155 (0.105)					0.006 (0.010)				0.077 (0.047)
Work unobservable					-0.031 (0.015)				-0.202 (0.126)									
Wants to work					0.055 (0.014)				0.551 (0.127)									
Reciprocity					-0.034 (0.017)				0.178 (0.139)					-0.037 (0.010)				-0.227 (0.049)
Verifiable shocks					-0.417 (0.021)				-1.590 (0.194)									
Excuse for cash														-0.037 (0.008)				-0.139 (0.037)
Fixed effects																		
Respondent	Y	N	N	N	Y	N	N	N	Y	Y	N	N	N	Y	N	N	N	Y
Mean outcome	0.87	0.87	0.87	0.87	0.70	6.09	6.17	6.09	5.01	0.88	0.88	0.89	0.88	0.71	3.00	3.06	3.00	2.16
Obs.	8,778	8,778	6,820	8,778	27,806	399	310	399	2,786	9,878	9,878	8,360	9,878	22,448	449	380	449	3,208

Table 2: Work redistribution choices. *Note:* Data: main experiment (September 2022; columns 1–4, 6–8, 10–13, and 15–17) and multi-scenario replication (July 2024; columns 5, 9, 14, and 18). Work: binary for work-versus-cash choice at given wage and transfer. WTP: maximum willingness to pay for work (thousands UGX). Wage (log): wage at choice (500–10,000 UGX). Transfer (log): transfer at choice (500–6,500 UGX). No-value tasks: binary, equals one for busywork or sweeping task assignment. Effort: Employer-assessed task effort (1–4 scale), standardized. Piece rate: employer-reported task piece rate, standardized; N/A for sweeping. Tenure requirement: employer-reported, standardized tenure required for a worker to perform the task unsupervised. Busywork piece rate, effort, and tenure are imputed from Loading. Unfamiliar task: binary indicator for task not usually done at firm or by worker. Sealing, Weighing, Busywork, and Sweeping are binary task assignment indicators; Loading is omitted. Worker regressions: Tenure requirement and Effort are imputed from employer responses (mean). Reference category: baseline scenario; details are in Online Appendix C. Standard errors: clustered at respondent level for Work regressions and WTP regressions with multiple scenarios (columns 9 and 18).

1 On the demand side, these results imply that employers pay for zero marginal prod-
 2 uct work. A large majority of employers (86.4%) are willing to pay as much as UGX
 3 10,000—three times the market wage—for a worker to do busywork rather than provide
 4 a smaller unconditional cash transfer, and we observe similar patterns for the sweeping
 5 task. Employers’ average willingness to pay is UGX 6,386 for busywork and UGX 5,750
 6 for sweeping, nearly twice the market wage for standard tasks and over eight times the
 7 UGX 671 market wage for sweeping. These values are not statistically different from
 8 willingness to pay for standard tasks.

9 We rigorously test for the effect of task value on experimental choices using the
 10 following regression model:

$$Y_{ij} = \alpha + \beta_1 \log(\text{Wage}_j) + \beta_2 \log(\text{Transfer}_j) + \beta_3 \mathbf{1}\{\text{NoValueTasks}_i\} + \delta' \mathbf{X}_i + \varepsilon_{ij}, \quad (2)$$

11 where Y_{ij} is either a binary work choice (at wage-transfer combination j) or willingness
 12 to pay for respondent i . The coefficient of interest is β_3 on $\mathbf{1}\{\text{NoValueTasks}_i\}$, which
 13 indicates assignment to busywork or sweeping.

14 Because the two outcomes are defined at different levels of observation, the specifica-
 15 tion is implemented slightly differently across them. For the binary work-choice outcome,
 16 we observe multiple choices per respondent, at various prices, allowing us to control for
 17 the wage-transfer combination and to cluster standard errors at the respondent level.
 18 For the willingness-to-pay outcome, there is only a single observation per respondent,
 19 and wage and transfer do not vary mechanically. We therefore estimate a simplified
 20 cross-sectional version of equation 2 that omits $\log(\text{Wage}_j)$ and $\log(\text{Transfer}_j)$ and uses
 21 robust standard errors. Apart from this mechanical adjustment, the specification follows
 22 the same structure.

23 Columns 2, 6, 11, and 15 of Table 2 summarize the results from the baseline speci-
 24 fication without controls ($\mathbf{X}_i = \emptyset$), while columns 3, 7, 12, and 16 add controls for task
 25 characteristics (Effort, Piece rate, Tenure requirement) and whether the task was never
 26 performed by the worker or at the employer’s firm (Unfamiliar task). For robustness,
 27 we also estimate a version of equation 2, replacing the pooled “No-value task” indicator
 28 with binary indicators for each task (see columns 4, 8, 13, and 17).

29 Regression estimates confirm that the assignment to either the busywork or sweeping

1 tasks does not affect work choices—whether employers’ decisions to give work (p -value
2 0.686), workers’ decisions to receive work (p -value 0.372), or willingness to pay for work
3 for both employers (p -value 0.391) and workers (p -value 0.781).

4 Task characteristics generally do not correlate with outcomes, with two exceptions.
5 First, task piece rate negatively correlates with workers’ willingness to pay for work.
6 This makes sense, as it implies that workers are less willing to work at the experimental
7 wage when assigned to tasks that command relatively higher market piece rates. Second,
8 unfamiliar tasks (never performed by the worker or at the employers’ firm) significantly
9 reduce workers’ willingness to pay for work. However, the results are robust both to the
10 inclusion of these controls and the alternative definition of task assignment.

11 In summary, employers’ and workers’ hiring and work choices, as well as their will-
12 ingness to pay for work, are unaffected by task value, implying that the preferences for
13 work redistribution are not driven by the production value of work.

14 **4.3 The Role of Other Instrumental Benefits for Work Choices**

15 Beyond the production value of work, work choices could reflect relational or signaling
16 benefits related to the interactive nature of work. While our design limits these chan-
17 nels through anonymity, distance, and privacy, some concerns remain because choosing
18 work implies meeting a new worker/employer and because work is inherently observable.
19 Moreover, rule-of-thumb behavior driven by inattention to experimental conditions may
20 also be a concern.

21 We test these alternative explanations using the multi-scenario replication in July
22 2024, introduced in Section 3.4, where respondents make choices under different scenar-
23 ios, each varying only one feature:

- 24 • **No rule of thumb:** Explains that choices are private and emphasizes the implications—
25 namely, that no future contact is therefore possible—to limit inattention or default
26 choices.
- 27 • **Cash delivered in person:** Employer delivers cash in person, equalizing net-
28 working opportunities across choices.
- 29 • **Work unobservable (employer only):** Worker performs task at their location
30 with completed work transported to the firm, eliminating signaling value of work.

1 We compare behavior in these three scenarios to the baseline scenario, which repli-
 2 cates the main experiment and is always presented first to all respondents.²⁵ The order
 3 of the other three scenarios is randomized. If a modified scenario successfully eliminates
 4 a driver of work redistribution, we expect a significant and economically meaningful
 5 reduction in work choices and willingness to pay for work relative to baseline.

6 Figure 4, Panel A shows that work preferences are stable across all three scenar-
 7 ios. Both employers and workers continue to prefer work redistribution to cash when
 8 we remind them that choices are private and explain the implications, when network-
 9 ing opportunities are held stable across work and cash conditions, and when work is
 10 unobservable.

11 To test this formally, we estimate the following regression with “Work”:

$$Y_{ijk} = \beta_1 \log(\text{Wage}_j) + \beta_2 \log(\text{Transfer}_j) + \sum_s \gamma_s \mathbf{1}\{\text{Scenario}_{ij} = s\} + \lambda_i + \varepsilon_{ijk}, \quad (3)$$

12 with respondent-level fixed effects λ_i and s indexes the scenario. As before, we apply
 13 equation 3 to both the binary work-choice outcome and the willingness-to-pay outcome.
 14 For work choices, the wage and the transfer vary within respondent and enter the spec-
 15 ification as shown. For willingness to pay, wage and transfer do not vary mechanically;
 16 these terms therefore drop out. The scenario indicators and respondent fixed effects
 17 remain in all specifications, and standard errors are clustered at the respondent level.

18 The demand-side results are presented in Table 2, column 5 (“Work”) and 9 (“Will-
 19 ingness to pay”). Whether the opportunity to signal generosity or success by making
 20 unobservable are removed (work unobservable, p -value 0.291), networking is kept con-
 21 stant across cash and work redistribution (cash-in-person scenario, p -value 0.664), or
 22 the implications of the experimental anonymity and privacy are emphasized (no rule-
 23 of-thumb scenario, p -value > 0.999), employers consistently choose to redistribute by
 24 via work rather than cash.²⁶ The willingness to pay for work is similarly unaffected by
 25 scenario assignment.

26 On the supply side, our key finding is that networking expectations do not drive

²⁵Online Appendix Table H.1 compares results from the main experiment to the baseline scenario. The results are broadly consistent. The work semi-elasticity is slightly higher among workers in July 2024, consistent with lean-season conditions when workers’ outside earnings are lower.

²⁶All p -values are adjusted for multiple hypothesis testing using the Holm correction.

1 work choices. As shown in column 14, work choices in the cash-in-person scenario are
2 statistically indistinguishable from the baseline. This is consistent with evidence that
3 casual workers—who likely value networking more—make similar choices as permanent
4 workers (Online Appendix Figure G.5).

5 When the implications of anonymity and privacy are emphasized, workers show a
6 modest but significant reduction in work choices (p -value 0.021), explaining about 4.5%
7 of the willingness to pay for work (p -value 0.070). These effects could reflect not only
8 minor image concerns but also expectations of lower social taxation of income relative
9 to unearned cash.²⁷ Even so, workers still display a strong preference for work redistri-
10 bution: on average, 70.2% of choices are for work.

11 4.4 Normative Drivers of Work Redistribution Preferences

12 When asked to explain their choices, the most common motivation—cited by 59.1% of
13 employers and 44.9% of workers—is that recipients must work for money and not receive
14 it for free. For example, respondents state “Money is supposed to be worked for” and
15 “Money should be earned through hard work.” The consistency and moral framing of
16 these justifications, combined with the price inelasticity observed earlier, suggest that
17 work redistribution may be sustained by an internalized norm.

18 We assess this interpretation using [Bicchieri \(2016\)](#)’s diagnostic framework, designed
19 to separate norms from other common social behaviors, like habits. First, we rule
20 out that work redistribution is a habit: the preference for work redistribution persists
21 even when respondents carefully evaluate trade-offs (rule-of-thumb scenario, July 2024).
22 Second, work choices are price-inelastic despite private decisions and persist even when
23 costly. This rules out custom or descriptive norms, which are characterized by being
24 the convenient or rational choice based on the expectations of another person’s behavior
25 or beliefs. Combined with the moral flavor of motivations, this framework supports the
26 interpretation of work redistribution as governed by a moral or social norm.

27 The normative interpretation is further supported by respondents’ choices as specta-
28 tors. Respondents make statistically identical decisions and provide similar justification
29 whether choosing for themselves or as impartial spectators deciding for others.²⁸ Aligned
30 results across stakes and spectator conditions indicate that choices reflect intrinsic social

²⁷In the survey, workers expect cash transfers to face 21.1% higher informal taxation than earnings.

²⁸The Spectator experiment was implemented in 2022; see Online Appendix C for details and results.

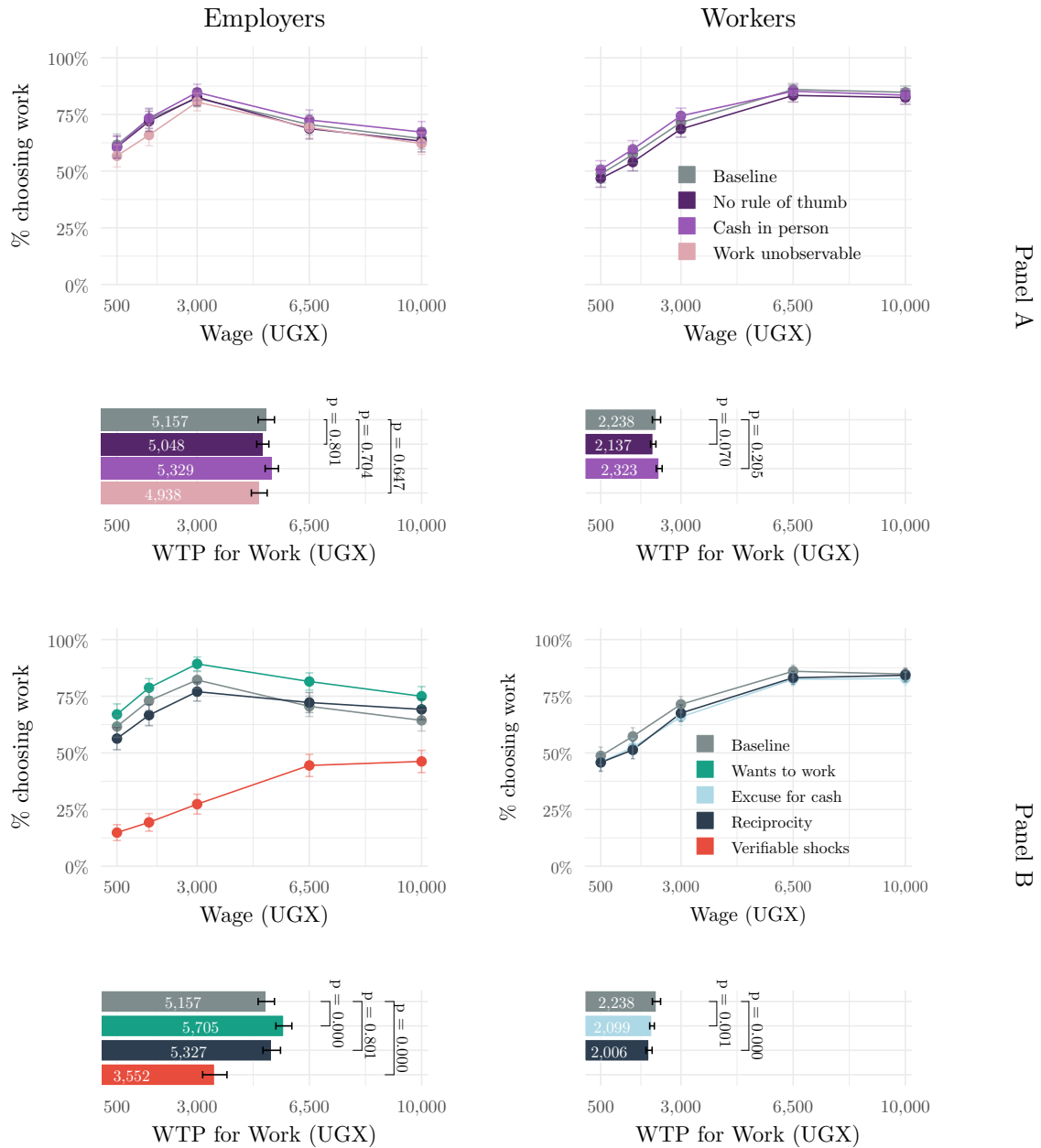


Figure 4: Work redistribution choices by scenario. *Note:* Data: multi-scenario replication (July 2024; N = 405 employers, N = 652 workers). Panel A: scenarios providing robustness to main results. Panel B: scenarios testing drivers of work redistribution norm. Scenario details and scripts: see Online Appendix B.2. Choices displayed: wage-varying choices (500–10,000 UGX) with alternative UGX 3,000 unconditional cash transfer; other choices are in Online Appendix Figure G.6, Panels B and C. Confidence intervals: 95% level. *p*-values: from regressions following equation 3 (Table 2, columns 9 and 14) and adjusted for multiple-hypothesis testing (Holm method).

1 preferences or norms rather than the incentives of the stakes experiment. Identifying
2 the type of norm, whether social or moral in nature, is beyond the scope of this paper.²⁹
3 We focus instead on understanding what drives this internalized norm.

4 **4.4.1 Employers: Incentive Arguments for Informal Workfare**

5 Given that informal redistribution functions as welfare in this setting—the primary social
6 safety net absent formal social protection (Firth, 1951)—we test whether the norm for
7 work redistribution is grounded in the provision of “appropriate incentives” to welfare
8 recipients (Nichols and Zeckhauser, 1982; Besley and Coate, 1992).

9 In the theory of workfare, work requirements can maximize social welfare by align-
10 ing giver and receiver incentives. They serve two functions: screening and deterrence.
11 When earnings potential is unobservable, work requirements improve targeting to the
12 truly needy (screening). When poverty is partly endogenous to own behavior (not just
13 luck), work requirements encourage human capital investment and discourage depen-
14 dency (deterrence).

15 We test this hypothesis using an additional scenario where workers are pre-screened
16 to need money due to a verifiable emergency (e.g., funeral costs) but remain able to
17 work.³⁰ In this case, neither screening nor deterrence applies: need is observable and
18 luck-driven. Under the workfare hypothesis, employers’ work redistribution preferences
19 should drop substantially compared to the baseline scenario.

20 Figure 4, Panel B and Table 2 (columns 5 and 9) present the results on the employer
21 side: work requirements disappear when need is verifiable and luck-driven. Only 27.4% of
22 employers choose to give work when wages equal transfers and workers are pre-screened
23 for emergencies—a 54.8 percentage point reduction from the baseline (p -value < 0.001).
24 Average willingness to pay for work falls to UGX 3,552, equivalent to the market wage.
25 Most notably, employers’ work-choice patterns are now consistent with generosity, as
26 they are more likely to offer work when it represents the more generous option.

²⁹The key distinction between moral and social norms is that the latter depends on beliefs about normative expectations. However, this distinction can be blurry. For example, Bicchieri (2016) shows that fairness may be a social norm for some people but a deeply held moral norm for others. In contrast, descriptive norms lack the normative component and may include, for example, a custom like open defecation, a fashion like wearing high heels, or the use of a common signaling system, like traffic lights or language, for coordination purposes.

³⁰We leverage the July 2024 multi-scenario replication described in Section 3.4 to include scenarios to test for normative drivers. p -values are from a regression specification equivalent to equation 3. Details and wording for the scenarios described in this section are provided in Online Appendix B.2.

1 We test additional drivers on the employer side but find no evidence for two plau-
2 sible alternatives: reciprocity or screening for moral deservingness. To test whether
3 work redistribution facilitates reciprocity, we leverage a scenario where recipients can
4 reciprocate cash transfers with cash as a token of appreciation. If reciprocity drove
5 work preferences, employers should switch to cash transfers when recipients can send
6 back cash, relative to the baseline. We find no change in work preferences even though
7 employers accurately predict workers’ reciprocation behavior.

8 To test whether employers use work requirements to screen for moral deservingness—
9 that is, to reward individuals who prefer to work rather than accept handouts—we
10 introduce the “wants to work” scenario, in which employers are informed that workers
11 were pre-selected for choosing work over an equivalent cash transfer. If screening for
12 character drove work requirements, employers should be more willing to give cash once
13 screening has already occurred. We find the opposite pattern: employers are more likely
14 to give work in this scenario than at baseline.

15 **4.4.2 Workers: Reciprocity and Dignity from Earning**

16 Turning to workers, reciprocity explains a small share of worker preferences for receiving
17 work over cash. The results are summarized in Figure 4, Panel B, and Table 2 (columns
18 14 and 18). When workers can reciprocate cash transfers, the likelihood of choosing work
19 over cash declines by 3.9 percentage points (p -value 0.003). Reciprocity explains about
20 10% of workers’ willingness to pay for work, from UGX 2,238 to UGX 2,006 (p -value <
21 0.001).

22 We also observe that workers with verifiable emergencies request work at the same
23 rate as those without (p -value 0.929, Online Appendix Table H.2, column 7), which
24 indicates that feeling deserving of help does not crowd out worker preferences or that
25 signaling need is not why workers choose to work. Instead, conversations with workers
26 consistently suggest that they derive dignity from interpreting income as earned.

27 Testing dignity considerations is inherently difficult. We therefore design a scenario
28 inspired by the “moral wiggle room” concept in Dana et al. (2007). By adding to the
29 standard script that workers may think of the cash as payment for work they did for
30 us, we prime them to interpret cash as earned rather than as a handout. This minimal
31 reframing reduces work choices by 5% (p -value < 0.001) and willingness to pay by 6.2%
32 (p -value 0.001). These results, combined with their otherwise stable preference for work

1 across experimental contexts, suggest that the dignity of earning through labor drives
2 workers' redistribution preferences.

3 **4.4.3 Discussion**

4 Across the scenarios, we identify two distinct but connected mechanisms behind the
5 work-redistribution norm. For employers, choices align with an informal workfare logic:
6 work requirements are relaxed only when need is verifiable and luck-driven, consistent
7 with the screening and deterrence functions emphasized in the workfare literature. For
8 workers, preferences are far more persistent and only modestly responsive to reciprocity
9 or privacy. Instead, the stability of their choices and the sensitivity to framing indicate
10 that the dignity of earning plays a central role, in line with qualitative accounts. As
11 noted in [Ferguson \(2015\)](#), “[In sub-Saharan Africa, grants] have been long-established
12 [...] but they are specifically targeted at social categories conventionally recognized as
13 legitimately ‘dependent’ [...] [F]or able-bodied adult men in the prime of life, the receipt
14 of a grant may seem inappropriate, and it is still the promise of jobs that beckons.”

15 **5 Work Redistribution Outside the Experiment**

16 To understand the prevalence of work redistribution beyond the experimental setting,
17 we leverage employers' self-reported giving and firm survey data from July 2024.

18 **5.1 Validation of Experimental Redistribution Preferences**

19 We validate our experimental measure by testing whether employers with stronger pref-
20 erences for work redistribution in the experiment actually hire more workers in their
21 firms. A key challenge in correlating work redistribution preferences with firm size is
22 that firm success or employer wealth could confound the results. Employers at larger,
23 more successful firms may be wealthier and thus more generous in the experiment re-
24 gardless of the channel. These same employers may also be willing to pay higher wages,
25 leading them to mechanically select more work redistribution in the experiment. An
26 additional problem is reverse causality: larger and more successful firms may be more
27 labor-constrained and thus more willing to pay for work in the experiment.

28 To address these concerns to the extent that our data allow, we control for measures

1 of employers' generosity by including the maximum amount the employer gave in the
 2 experiment, regardless of channel (work or cash). We also proxy firm success by control-
 3 ling for firm revenue. However, firm revenue may itself be affected by work redistribution
 4 preferences, making it a potentially bad control. To address this trade-off transparently,
 5 we present results both with and without these controls side by side.

6 We estimate the following regression model:

$$Y_i = \alpha + \beta_1 \textit{GivingViaWork}_i + \beta_2 \textit{MaxAmountGiven}_i + \delta' \mathbf{X}_i + \mu_i. \quad (4)$$

7 In Panel A, Y_i is one measure of employer i 's firm size: worker headcount, permanent
 8 worker headcount, or total monthly work hours. Panel B reports results for intermediate
 9 inputs: worker earnings, number of tools, and number of machines. Panel C examines
 10 firm output: revenue, profits, and sales, expressed either in levels or normalized by total
 11 monthly work hours.

12 $\textit{GivingViaWork}_i$ captures the employer's sum of work choices in the main exper-
 13 iment. $\textit{MaxAmountGiven}_i$ measures the maximum amount the employer gave in the
 14 experiment, regardless of channel (work or cash), serving as a proxy for altruism or gen-
 15 erosity. The coefficient of interest, β_1 , captures differences in inputs or outputs across
 16 firms whose employers are marginally more inclined to give via work.

17 For all outcomes, we estimate the regression separately with and without the generos-
 18 ity control. For Panels A and B, we also vary the control vector \mathbf{X}_i , which includes either
 19 no controls ($\mathbf{X}_i = \emptyset$) or firm revenue. In Panel C, where the outcomes are measures of
 20 firm output, \mathbf{X}_i is mechanically the empty set.

21 We find that one additional decision to give via work in the experiment is associated
 22 with more workers at the firm (in the simplest specification: 0.036, p -value < 0.001),
 23 especially permanent workers (0.046, p -value < 0.001), and total monthly hours worked
 24 (0.034, p -value < 0.001), as shown in columns 1, 5, and 9 of Table 3, Panel A. Columns
 25 4, 8, and 12 show that these results are robust when estimating the more complex
 26 specification including controls for generosity and firm revenue. These results validate
 27 our measure of preferences for work redistribution and suggest that our experimental
 28 work choices are a meaningful measure of labor demand at the firm.

29 Next, we examine the correlation between work-redistribution preferences and firm
 30 output. As shown in Table 3, Panel C, when controlling for a measure of generosity, work
 31 redistribution in the experiment is mildly negatively correlated with revenue (-0.037

1 log points, p -value 0.305), profits (-0.062 log points, p -value 0.024), and sales (-0.039
2 log points, p -value 0.269) and is more strongly negatively correlated with productivity
3 measures, such as revenue per hour (-0.046 log points, p -value 0.066) and profits per hour
4 (-0.057 log points, p -value 0.006). These findings are consistent with our experimental
5 evidence, suggesting that the additional work generated by redistribution preferences is
6 not necessarily productive.

7 **5.2 Estimates of Work Redistribution**

8 We quantify the extent of work redistribution at firms using survey data on employers'
9 self-reported giving patterns. The survey evidence is essential because the experiment
10 only measures willingness to pay for work at the margin; it cannot be used to estimate
11 total or average levels of work redistribution. Moreover, the experimental measures
12 only capture one extreme form of work redistribution, hiring for no-value tasks, but
13 in practice work redistribution may take various forms. These include paying above-
14 market wages for productive tasks, assigning workers to tasks that appear productive but
15 are not actually needed, hiring redundant workers for tasks already covered by others,
16 or compensating workers for idle time. Importantly, work redistribution is difficult
17 to identify through direct observation. As Panel C of Figure 1 illustrates, most tasks
18 classified as symbolic by employers are observationally indistinguishable from productive
19 tasks. These challenges motivate our approach.

20 In July 2024, we ask employers directly about their hiring motives, specifically (1)
21 whether they hired to help out versus for production needs, (2) whether the work assigned
22 was symbolic (not needed) or represented idle time, and (3) how many hours they gave
23 (both in total and only symbolic or idle). We ask all questions with reference to the
24 past month.³¹

25 We leverage a bounding approach to estimate the extent of work redistribution that
26 was unproductive: the upper bound includes all hours given to help, while the lower
27 bound includes only hours that employers identify as explicitly assigned to symbolic tasks
28 or idle time. Symbolic work represents only the most extreme and directly identifiable
29 form of redistribution; using it alone would understate the broader phenomenon, for

³¹We ask: “In the past month, how many hours of work to help out did you offer in total? [...] Consider the whole month and only the people you gave work to support them financially.” and “Of the work hours given to help out in the past month, how many hours were not needed (assigned to symbolic tasks or idle time, like waiting for work)?”

Panel A: Firm size

	Workers (standard day, std.)				Permanent workers (standard day, std.)				Hours worked (standard month, std.)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Work	0.036 (0.009)	0.030 (0.008)	0.012 (0.018)	0.030 (0.015)	0.046 (0.010)	0.043 (0.010)	0.048 (0.017)	0.058 (0.017)	0.034 (0.010)	0.029 (0.008)	0.007 (0.017)	0.024 (0.014)
Max amount given			0.053 (0.025)	-0.000 (0.021)			-0.005 (0.026)	-0.033 (0.026)			0.060 (0.023)	0.012 (0.019)
Controls												
Firm revenues	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
MDE	0.023	0.020	0.044	0.037	0.026	0.025	0.042	0.042	0.024	0.020	0.043	0.035
Mean outcome	5.19	5.19	5.19	5.19	1.70	1.70	1.70	1.70	1,472	1,472	1,472	1,472
Obs.	321	321	321	321	321	321	321	321	321	321	321	321

Panel B: Workers' earnings and other firm input

	Workers' earnings (monthly, std.)				Tools (std.)				Machines (std.)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Work	-0.002 (0.016)	-0.004 (0.016)	-0.008 (0.028)	-0.001 (0.027)	0.037 (0.013)	0.033 (0.013)	0.036 (0.021)	0.045 (0.024)	0.015 (0.014)	0.011 (0.012)	-0.016 (0.029)	-0.006 (0.027)
Max amount given			0.012 (0.041)	-0.006 (0.039)			0.002 (0.039)	-0.024 (0.042)			0.066 (0.041)	0.037 (0.039)
Controls												
Firm revenues	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
MDE	0.040	0.039	0.069	0.066	0.033	0.034	0.053	0.059	0.034	0.030	0.072	0.067
Mean outcome	284.0	284.0	284.0	284.0	2.46	2.46	2.46	2.46	1.18	1.18	1.18	1.18
Obs.	307	307	307	307	265	265	265	265	263	263	263	263

Panel C: Firm output

	Revenues				Profits				Sales			
	(log)		per hour (log)		(log)		per hour (log)		(log)		per hour (log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Work	0.017 (0.020)	-0.037 (0.036)	-0.009 (0.016)	-0.046 (0.025)	-0.021 (0.018)	-0.062 (0.027)	-0.037 (0.015)	-0.057 (0.020)	0.005 (0.022)	-0.039 (0.035)	-0.036 (0.021)	-0.062 (0.030)
Max amount given		0.119 (0.056)		0.082 (0.043)		0.089 (0.051)		0.044 (0.044)		0.098 (0.054)		0.058 (0.047)
MDE	0.051	0.089	0.041	0.062	0.046	0.068	0.039	0.051	0.054	0.088	0.052	0.075
Mean outcome	31,764	31,764	19.79	19.79	3,529	3,529	2.81	2.81	19.93	19.93	0.02	0.02
Obs.	321	321	321	321	291	291	291	291	369	369	321	321

Table 3: Work redistribution in the experiment and firm outcomes. *Note:* Data: main experiment and firm input and output data from employer survey in 2022. Firm inputs: Workers (standard day), Permanent workers (standard day), Hours worked (standard month) defined as number of workers on standard day \times number of hours on standard day (worker reported) \times 26 working days per month, and Workers' earnings (thousands UGX/month). Firm outputs: Revenue; Profits (thousands UGX/month); and Sales (tonnes/month), trimmed at bottom and top 1%. Work: sum of respondent's work choices in main experiment, trimmed at bottom 5% to reduce the influence of outliers; robust to trimming 1%, 2%, or 10%. Max amount given: maximum amount given in experiment (UGX), either cash or wage. Dependent variable means are in levels. MDEs: calculated for one-sided test with $\alpha=0.05$ and 80% power.

1 example, by excluding productive work that is paid above the marginal product of labor
2 or fully redundant work. We calculate the share of work hours that are redistributive
3 using total firm hours as the denominator (workers at the firm on typical day \times daily
4 hours worked on typical day \times 26 working days per month). The estimates, shown in
5 Figure 5, are conservative, especially for symbolic work, because July 2024 falls in the
6 lean season, when fewer employers provide symbolic work as shown in Figure 1, Panel B.

7 Employers in firms that give work report an average of 94.8 hours per month given to
8 help out, of which 55.8 hours are assigned to symbolic tasks or spent idle.³² Across firms
9 that give work, these figures represent 11.3% and 6% of total monthly hours worked at
10 the firm, respectively. For context, in 2024, the average firm employs four workers for
11 about 10 hours a day, six days a week; the average total hours worked per month is
12 970.³³

13 We also measure the monetary value of work hours given. Among firms that give
14 work, total work redistribution accounts for 4.5% of firm profits (UGX 126,460 per
15 month, equivalent to USD 33.3), while symbolic or idle redistribution accounts for 2.3%
16 of profits (UGX 45,630 per month, equivalent to USD 12.0). Work redistribution is also
17 economically meaningful from the workers' standpoint. On average, firms that engage
18 in work redistribution give work to "help out" about three people, 32 hours each per
19 month, which is about 12% of a full-time schedule or 63.3% of average weekly earnings.

20 A relevant question is how work redistribution can reflect actual costs for the firm,
21 particularly given that piece-rate pay is common in this setting. Under piece-rate com-
22 pensation, pay should theoretically be aligned with output. First, a non-negligible share
23 of workers (31%) receives some form of salary rather than piece-rate pay. Second, even
24 under piece-rate systems, employers can compensate workers above their marginal prod-
25 uct of labor through several mechanisms, such as paying higher implied piece rates to
26 redistribution workers, compensating for tasks that are not strictly necessary, or hiring

³²We conservatively exclude six firms whose employers reported redistribution hours exceeded total hours and one outlier with more than 96% of hours in redistribution.

³³As a robustness check, we construct an alternative measure using a worker-task roster. For each redistribution worker (hired to help out), employers list all tasks performed. For each task, the employer indicates whether it was symbolic and reports the time actively spent on the task. Summing across all redistribution workers' hours yields a roster-based measure of total redistribution hours (upper bound). Summing only hours on symbolic tasks yields a roster-based measure of symbolic redistribution work hours (lower bound). The roster lower-bound measure is mechanically smaller (excludes idle time by design). Both measures are calculated as shares of total firm hours from the complete worker roster (including non-redistribution workers). The roster-based estimates are provided in Online Appendix F.

1 redundant workers. As a broad sanity check, we show that the implied hourly wage
2 of redistribution workers (both needed and symbolic) is higher than that of standard
3 workers, as summarized in Figure 5, Panel C. On average, redistribution workers are
4 paid UGX 1,862 more per hour (USD 0.49, 34.9%, p -value 0.004) and symbolic workers
5 are paid UGX 2,280 more (USD 0.60, 43%, p -value 0.091). The premium cannot be
6 explained by worker characteristics such as role, social closeness, or skills. This provides
7 additional evidence that work redistribution is indeed costly for firms.

8 **5.3 Implications for Measuring Firm Size and Productivity**

9 Using our estimates, we examine how work redistribution alters measured firm size and
10 productivity. We implement a bounding exercise using the two self-reported measures:
11 total work redistribution hours (upper bound) and symbolic/idle work redistribution
12 hours (lower bound). We present estimates both for the subsample of firms that give
13 work and for the full sample of firms, assigning zero redistribution hours to firms that
14 do not engage in work redistribution. We compute firm-level differences of observed and
15 effective size and revenue per work hour and then report the mean of each. All bounds
16 are statistically significant at the 1% level.³⁴

17 Accounting for work redistribution reveals that firms appear significantly larger than
18 they actually are, as shown in Figure 5, Panel A. As mentioned above, among firms
19 that redistribute work, effective work hours (observed hours minus redistribution hours)
20 are 6%–11.3% lower than observed hours, depending on whether we use only explicit
21 symbolic/idle work redistribution (lower bound) or total work redistribution (upper
22 bound) as our measure. In the aggregate, that is, on the full sample of firms assigning
23 zero redistribution hours to firms not giving work, observed firm size overstates effective
24 firm size by 4.3% to 10%.

25 We next examine how work redistribution affects productivity measures. To do so,
26 we compare a standard metric of productivity—revenue per work hour—and build an
27 effective metric that adjusts for work redistribution by calculating revenue per effective
28 hour worked (hours worked minus redistribution hours). Under the standard measure,
29 firms mechanically appear less productive, as work redistribution hours inflate total
30 hours worked.

³⁴Estimates and statistical tests are provided in Online Appendix Table H.3. Statistical significance is assessed using a two-sided paired t -test at the firm level.

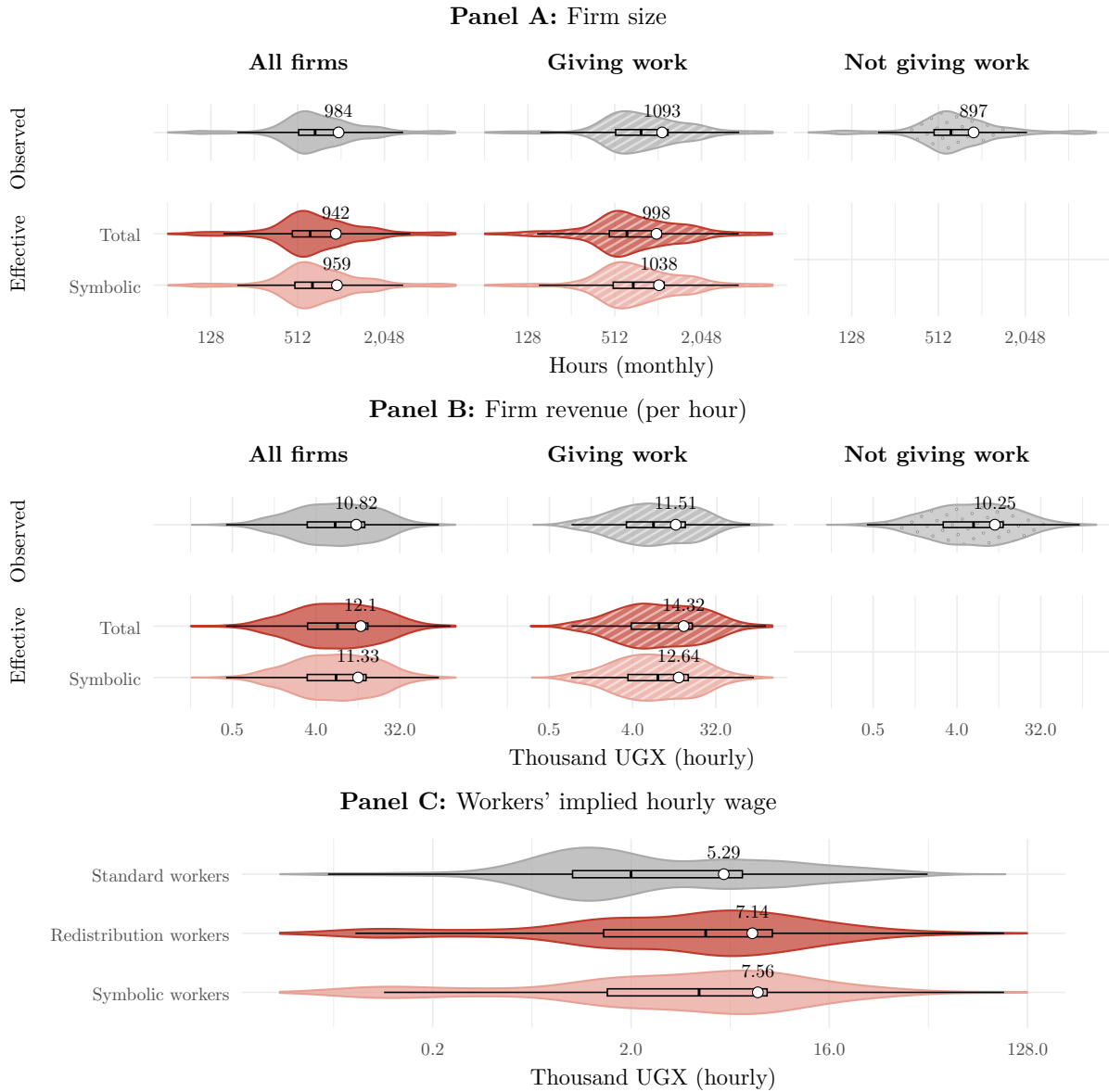


Figure 5: Firm size, revenue per hour, and hourly wage distributions. *Note:* Data from July 2024 survey. Excludes one outlier (hours given above 95%) and six data-entry mistakes where reported hours given were above 100% of total hours. Panel A: firm size. Observed: self-reported monthly hours (workers on standard day \times hours on standard day \times 26 working days). Effective total: self-reported monthly hours minus total redistribution hours. Effective symbolic: self-reported monthly hours minus symbolic/idle redistribution hours. Panel B: revenue (per hour). Observed: self-reported firm revenue (thousand UGX) divided by self-reported monthly hours (on standard day); effective revenue per hour: self-reported revenue divided by work hours minus total redistribution hours. Effective symbolic: self-reported revenue divided by work hours minus symbolic/idle redistribution hours. Panel C: from worker roster, in the past month. Standard workers: workers employed on typical day, from roster; Redistribution workers: workers hired “to help out”; Symbolic workers: workers hired “to help out”, where work given was symbolic or idle time. White dots: means. Boxplots: interquartile ranges. x-axes: log-scaled and truncated for readability. Statistics: computed on full sample.

1 As shown in Figure 5, Panel B, among firms that redistribute work, revenue per
2 effective work hour is UGX 2,808 (USD 0.74) larger than standard measures, on average,
3 and UGX 1,212 (USD 0.32) when accounting only for symbolic or idle work hours.
4 For context, the average revenue per hour in the full sample of firms is UGX 10,822
5 (USD 2.85) and in the subsample of firms that give work is UGX 11,514 (USD 3.03). In
6 the aggregate, standard productivity measures underestimate effective firm productivity
7 by 2.8% to 5.1%.

8 We also compare the organization of production across firms that self-report giving
9 work and those that do not to assess the extent to which work redistribution helps explain
10 observable differences between these two groups. Descriptively, as shown in Figure 5,
11 Panel A, firms that engage in work redistribution employ significantly more workers (0.64
12 more workers, p -value 0.071) and have more work hours (196 more hours, p -value 0.070)
13 but are not more productive (1,267 UGX/h revenue per hour worked, p -value 0.456).³⁵
14 Descriptively, accounting for work redistribution explains between 28% and 48% of the
15 observed difference in firm size (hours), depending on whether we use total or symbolic
16 hours given. In a regression framework, once we adjust for work redistribution, firms
17 that give work are not larger than firms that do not give work in a statistical sense.³⁶
18 Turning to productivity, once we account for work redistribution, firms that engage in
19 work redistribution emerge as substantially more productive, earning on average UGX
20 4,074 (USD 1.07, p -value 0.036) more per effective hour worked.

21 6 Conclusion

22 This paper documents the role of work as informal redistribution. We show that both
23 labor demand and supply are driven by a preference for giving and receiving via work,
24 instead of cash transfers, which is orthogonal to production and consumption motivations
25 as well as other instrumental relational benefits. We micro-found these preferences with
26 an internalized norm for work redistribution rooted in workfare incentives and the dignity
27 of earning. This implies that social preferences and internalized norms can be a source

³⁵The coefficients refer to a simple regression of firm outcomes on a binary indicator for giving via work, with robust standard errors.

³⁶The coefficient of a simple regression of effective firm size (hours worked minus redistribution hours) on a binary indicator for whether the firm gives via work is 101 (p -value 0.350) when considering total work redistribution and 141 (p -value 0.193) when considering only symbolic work hours.

1 of separation failures (Benjamin, 1992; LaFave and Thomas, 2016).

2 The results provide proof-of-concept evidence that Lewis (1954)’s zero marginal prod-
3 uct assumption—the idea that with surplus labor the marginal product of the last worker
4 is zero—holds in wage employment by showing that employers willingly hire workers for
5 tasks with no value. Combined with the survey evidence indicating that a significant
6 share of work hours are symbolic, the results point to disguised unemployment within
7 the firm, not only in self-employment (Breza et al., 2021). These patterns have measure-
8 ment implications, leading to overestimating firm size and underestimating productivity
9 in settings where work redistribution is common.

10 The preferences for work redistribution, together with the psychosocial benefits of
11 work (Hussam et al., 2022), introduce a new dimension for evaluating workfare beyond
12 the traditional efficiency-targeting trade-off (Bertrand et al., 2021; Hanna and Olken,
13 2018). The results also suggest an understudied mechanism: welfare programs may
14 impact the organization of production by reducing redistribution pressures on employers.

15 Several important ambiguities remain. The evidence suggesting that redistribution
16 workers are not different from standard workers is consistent with a labor rationing model
17 characterized by downward wage rigidities (Kaur, 2019; Breza et al., 2021), where labor
18 supply exceeds labor demand at the current wage. Employer preferences for work redis-
19 tribution can partially offset this rationing by creating jobs for redistribution purposes.
20 A surplus of workers may appear in contradiction with previous work showing that firms
21 are labor-constrained (Hardy and McCasland, 2023) but may reflect heterogeneity across
22 worker types: firms may face binding constraints for skilled workers while over-staffing
23 with short-term, unskilled workers for redistribution purposes. Moreover, while employ-
24 ers and workers align on preferring work redistribution, they may diverge on amounts,
25 especially in repeated interactions: successful entrepreneurs may face pressures to pro-
26 vide jobs beyond what they would voluntarily choose (Swanson, 2024). Workers’ demand
27 for extra work—despite the low take-up of higher-paying factory jobs in similar contexts
28 (Blattman and Dercon, 2018)—also suggests that job amenities play an important role
29 in labor supply, a factor that remains relatively understudied in poor-country settings.

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1 A Appendix Figures

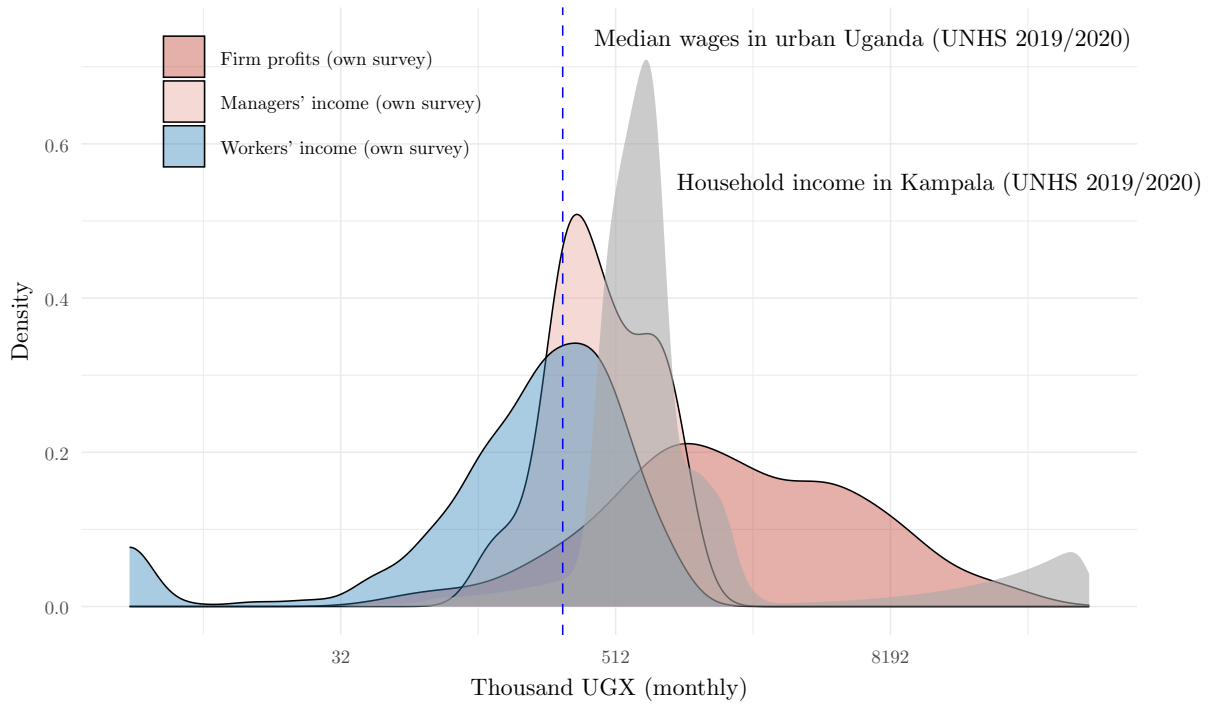


Figure A1: Respondents' income distribution. *Note:* Data: 2019/2020 Uganda National Household Survey and September 2022 survey. Household income is derived from yearly brackets in the national survey, adjusted to a monthly basis. Workers' incomes are based on self-reported weekly earnings from the last week of August 2022, multiplied by four to estimate monthly income. Managers' incomes are self-reported monthly earnings, and firm profits are trimmed at the 99th percentile. The x-axis is presented on a logarithmic scale.