Creating (Digital) Labor Markets in Rural Tanzania

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Abstract

Job search costs are high in rural labor markets in developing countries. Consequently, the flow of information on jobs and wages is limited, and wages tend to be dispersed. To lower search costs, I develop an SMS-based messaging app that connects agricultural workers and employers. The treatment reduces within-village wage dispersion by 16-40 percent. Wage compression occurs from both sides of the wage distribution, leaving the average wage unchanged. Consistent with reduced wage dispersion, I find evidence that labor is reallocated within villages. Dispersion in per-acre labor input across farms decreases. Workers divert job applications from lower-paying to higher-paying employers.

JEL Codes: D83, E24, J21, J31, J42, J43, O12

Keywords: search frictions, rural labor market, wage dispersion, messaging app

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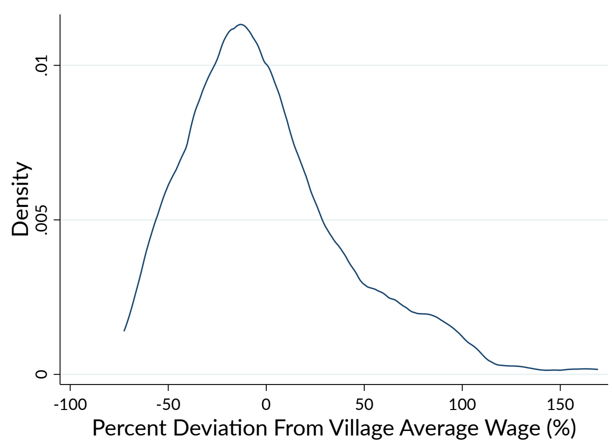
1 Introduction

Job search costs are high in rural labor markets in developing countries. Most farmers do not have access to the internet and there are no online job markets for agricultural daily laborers. There is rarely a central place where workers are gathered. Employers tend to rehire the same workers whom they had hired in previous seasons. As a consequence, the flow of information on jobs and wages is imperfect, and the law of one price may fail to hold. In my study area of rural Tanzania, I find evidence that there exists substantial within-village wage dispersion. Figure 1 presents the percent deviation of an individual daily wage relative to the village average. Only about half the reported wages are within a 25 percent deviation from the village average wage, which is surprising given how jobs are relatively homogeneous for manual farm work.[1]

Figure 1: Wage Dispersion In Rural Labor Markets



I study the effect of reducing search frictions on wage dispersion through a field experiment in Tanzania. To reduce job search costs, I develop an SMS-based messaging app that connects agricultural workers and employers. The app was designed to mimic an online job portal like *monster.com*, except that ads are announced over feature phones without internet data. Employers post a job ad to a gateway phone and the ad is sent to all registered workers in the village. Once a worker replies to the job ad, the worker's information is instantly forwarded back to the employer who initiated the request. This service

[1]This data is collected by the author across 66 villages in rural Tanzania in 2019 and the distribution is at the employer-hiring event level. In my study area, a daily wage ranges from $1.2 to $6.5 with a mean of $3.1.

effectively connects all employers and workers at near-zero user cost, increasing the size of labor markets.[2] Treatment villages were offered to use the app service throughout the 2019 agricultural season, while control villages received nothing.

I find that the app has a sizeable effect. It reduces within-village wage dispersion by 16-40 percent (depending on how dispersion is measured).[3] The results are robust to controlling for wage seasonality as well as job characteristics. Labor market search theory predicts that lower search cost may raise wage by creating more jobs (Pissarides 2000; Van den Berg and Van Vuuren 2010). However, while there is a clear reduction in the wage dispersion, I find no effect on job creation or the average wage.

To reconcile the wage compression result along with the null effect on the average wage, I look at heterogeneity in the initial level of wage paid by employers. I first identify the employers who paid a higher wage relative to other employers in the same village before the intervention. I find that the treatment induces initially high-paying employers to reduce the wage. On the other hand, lower-paying employers increase the wage. These competing effects cancel each other out, resulting in little change to the average wage.

A primary effect of the messaging app is that it increases the size of labor markets. By sending a job ad to all registered workers in the village, it is easier for employers to consider a new set of workers whom they had not hired in the past. In addition to integrating previously disconnected employers and workers, the app can also change other aspects of labor market conduct. One feature of the app is that it asks employers (workers) to specify the wage they would like to pay (get paid) to facilitate the transactions. This bidding feature could potentially affect the way participants bargain over wages, for example by encouraging participants to bid more aggressively and effectively. Second, the wage signal in the job ads and job applications might help market participants to update their beliefs

[2]SMS costs are borne by farmers. An SMS voucher costs as little as 22 cents for 1000 messages, while an average daily wage is $3.1. Additionally, most talk-time vouchers already come with free text messages. From the project side, the annual cost of keeping the messaging app is $950 (= A subscription fee of a 3rd party platform ($610) + SMS and mobile data plans ($72) + operation cost ($268)).

[3]The measures include standard deviation, coefficient of variation (i.e., the standard deviation divided by the mean), p50-p10 percentile wage ratio, and mean-min wage ratio. The magnitude is in the range of estimates found in the price dispersion literature. For comparison, Aker (2010) finds a 10-16 percent reduction in grain price dispersion and Jensen (2007) finds a 75 percent reduction in fish price dispersion after the introduction of mobile phone service.

on prevailing market wages. If information frictions are prevalent, the size of the update can be large, influencing market wages.

I isolate the channel of search frictions from the change in bargaining behavior and wage signaling by randomizing the disclosure of wage information. In a random subset of treatment villages, I remove the wage information from job ads and/or job applications before sending out a message. In those villages, the app does not carry any explicit wage signal and therefore there is no bargaining effect through the information channel. I find no evidence that the wage disclosure feature has any impact on wage compression. Moreover, I find modest evidence that the overall treatment induces initially high paying employers to increase the probability of hiring a new worker after the intervention. Those employers also face an increased number of applicants per vacancy. Taken together, these findings suggest that the app improves the competitiveness of labor markets, and sharing job availability alone is sufficient to improve the functioning of labor markets (without explicit wage information).

One consequence of wage dispersion is that employers face different prices for labor due to market imperfections, which contributes to the dispersion in labor demand. By reducing wage dispersion, my intervention is predicted to reduce dispersion in labor input for farmers in the same labor market. Consistent with this prediction, dispersion in per-acre labor input across farms is lower in treatment villages by 20-30 percent, suggesting that labor allocation has improved.

My paper is the first study to examine the role of search frictions on wage dispersion in rural labor markets. While there exist many studies on the effect of information communication technologies (ICTs) on price dispersion, they mostly focus on commodity prices (Aker 2010; Aker and Fafchamps 2014; Allen 2014; Goyal 2010; Jensen 2007).[4] More recent studies on labor markets in developing countries use experiments to reduce frictions in urban labor markets by organizing job fairs (Abebe et al. 2018 ; Beam 2016), offering monetary incentives to travel to job sites (Abebe et al. 2019; Franklin 2017; Bryan

[4]The relationship between search cost and price dispersion depends on assumptions on search methods and market environments. Counterintuitively, some theories predict that lower search cost increases price dispersion (MacMinn, 1980). See Baye et al. (2006) for an excellent review of search-theoretic models and price dispersion.

et al. 2014), and providing information on skills of job-seekers (Abel et al. 2016; Bassi and Nansamba 2018; Groh et al. 2015).[5] A few related studies on rural labor markets show that labor market outcomes improve when villages are connected to outside markets through the construction of roads or footbridges (Aggarwal 2018; Brooks et al. 2019; Shamdasani 2019).

Another contribution of this paper is to document the extent of wage dispersion attributed to search frictions through a well-identified experiment. Early search-theoretic literature shows that wage dispersion is the equilibrium outcome of imperfect wage competition in a market with search frictions (Stigler 1961, Butters 1977, Burdett and Judd 1983, Mortensen 1988, and Burdett and Mortensen 1998). Notably, these papers show that wage dispersion may arise even in settings where workers and employers are identical.[6] However, search models do not agree empirically on the contribution of search frictions to observed wage dispersion. For example, depending on whether on-the-job search and/or sorting are incorporated in the models, some studies show that search frictions explain a large fraction of observed wage dispersion (Postel-Vinay and Robin 2002; Ortego-Marti 2016), while other studies find that search frictions explain little (Hornstein et al. 2011; Bagger and Lentz 2018). While these studies attempt to explain frictional dispersion through models, my paper takes a different approach and experimentally reduces frictions with the messaging app. My findings support the idea that search friction accounts for a sizable variation in wage dispersion.

This paper is also related to a recent development literature that focuses on imperfections in rural labor markets (LaFave and Thomas 2016; Foster and Rosenzweig 2017; Dillon et al. 2019). Recent papers explore possible mechanisms of labor market failures. Fink et al. (2018) find that seasonal liquidity constraints distort farm labor allocation because farmers choose to work on other people's farms to cope with food shortage even though returns are lower. Kaur (2019) and Breza et al. (2019) show that downward wage rigidity based on social norms prevents wages from fully adjusting in response to shocks.

[5] See McKenzie (2017) for excellent review of papers on this topic.

[6] On the other hand, Autor (2001) discusses that lower search cost may *increase* wage dispersion within skill groups if worker talents are heterogeneous and the levels of demand for talent are different across markets. The intuition is that heterogeneity in demand for talent across markets could hide the price difference in talent, which is revealed after market integration.

My paper adds to this literature by documenting another source of rural market inefficiency, i.e., search costs to find workers and jobs, which has not been studied extensively in a rural setting in developing countries.

Section 2 explains the messaging app and the intervention protocols. Section 3 describes sampling, data, and context of the study. Section 4 presents the experimental results. Section 5 discusses allocative consequences. Section 6 concludes.

2 Experimental Design

A key motivation of the intervention in this paper is to make hiring and job search much easier than traditional methods allow. While smart phones are still rare, feature phones shown in Appendix Figure A1 are almost universal. In the study regions of Tanzania, mobile phone ownership rate is 93 percent. Furthermore, the literacy rate is 84 percent,[7] making an SMS-based messaging app a feasible solution for digital labor markets.

I develop an app which works autonomously on a mobile messaging platform called *Telerivet*, a third party API that was integrated with JavaScript.[8] See Appendix Figure A2 for an example of the backend development. When farmers send a message to a gateway phone, the system first identifies whether the farmer is a registered user and whether the person is an employer or a worker. To register, an individual responds to six messages one by one to answer basic questions (e.g. name, location, age, gender, and whether the person intends to be an employer or worker).

A registered employer can post a job by answering a few questions about the job, e.g., the type of task, crop, starting day, and the wage (See Appendix Figure A4 for the full message interactions). Once posted, the ad is sent to registered workers located nearby. The messaging app allows employers to reach a large number of workers instantly, reducing search costs dramatically. A unique job code is attached to a given job ad, and workers can then text back with the job code to apply for the job. Workers' applications are forwarded

[7]The mobile phone ownership rate is from the author's own farmer survey data collected in 2019. The literacy statistics is computed from National Panel Survey (Wave 4) from National Bureau of Statistics, Tanzania, after restricting the regions to the study regions, Kilimanjaro and Manyara

[8]The JavaScript codes are available publicly on GitHub, https://github.com/regulusweb/ucsc-tz-labor.

to the original employer in real time. Both parties are given the phone numbers and names of each other, which they can use to negotiate details over the phone. A week after posting, a feedback survey is sent automatically via SMS to ask about the hiring result, the final wage paid, and the worker ratings.

Another useful feature of the app is the ability to disclose the wage information in a job ad and/or in a job application to facilitate transactions more efficiently. The app asks all users to specify the wage they would like to pay (for employers) and the wage they would like to get paid (for workers). While the bidding feature is intended to reduce transaction costs, it could affect the way people bargain over wages. For example, it might encourage users to bid more aggressively, thereby changing the wage. It also helps users to update the distribution of wage offers in the market. I isolate these two channels from the reduction in search cost, by randomizing the disclosure of wage information. The wage information could be displayed either in the job ad or in the job application. I cross-randomized the non-disclosure of wage information as shown in Table 1 and the example messages are in Appendix Table A1. Overall balance between control and treatment group at baseline is shown in Appendix Table A2 at a farmer level.[9] Another balance table using the recall data from the phone survey and endline survey for the pre-period is shown in Appendix Table A3 at a village level. At both farmer and village level, almost all of the differences between the treatment and control group are insignificant.

The intervention was rolled out in February and March 2019, as shown in the timeline in Appendix Figure A6. The village meeting was pre-announced before our visit and everyone interested in hiring and working was invited. They were also told to bring mobile phones. During the intervention period, field enumerators visited each treatment village to conduct two meetings. The first meeting was in the center of the village and the second was in a more remote part of the village. During the meetings, field enumerators conducted a hands-on training session to demonstrate how the messaging app works.

At the meeting, potential employers and workers were given instructions on how to

[9]While the randomization selected 30 control villages and 40 treatment villages, some villages are excluded from the analysis because not enough farmers reported hiring. In particular, I require at least three reported wage observations within a village-production stage when calculating dispersion measures. Therefore, the analysis involved 30 control villages and 36 treatment villages. To be consistent with the analysis sample, I report the balance table for the same set of villages.

Table 1: Treatment Design

	Show Employer's Wage in the Job Posting	Show Worker's Wage in the Application	Number of Study Villages
Treatment	No	No	10
	Yes	No	10
	No	Yes	10
	Yes	Yes	10
Control			30
Total			70

register, which they did by texting *SAJILI* ("register"). Some had no prior experience using SMS messages; thus, enumerators walked them through basic functions of sending and replying to messages on their feature phones. Once everyone was registered, employers were instructed to send a text *WAFANYAKAZI* ("workers") to post a job. The job ads were automatically sent to the workers sitting in the crowd, and field officers guided workers to apply to those jobs by helping them to send a text *KAZI* ("job") During the training session, one randomly selected person per village was given a mobile phone as a gift to incentivize the practice of the messaging app. See Appendix Figure A7 for an example of a village meeting and Appendix Figures A8 and A11 for the flyers distributed which also contain the step-by-step message flows.[10]

The users were sent reminder messages to encourage the use of the app, approximately five times throughout the agricultural season. Furthermore, to incentivize farmers to continue using the messaging app, one farmer for each village was randomly selected to win a $10 or the equivalent. The raffle was done three times throughout the 2019 agricultural season.[11]

[10]The original flyers were distributed in the local language, Swahili.
[11]Farmers were eligible to enter the raffle conditional on using the app.

3 Sampling, Context, and Empirical Specification

3.1 Sampling and Data

The study was conducted in two northern regions of Tanzania, Kilimanjaro and Manyara. I draw on the sample of study farmers from a related project (Aggarwal et al., 2019) where we had obtained a census of households from village offices, and had randomly sampled 18 farmers for each village. In the original study, 147 villages were randomly selected after stratifying by market in the two regions.

To study rural labor markets, I excluded villages located in Moshi town, the major hub in Kilimanjaro Region. I also excluded villages with mobile ownership less than 80 percent because the intervention relies on mobile phone technology. After removing pilot villages, I randomly sampled 70 villages out of 86 villages to be included in the study. Treatment was randomized at the village level, resulting in 30 control villages and 40 treatment villages. Within each village, those farmers who did not participate in rural labor markets at the time of the baseline survey were excluded from the study. The final study sample comprises 650 farmers from 70 villages. However, when constructing wage dispersion measures, I require at least three reported wages within a village-production stage. This drops four villages because few employers report hiring in those villages. The map of the study villages is shown in Figure A5. The average distance from a village centroid to any other nearest study village centroid is 15km, and the closest control-treatment pair is 3km apart by geodetic distance. Given that rural labor markets are formed closely within the village boundary, spillover effects between control and treatment villages are extremely unlikely. Furthermore, the registration for the app was declined if the user is not from a treatment village.

Note that the farmers who were treated by the intervention and the farmers who were part of the survey data collection are not entirely the same. *Everyone* in the treatment villages was invited to the village meetings and was eligible to use the messaging app. However, to ensure the comparability between the treatment and the control group, the random sample of 650 farmers was independently selected as explained above. Only those farmers were surveyed by phone and in-person interviews. The village meetings were followed by three rounds of phone surveys in April-July 2019 and endline surveys in September 2019. The compliance rates for each round of phone survey and endline survey are presented in Appendix Table A4 and A5. The phone survey compliance rates are slightly lower in treatment villages (59 percent vs. 62 percent in control), but the difference is statistically insignificant. The compliance rates for in-person endline interviews are quite similar (91 percent vs 90 percent).

The universe of hiring history from 2018 is constructed by merging the phone survey and the endline interviews. If a farmer was successfully surveyed on the phone, the hiring events that occurred after the phone survey are supplemented by the endline interview data. On the other hand, if a farmer was not reachable by phone, all hiring events data solely come from the endline interview data. The merged hiring events from the three rounds of phone survey and the endline survey form the basis of wage dispersion analysis. I also use reported wages by employers only. The data cover all hiring events, 1,867 events by 448 employers from 2018 to 2019 September.[12]

3.2 Context

In Tanzania, the North-Eastern regions including Kilimanjaro and a small part of Manyara region have two farming seasons annually: a longer, more productive "long rains" season, which runs from March to August, and a less productive "short rains" season from October to February.[13] The intervention was conducted right before the planting season of 2019 long rains. Panel A of Table 2 shows that rural villages are not small geographically. According to the 2012 Population and Housing Census of Tanzania, a typical village has 532 households. In the farmer surveys collected in 2019, farmers report that it takes on average 4 hours to walk from one end to the other end of the village. They also estimated that it will take 42 hours if they were to visit every single household in the village.

Farming in Tanzania is small-scale and labor intensive and most production is for subsistence. A median plot size is two acres, and most people plant a combination of maize

[12] While the messaging app also collected wage information through the system-generated follow-up texts, this data is not used for analysis. There is no comparison data in the control group because the access to the app was limited to treatment villages.

[13] See the agricultural cycle in Appendix Figure A10 during 2018 and 2019

Table 2: Village Size and Dispersion In Labor Input

	Mean	SD
A. Village Size (Village-Level)^{a}		
Number of Households in The Village (2012 Census)	532.48	373.03
Estimated Hours to Pass Through The Village	3.95	1.58
Estimated Hours to Visit Every Household	41.69	33.93
B. Labor Input (Household Level)^{b}		
On-Farm Labor Days	84.09	68.86
On-Farm Family Days	49.55	48.23
On-Farm Hired Labor Days	24.36	33.67
On-Farm Exchange Labor Days	3.26	8.00
Labor Per Acre	34.88	29.35

Notes: a.Village-Level statistics are from 66 villages, and are computed using the median value across farmers within village. b.Household-level statistics are based on 566 farmers in 66 villages who participated in the endline survey and cultivated in 2018 long rains. Labor input statistics are conditional on cultivating.

and beans. The average value of production was only $246 in 2018 and $141 in 2019.[14] The low productivity is in part due to low adoption of input technologies. In the study sample, only 20 percent of farmers used fertilizer and 50 percent used hybrid seeds in 2018 long rains. Lacking access to credit and farm machineries, the most important input to agricultural production for most farmers is manual labor. Panel B of Table 2 shows that the typical labor input amount in 2018 long rains is 84 labor days. Much of this is own family labor - about 60 percent of the total labor usage. However, casual workers also account for a large part of the labor force. About 30 percent of total labor input is provided by hired casual workers, while only 4 percent is covered by exchange labor scheme between fellow farmers. Note that there is a large variation in labor input amount across households. For example, the average labor days per acre is 35, while the standard deviation is 30.

Table 3 presents more detailed statistics on rural labor markets. As shown in Panel A, a large fraction of households participate in labor markets. Roughly 50 percent of farmers hired casual workers in the 2017 long rains, while 35 percent of households reported working as a casual worker. A small proportion simultaneously bought and sold labor (6

[14]Low production in 2019 is potentially due to low rainfall. Ninety percent of farmers said the rain in 2019 was lower than the typical rainfall, and 23 percent of them said it was the worst rain they had seen in their life.

percent).

Table 3: Rural Labor Markets

	Mean	SD
A. Labor Market Participation and Characteristics		
=1 if Employer[a]	0.49	0.50
=1 if Worker[a]	0.35	0.48
=1 if Both Employer And Worker[a]	0.06	0.24
Worker-Employer Ratio[b]	0.87	0.94
Number of hiring events	1.80	0.97
Job duration in days	2.73	2.39
Number of workers hired	6.81	4.58
Fraction of workers the employer hired outside the village	0.08	0.22
Fraction of workers the employer had hired previously	0.81	0.27
B. Search Methods By Employers		
=1 if I called or/and visited workers I know	0.62	0.49
=1 if Workers visited me asking for a job	0.66	0.48
=1 if Workers called me asking for a job	0.44	0.50
=1 if I went to a gathering place	0.10	0.30
=1 if I asked leaders/friends/families	0.09	0.28
C. Wage Compensation		
Daily Raw Wage Per Person (USD)	3.12	1.18
=1 if Paid Workers for Food	0.26	0.44
=1 if Paid Workers for Transportation	0.03	0.17
Daily Raw Wage And Benefits Per Person (USD)	3.24	1.20

Notes: *a*. Summary statistics are from the baseline survey in 2017 long rains from 566 farmers. *b*. The number of employers-workers ratio is at the village level. The remaining statistics are conditional on hiring in 2018 long rains, from 352 farmers in 66 villages.

The remaining statistics show responses from employers in the farmer surveys. Conditional on hiring, farmers typically hire two times during the season. As expected, job durations are short, typically lasting 2-3 days. In a given hiring event, seven workers are typically hired at a time. Another feature of rural labor markets is that employers rarely hire workers outside the village. Only 8 percent of workers are hired outside the employer's own village.[15] Eighty-one percent of workers are those whom the employer had already hired in previous seasons.

Employers in the village rely on traditional search methods. Panel B of the table shows

[15] An unreported survey response indicates that it is largely due to transportation cost rather than preferential treatment over own villagers.

that 62 percent of employers reported contacting workers whom they already know. However, an equally large fraction of employers reported being visited by workers, while 44 percent of them reported that workers called them first asking for a job. There is rarely a central place in rural areas where workers are gathered, a fact reported by only 10 percent of farmers. Furthermore, word of mouth is not a popular way to find workers, either. Only 9 percent of employers reported asking village leaders, friends, and families. This suggests that employers and workers try to find each other directly. Panel C of the same table shows that a daily wage is 3 USD. To measure the total wage compensation precisely, I also asked employers if they paid other benefits. 26 percent of employers reported paying for food on top of the wage and 3 percent of them paid for transportation. In the analysis section below, I show most of results for both raw wage as well as the total wage compensation which include food and transportation payments.

3.3 Empirical Specification

The main outcome of the study is wage dispersion. Wage dispersion is measured within village because the intervention treats everyone in the labor market at the village level. I use commonly used measures of dispersion in the literature: standard deviation, coefficient of variation, mean-minimum wage ratio, and p50-p10 percentile ratio. Because of seasonality in the agricultural production (See Panel B of Appendix Figure A10), the wage in lean season and the wage in peak season reflect different labor market conditions. Therefore, I divide agricultural production stages as follows: 2018 planting, weeding, harvesting, dry season, 2019 planting, weeding, and harvesting. The stages are chosen by the most popular job tasks reported in the farmer surveys in a given time period. I construct dispersion measures within village and agricultural production stage using wages reported by employers only. The main regression uses a simple difference-in-differences specification where the source of exogenous variation is the randomization of the treatment:

$$Dispersion_{vs} = \beta_0 + \beta_1 TREAT_v + \beta_2 TREAT_v \times Post_s + \delta_s + \varepsilon_{vs}. \tag{1}$$

$Post_s$ is a dummy variable to indicate whether a production stage s is after the intervention,[16] δ_s is a stage fixed effect, and $TREAT_v$ is a dummy variable indicating that village v is in the treatment group. β_2 estimates the effect of the intervention on wage dispersion, by differencing out pre-post difference as well as control-treatment difference.

While the main specification relies on the aggregated village level data, the raw wage data is collected at the individual-hiring event level. As a robustness check, I estimate the wage dispersion at a farmer-event level as well. I construct the absolute percent deviation of the individual wage from the village-stage average wage as follows:

$$abs\Big(\frac{w_{ivsh} - \bar{w}_{vs}}{\bar{w}_{vs}}\Big) = \beta_0 + \beta_1 TREAT_v + \beta_2 TREAT_v \times Post_s + \phi_{C(i,s,h)} + \eta_{J(i,s,h)} + \delta_s + \varepsilon_{ivsh}, \quad (2)$$

where w_{ivsh} is a wage paid by an employer i in village v in the production stage s for a hiring event index h, and $\bar{w}_{vs}$ is the average wage paid within village v and stage s. The $\{\phi_c\}_{c=1}^{C}$ are crop-specific effects on wage and C(i,s,h) is a function indicating the crop of the hiring event index h of an employer i in stage s. Similarly, the $\{\eta_j\}_{j=1}^{J}$ are task-specific effects of the hiring event, and δ_s is a stage fixed effect.

As noted in Table 1, the disclosure of wage information was randomized within treatment villages. A regression specification that tests whether wage dispersion is influenced by the additional bidding feature is:

$$\begin{aligned} Dispersion_{vs} = \beta_0 &+ Post_s \times (\gamma_1 TREAT_v + \gamma_2 TREAT\_BID_v) \\ &+ \gamma_3 TREAT_v + \gamma_4 TREAT\_BID_v + \delta_s + \varepsilon_{vs}, \end{aligned} \quad (3)$$

where

$$TREAT\_BID_v = \begin{cases} 0 & \text{if village } v \text{ is in the control group or the wage is not disclosed} \\ 1 & \text{if village } v \text{ is in the treatment group and the wage is disclosed} \end{cases}$$

In this equation, the coefficient γ_2 captures the additional effect of the bidding feature on wage dispersion.

One caveat of the wage dispersion analysis is that it relies on the wages reported by

[16]Village meetings took place for a month. I use a uniform meeting date across treatment and control villages to define $Post_s$. The results are robust to using the median village meeting date as well as the last day of all village meetings.

employers. The results would suffer from endogenous selection of farmers if the treatment causes some farmers to become employers. Therefore, I explore the treatment effect on hiring and other labor input measures using farmer-crop season level, which include all study farmers regardless of whether they participate in the labor market:

$$Y_{ivr} = \beta_0 + \beta_1 TREAT_v + \beta_2 TREAT_v \times Post_r + \rho_r + \varepsilon_{ivr}, \tag{4}$$

where Y_{ivr} measures various outcomes at the crop season level including whether a farmer i in village v hired workers during agricultural season r. ρ_r is a season fixed effect. Farmers were asked questions for three rainy seasons, 2018 long rains, 2018 short rains, and 2019 long rains. Some farmers cultivated in all three seasons, while other farmers cultivated in only one or two seasons.

4 Results

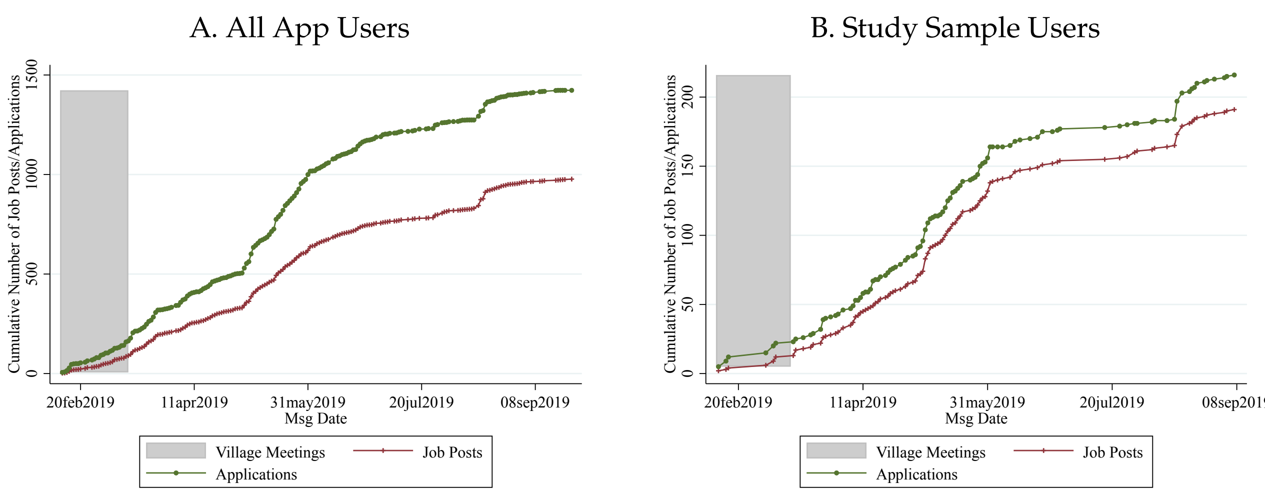
4.1 Take-up

The message app has been used extensively by users since its adoption in early 2019. Figure 2 shows the number of job posts and applications for all users as well as for the study farmers in each panel, respectively. Almost 1,000 jobs have been announced by 250 employers during 2019 crop season. Job ads were sent to more than 1,000 unique workers during this period. 640 workers sent back almost 1,500 job applications. The large and persistent usage suggests that this technology is simple to use and useful for farmers. The results are noteworthy given that labor demand was quite low in 2019 season due to low rainfall.

I report the take-up of the messaging app for the village meeting sample as well as the study sample. Table 4 shows that on average 64 farmers attended the meeting, among them 29 employers and 35 workers. Among those who came to the meeting, 69 percent of them registered for the service. 33 percent of them posted a job as an employer or applied to a job as a worker through the app.

Among the randomly selected study sample, the administrative data from the app database indicates that 39 percent of treatment farmers registered for the service, while 16 percent used the app to find workers or jobs. According to the self-report in the endline survey, 69 percent of treatment farmers heard about the messaging app while 14 percent reported using it. While the usage among study farmers appear modest, the treatment intervention was at the village level and hence the study farmers can be affected without using the app directly.

Figure 2: Job Posts and Applications



Notes: Almost 1,000 jobs have been announced by 250 employers. And the job ads were sent to more than 1,000 workers during this period. Among those, 640 workers sent almost 1,500 job applications as of the end of September 2019.

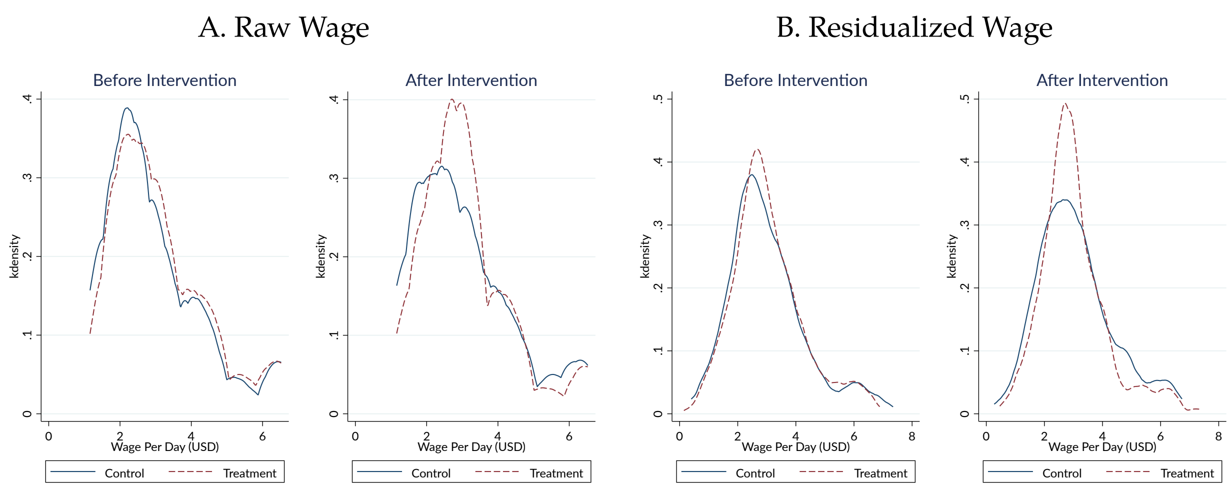
Table 4: Take-up of The Search App

	Mean	SD	N
A. Village Meeting Sample			
Meeting Turnout	64.17	44.81	40
Meeting Turnout: Employer	28.60	23.28	40
Meeting Turnout: Worker	35.58	28.41	40
Proportion Registered	0.69	0.41	40
Proportion Used	0.33	0.24	40
B. Study Sample			
Proportion Registered (Admin Data)	0.39	0.49	370
Proportion Used (Admin Data)	0.16	0.37	370
Proportion Heard About The App (Self-Report)	0.69	0.47	324
Proportion Used (Self-Report)	0.14	0.34	324

4.2 Wage Dispersion And Search Costs

Before I formally analyze wage dispersion using regression analysis, I first examine wage dispersion visually in Figure 3. Using the daily wage reported by employers, the wage distributions before the intervention in Panel A are quite similar between control and treatment group. However, after the intervention, the wage distribution of treatment villages is more compressed than the distribution of control villages. I further regress the raw wage on crop, task, production stage, and village fixed effects, and plot the distribution of the residualized wage in Panel B. The same pattern is observed – the two distributions are similar for control and treatment villages before intervention, but the wage distribution of treatment group is less dispersed after the intervention. As shown in Appendix Table A6, I cannot reject that the variances of the two distributions are equal in pre-period, while this hypothesis is rejected in post-period.

Figure 3: Reduction in Wage Dispersion



Notes: Raw wage is the salary paid to workers. Residualized wage is the residual from the regression of raw wage on crop, task, production stage, and village fixed effects. The residuals are plotted after centering at the median of the raw wage.

Table 5 confirms the wage compression by estimating Equation (1). Column 1-2 explore the standard deviation in wage, while columns 3-4 explore the standard deviation in residualized wage, which is the residual from the regression of raw wage on crop, task, season, production stage, and village fixed effects. Odd columns use raw wage to calculate the standard deviation and even columns use the combined wage and benefits, which is the sum of the wage and food and transportation payments. The result shows that there is a large and significant reduction in the standard deviation. As explained in section 3, I require at least three reported wages within a village-production stage when calculating standard deviation and coefficient variation, and this drops four villages. To avoid this exclusion, I collapse all pre- and post-treatment time periods and run a Analysis of Co-variance (ANCOVA) estimation as in McKenzie (2012). Appendix Table A7 shows that the results are qualitatively similar.

Table 6 explores the wage dispersion using other dispersion measures, as the standard deviation can be sensitive to outliers. Using the coefficient of variation, p50-p10 percentile wage ratio, and mean-minimum wage ratio, the treatment villages experience 16-30 percent reduction in wage dispersion. In all regressions reported in Table 5 and 6, wage is winsorized at p5 and p95 to make sure that results are not driven by a few outliers.

Table 5: Reduction in Wage Dispersion (Village-Stage Level)

	SD in Wage		SD in Residualized Wage	
	(1)	(2)	(3)	(4)
	Wage	Wage&Benefits	Wage	Wage&Benefits
TREAT	0.113	0.0937	0.0999	0.0787
	(0.111)	(0.105)	(0.104)	(0.0984)
TREAT $\times$ Post	-0.467***	-0.435***	-0.458***	-0.426***
	(0.170)	(0.162)	(0.166)	(0.160)
Stage FE	X	X	X	X
Observations	268	268	268	268
Villages	66	66	66	66
Control Mean	1.133	1.151	1.123	1.147

Notes: Raw wage is the salary paid to workers. Wage and benefits include wage payment, food, and transportation payment. Residualized wage is the residual from the regression of raw wage on crop, task, season, production stage, and village fixed effects. Standard errors clustered at the village level.

While the analysis at the village level is intuitive, the raw wage is collected at the hiring event level. Table 7 further confirms the wage compression result by estimating Equation (2). In columns, I control for production stage, job task type, and crop type fixed effects. I also report results with and without winsorization of wages. Across specifications in columns 1-4, the treatment villages have a lower wage dispersion than the control villages

Table 6: Reduction in Wage Dispersion - Various Measures of Dispersion

	Coefficient of Variation		p50-p10 Ratio		Mean-Min Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
	Wage	Wage&Benefits	Wage	Wage&Benefits	Wage	Wage&Benefits
TREAT	0.00849	0.0100	0.0704	0.0565	0.0643	0.0769
	(0.0319)	(0.0297)	(0.0957)	(0.0922)	(0.0921)	(0.0878)
TREAT $\times$ Post	-0.126**	-0.121***	-0.260**	-0.260**	-0.333***	-0.352***
	(0.0479)	(0.0440)	(0.126)	(0.124)	(0.117)	(0.114)
Stage FE	X	X	X	X	X	X
Observations	268	268	269	269	269	269
Villages	66	66	66	66	66	66
Control Mean	0.379	0.369	1.627	1.621	1.788	1.753

Notes: Raw wage is the salary paid to workers. Wage and benefits include wage payment, food and transportation payment. All numbers are in USD. Standard errors clustered at the village level.

roughly by 20 percent.[17] In columns 5-6 of the same table, I report the treatment effect on wage. Interestingly, the average wage in level in the treatment villages is not significantly different from the average wage in the control villages. Not only insignificant, but also the magnitude of the wage change is quite small (i.e., 4 percent of the control mean wage before the intervention).

4.3 Mechanism: Heterogeneous Effects Across Employers

To reconcile the wage compression result along with the null effect on average wage, I explore the characteristics of farmers who are affected differently by the treatment. I first look at the treatment effect by the initial wage paid by employers. If search frictions are symmetric between workers and employers, search theory predicts that initially high-paying employers reduce the wage, while initially low-paying employers raise the wage. Using the pre-period wage data, I categorize employers into terciles: initially low-paying employers, medium-paying, and high-paying. Because labor markets are at the village level, I define an individual percent wage deviation from the village average wage to determine the categories using pre-intervention wage data.

Column 1 in Table 8 presents the results. It shows that initially high-paying employers

[17] The results are similar with and without fixed effects.

Table 7: Reduction in Wage Dispersion (Farmer-Hiring Event Level)

	No Winsorization		Winsorized at p5 and p95		Wage In Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	Wage	Wage&Benefits	Wage	Wage&Benefits	Wage	Wage&Benefits
TREAT	-0.0154	-0.00884	-0.0120	-0.00797	0.202	0.139
	(0.0254)	(0.0255)	(0.0219)	(0.0216)	(0.131)	(0.134)
TREAT × Post	-0.0643**	-0.0715**	-0.0636**	-0.0641**	-0.116	-0.0176
	(0.0298)	(0.0306)	(0.0271)	(0.0268)	(0.160)	(0.168)
Stage FE	X	X	X	X	X	X
Task FE	X	X	X	X	X	X
Crop FE	X	X	X	X	X	X
Observations	1613	1613	1613	1613	1613	1613
Farmers	439	439	439	439	439	439
Villages	66	66	66	66	66	66
Control Mean	0.323	0.319	0.300	0.293	2.946	3.095

Notes: This is regression at a farmer-hiring event level data. Outcomes are individual percent deviations from the village mean wage and/or benefits in USD. The results are robust to using the deviation from the village median wage as opposed to village average wage. Standard errors clustered at the village level.

reduce the wage significantly relative to initially medium-paying employers (in comparison to the control group). On the other hand, I do not find evidence that an increase in wage by initially low-paying employers is significantly different from the medium-paying employers. I also standardize the initial individual wage deviation to explore the result in a continuous fashion. Column 2 suggests that one standard deviation increase in initial wage deviation is associated with a 12 cent reduction in wage only in the treatment group, although insignificant.[18] The asymmetric result found in the table implies that the average wage level does not change because initially low- and medium-paying employers together raise the wage while initially high-paying employers reduce the wage.

The app is designed to promote a competitive market environment by integrating fragmented markets. Table 9 further explores if the mechanism of wage compression is due to increased competition. I use three proxies of competition: (i) whether an employer hires a new worker whom the employer had not hired previously in a hiring event, (ii) the fraction of new workers from the employer's labor force, and (iii) the ratio of the number of

[18]Note that I lose a few farmers in columns 1 and 2 because they did not report hiring pre-period and their initial wage level is undefined.

Table 8: Heterogeneous Effects on Wage

	Dep.Variable: Wage In Level	
	(1)	(2)
TREAT × Post	0.317*	-0.0669
	(0.185)	(0.142)
TREAT × Post × Pre-Period Wage: Low	-0.288	
	(0.314)	
TREAT × Post × Pre-Period Wage: High	-0.721**	
	(0.287)	
TREAT × Post × Pre-Period Std(Wage Deviation)		-0.122
		(0.163)
Observations	1567	1567
Farmers	409	409
Villages	64	64
Control Mean	2.946	2.946

Notes: Some farmers are dropped in columns 1 and 2 because they did not report hiring pre-intervention period. Initial low vs. high wage is defined at the individual farmer level. All specifications include crop, task, and production stage fixed effects as well as the full interaction variables on the triple differences. All numbers are in USD. Standard errors clustered at the village level.

applicants to the number of hired workers. By reducing search frictions, employers are more likely to consider new workers outside of an exisiting network and face higher job competition measured by the number of applications per vacancy. While some coefficients suffer from a lack of power, I find modest evidence that initially high-paying employers are more likely to hire a new worker with an increased fraction of new workers in the labor force. Moreover, they experience an increased job competition, consistent with the reduction in wage in Table 8. Overall, the intervention seems to have improved competitiveness of the labor markets.

4.4 The Effect of The Wage Bidding

One feature of the messaging app is the ability to disclose wage information which may change the bargaining behaviors as well as the belief on the distribution of wage offers. To isolate these channels from the reduction in search cost, the wage disclosure was randomized in a subset of treatment villages. I explore the difference in the treatment effect between villages with and without wage disclosures in Table 10 by estimating regression

Table 9: Heterogeneous Effects on Labor Supply

	$\mathbb{1}$(Hired a New Worker)		New Worker Ratio		Job Competition	
	(1)	(2)	(3)	(4)	(5)	(6)
TREAT × Post × Pre-Period Wage: Low	-0.0703		-0.00184		0.124	
	(0.0886)		(0.0475)		(0.163)	
TREAT × Post × Pre-Period Wage: High	0.133		0.0781		0.277*	
	(0.116)		(0.0526)		(0.163)	
TREAT × Post × Pre-Period Std(Wage Deviation)		0.0896*		0.0300*		0.0965
		(0.0455)		(0.0173)		(0.0717)
Stage FE	X	X	X	X	X	X
Crop FE	X	X	X	X	X	X
Task FE	X	X	X	X	X	X
Observations	1567	1567	1567	1567	1567	1567
Farmers	409	409	409	409	409	409
Villages	64	64	64	64	64	64
Control Mean	0.395	0.395	0.161	0.161	1.595	1.595

Notes: Some farmers and villages are dropped because they did not report hiring pre-intervention period. $\mathbb{1}$(Hired a New Worker) is a dummy that indicates whether a hiring event included a new worker that the employer did not hire previously. New Worker Ratio is the number of new workers divided by the number of hired workers in a hiring event. Job Competition is the number of applicants over the number of hired workers. All specifications include crop, task, and production stage fixed effects as well as the full interaction variables on the tripple differences. Standard errors clustered at the village level.

equation (3).

In the table, the coefficient of *TREAT_BID* × *Post* measures the additional treatment effect of the bidding feature relative to the villages where the wage information was not disclosed. The evidence suggests that displaying the wage information in the job ad and/or in the worker application does not contribute more to the wage compression. Appendix Table A8 also shows the results at the farmer-hiring event level. Again the additional bidding feature does not reduce wage dispersion more than the regular treatment group without the bidding feature. Overall, the results seem to suggest that announcing the job availability among a large number of workers alone is sufficient to compress the wage.

5 Efficiency of Labor Markets

5.1 Labor Allocation

The main wage compression results used wages reported by employers only. While the main results are at the village level, the results might suffer from the endogenous selec-

Table 10: The Effect of The Bidding Feature

	SD in Wage		Coefficient of Variation		p50-p10 Ratio		Mean-Min Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Wage	Wage&B	Wage	Wage&B	Wage	Wage&B	Wage	Wage&B
TREAT	0.147	0.131	0.00490	0.00969	0.0320	0.0171	-0.0347	-0.0121
	(0.176)	(0.165)	(0.0441)	(0.0427)	(0.149)	(0.154)	(0.129)	(0.132)
TREAT_BID	-0.0456	-0.0501	0.00481	0.000422	0.0515	0.0529	0.133	0.119
	(0.182)	(0.174)	(0.0451)	(0.0444)	(0.155)	(0.158)	(0.133)	(0.136)
TREAT $\times$ Post	-0.494**	-0.473**	-0.138**	-0.129**	-0.158	-0.134	-0.258**	-0.266*
	(0.225)	(0.217)	(0.0594)	(0.0558)	(0.159)	(0.166)	(0.129)	(0.134)
TREAT_BID $\times$ Post	0.0365	0.0514	0.0131	0.00982	-0.129	-0.158	-0.104	-0.116
	(0.198)	(0.195)	(0.0502)	(0.0485)	(0.155)	(0.161)	(0.121)	(0.134)
Stage FE	X	X	X	X	X	X	X	X
Observations	268	268	268	268	269	269	269	269
Villages	66	66	66	66	66	66	66	66
Control Mean	1.159	1.175	0.387	0.374	1.635	1.626	1.792	1.758

Notes: Raw wage is the salary paid to workers. Wage and benefits include wage payment, food, and transportation payment. Standard errors clustered at the village level.

tion of employers if the intervention caused some farmers to become employers or caused employers to hire more workers. Table 11 examines the changes in hiring outcomes by estimating Equation (4). All specifications use farmer-crop season level data, including all study farmers regardless of whether the farmers are in the labor market or not. Column 1 shows that treatment farmers are no more likely to become an employer.

In columns 2-5 of Table 11, various types of labor input are examined. The results are conditional on cultivating in a given rainy season, and hence have a smaller number of observations than column 1. Overall, the intervention did not seem to have affected the average labor input. Treatment farmers are no more likely to use family labor, hired labor, and exchange labor than control farmers. The total labor input amount is also similar between control and farmers.

While there is no treatment effect on the different types of labor input measures, the wage compression result has allocative implications. Agricultural production theory predicts that the marginal product of labor must be equal across households if markets are complete and prices and productivities are controlled for (Benjamin 1992; LaFave and Thomas 2016; Dillon et al. 2019). However, the existing wage dispersion due to market imperfections implies that employers face different prices for labor which contributes to

Table 11: Treatment Effects On Labor Allocation

		Types of Labor Input In Person Days			
	(1)	(2)	(3)	(4)	(5)
	=1 if Hired	On-Farm Labor	Family Labor	Hired Labor	Exchange Labor
TREAT	-0.006	-3.770	-6.170	-0.299	1.558***
	(0.039)	(9.991)	(7.864)	(3.018)	(0.585)
TREAT $\times$ Post	0.040	4.244	5.427	2.118	-0.620
	(0.057)	(6.243)	(3.906)	(2.624)	(0.689)
Observations	1698	1139	1139	1139	1139
Households	566	555	555	555	555
Villages	66	66	66	66	66
Season FE	X	X	X	X	X
Region FE	X	X	X	X	X
Control Mean	0.36	71.70	45.06	18.79	2.53

Notes: A crop season fixed effect is included. Standard errors clustered at the village level.

the dispersion in labor input. In other words, if lower search cost reduces market frictions, then it is predicted that the dispersion in labor input also decreases.

I test this prediction in Table 12 using the dispersion in log labor days per acre as an outcome. For three out of the four dispersion measures, I find that the labor input dispersion is lower in treatment villages by 17 to 30 percent. The result offers suggestive evidence that the messaging app helps to reduce the misallocation of labor in rural labor markets.

5.2 Harvest Output

The improved labor allocation is predicted to increase the aggregate output level in theory. This section explores this downstream effect on harvest output. One challenge of estimating the effect on harvest level is that many farmers reported that their entire crops were wasted due to various shocks including low rainfall, resulting in zero harvest. About 16 percent of farmers indicated that they cultivated and ended up harvesting nothing in a given season. To retain the farmers with zero harvest output, I convert the output using an inverse hyperbolic transformation.

Since some farmers grow multiple crops, the value of each crop is evaluated at the prevailing market price and aggregated across crops to compute the total harvest output

Table 12: Dispersion In Labor Input

	Dep. Var: Dispersion in $\text{Log}(\frac{\text{Labor Days}}{\text{Acre}})$			
	SD	CV	p50-p10	Mean-min
TREAT	-0.038	-0.014	0.005	-0.068
	(0.064)	(0.034)	(0.140)	(0.160)
TREAT × Post	-0.134*	-0.077**	-0.360*	-0.202
	(0.075)	(0.035)	(0.181)	(0.252)
Observations	169	169	173	173
Villages	66	66	66	66
Season FE	X	X	X	X
Region FE	X	X	X	X
Dep.Var. Mean	0.81	0.27	1.56	1.69

A rainy season fixed effect and a region fixed effect is included. Standard errors clustered at the village level.

value. As a robustness check, I also show the result using physical output in kg, given that the large proportion of harvests comprises maize and/or beans only. The regressions also include other controls such as the use of fertilizer or seeds and agricultural shocks. Columns 1-4 in Table 13 show inconclusive evidence that treatment villages had more harvest than control villages. While the coefficients are positive, the harvest data is extremely noisy and the treatment effects are not distinguishable from zero.

Another measure of farmer welfare is consumption. Columns 5-6 show that treatment farmers are less likely to skip a meal due to food shortage in the past 3 and 6 months. One explanation might be that it is now easier for workers to find a job and to cope with food shortage with the help of the app. But since the village-level employment did not increase as shown in Table 11, it is difficult to conclude whether the increase in consumption is driven by the imbalance at the baseline between treatment and control groups. This outcome is measured at the endline only and therefore the possible baseline difference is not controlled for. Also, recall that two people per village were randomly selected to get 10 USD if they used the app during the 2019 agricultural season. The robustness check controlling for winning a raffle prize of cash $10 is shown in Appendix Table A9, and the results are similar. [19]

[19] Note that the random selection includes all users (not just study farmers who were interviewed).

Table 13: Treatment Effect on Output Level

	Harvest Output (HH-Season Level)				Skip Meals (HH Level)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Kg	Kg	USD	USD	Past 6m	Past 3m
TREAT	0.468	0.445	0.377	0.367	-0.034*	-0.031*
	(0.316)	(0.287)	(0.274)	(0.252)	(0.020)	(0.018)
TREAT × Post	0.361	0.370	0.196	0.204		
	(0.478)	(0.440)	(0.385)	(0.357)		
Observations	1069	1069	1069	1069	566	566
Households	554	554	554	554	566	566
Villages	66	66	66	66	66	66
Season FE	X	X	X	X		
Input Controls	X	X	X	X		
Shock Controls		X		X		
Control Mean	6.534	6.534	5.187	5.187	0.075	0.051
Control Mean (before IHS)	1001.85	1001.85	224.21	224.21		

Notes: Harvest values are computed by evaluating the crop harvest at market prices and adding them up across crops. Harvest output measures in columns 1-4 are converted using inverse hyperbolic transformation. HH Endowment means the dummies of the number of household members in gender-age bracket (e.g. male from 0-14 years old, male from 15-19 years old, etc). Input controls include the use of fertilizer, seeds, herbicides, insecticides, and irrigation. Shock controls include whether the harvest was affected by low rainfall, flood, crop diseases, insects, birds or animals, thefts, or lack of casual workers. The last row for columns 1-4 shows the mean of the control group before intervention and before inverse hyperbolic transformation. Standard errors clustered at the village level.

6 Conclusion

Understanding the sources of inefficiency in labor markets is crucial to improving market outcomes. Labor is the most abundant input factor in rural economies of developing countries. More importantly, misallocation of labor implies that some farmers use too much or too little labor on their farm relative to what is optimal in a frictionless environment. Therefore, simply correcting the misallocation of labor can improve aggregate output without any technological innovations. In this paper, I find evidence that search frictions are a constraint for efficient labor allocation even in tightly connected rural economies. Offering a cost-effective SMS app technology can connect a large number of workers and employers and compress the dispersion of prevailing wages and labor input.

The use of digital technology in African agriculture is becoming increasingly common with hopes to improve agricultural productivity and farmers' welfare. For example, *Hello Tractor* and *Trotro Tractor* connect smallholder farmers with nearby tractor owners using a mobile app so that farmers can hire a tractor even if they cannot afford to own. Additionally, several companies offer frequent updates on weather and market prices and provide tips on farming and financial management via SMS.[20] In particular, $WeFarm$ formulates a farmer-to-farmer digital network where farmers can ask and answer questions through text messages, just like an online forum for farmers in developed countries.

The messaging app I developed to create digital rural labor markets is an example of this trend. Feedback survey presented in Appendix Table A10 suggests that there is enough demand for the app and scope for the profitability of this service. Among the study sample app users, 93 percent indicated that the app service was useful. Most of them reported that they were able to find workers and jobs faster and it required less effort and lower costs. Furthermore, 50 percent of treatment farmers indicated that they plan to use the app in the next season. 74 percent of those who plan to use the app are willing to contribute an average of 1.5 USD per season. A back-of-the-envelope calculation implies that the payments from 630 users are enough to cover the cost of the service to

Among the study sample, six farmers won the phone during the village meeting, and seven farmers won the 10 USD. This is 2 percent of the study sample (13/584 = 0.02).

[20] A list of selected companies include *AgroSpaces*, $AgroCenta$, $Farmerline$, $iShamba$, $MFarm$, *Sokopepe*, and $WeFarm$.

make it sustainable.[21] Given that the labor demand was particularly low in the year of the intervention due to low rainfall, it seems that there is a potential for this messaging app to be scaled up to benefit a large number of farmers.

[21]The annual maintenance cost of the app is \$950, which can be covered by 630 users if each pays 1.5 USD per season.

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Figure A1: Search App: Feature Phone

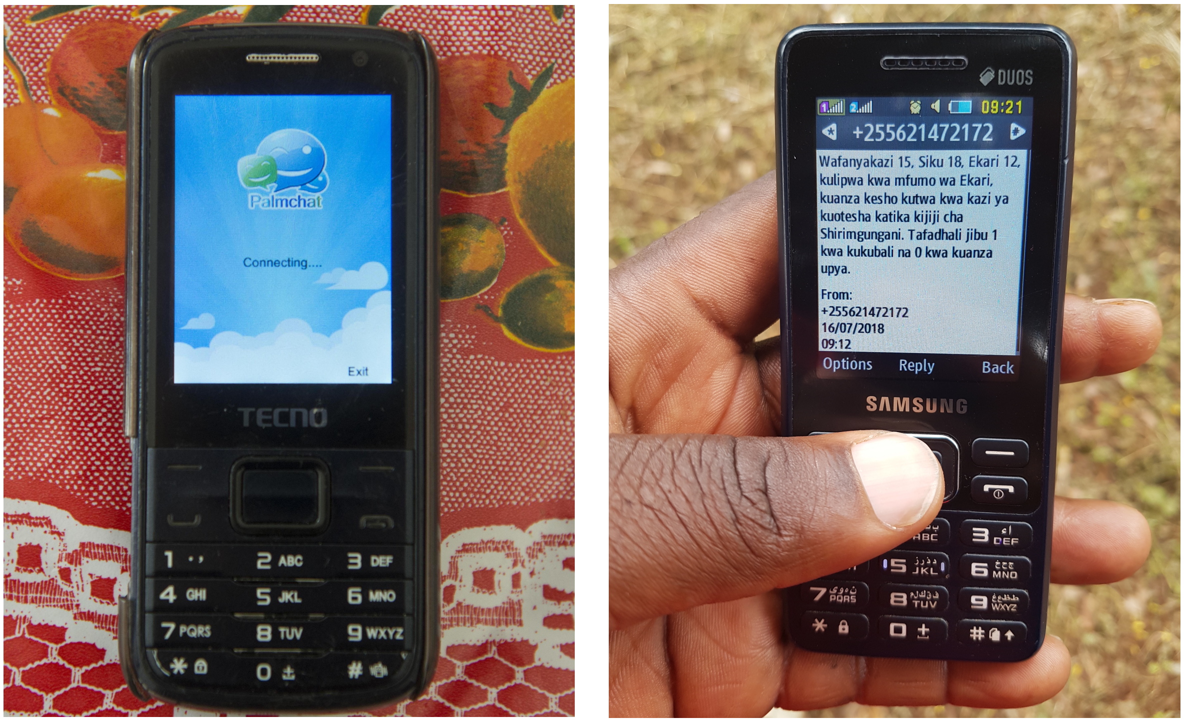


Figure A2: Search App Development Using A Mobile Messaging Platform, Telerivet

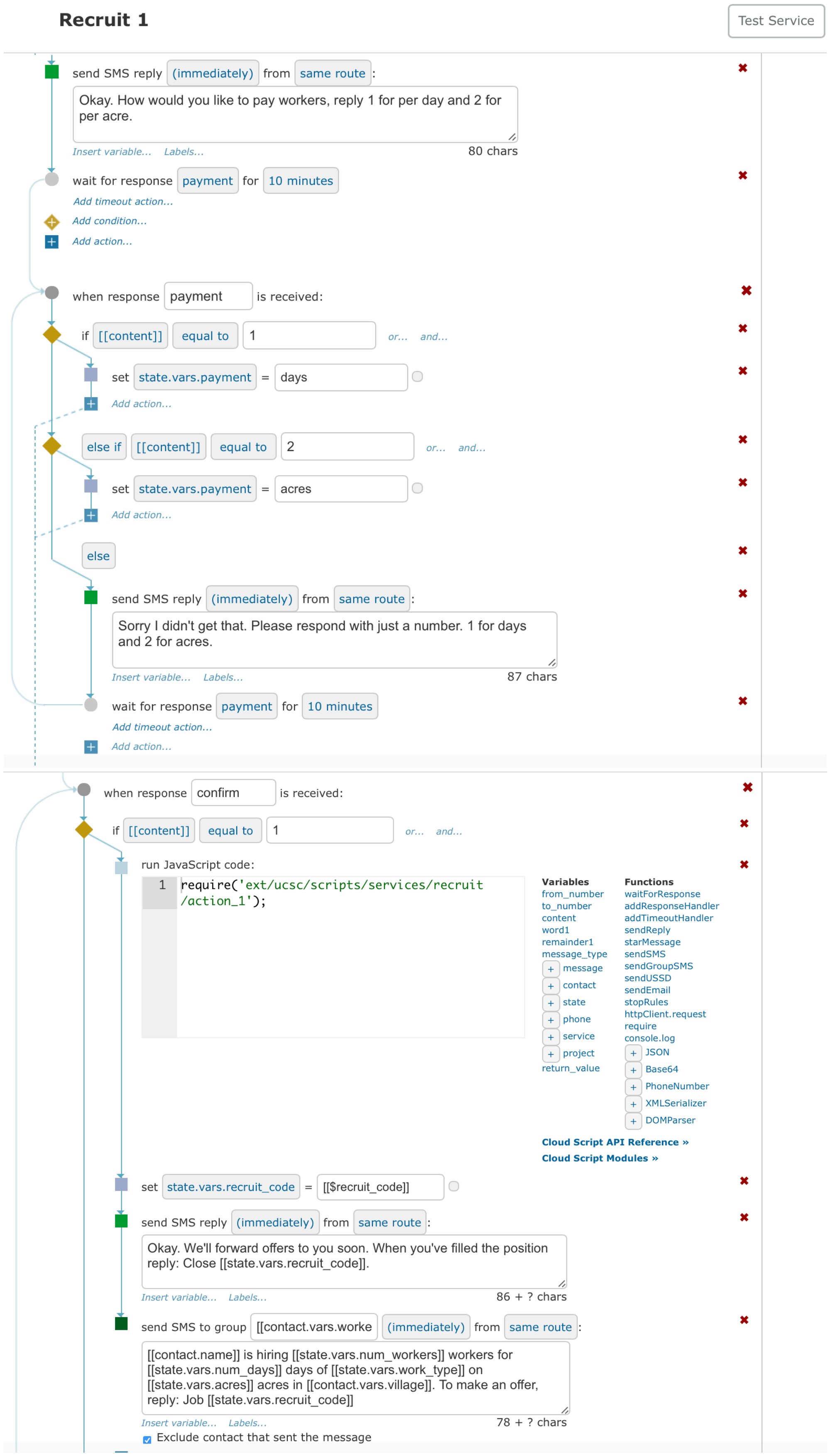


Figure A3: How the Messaging App Works

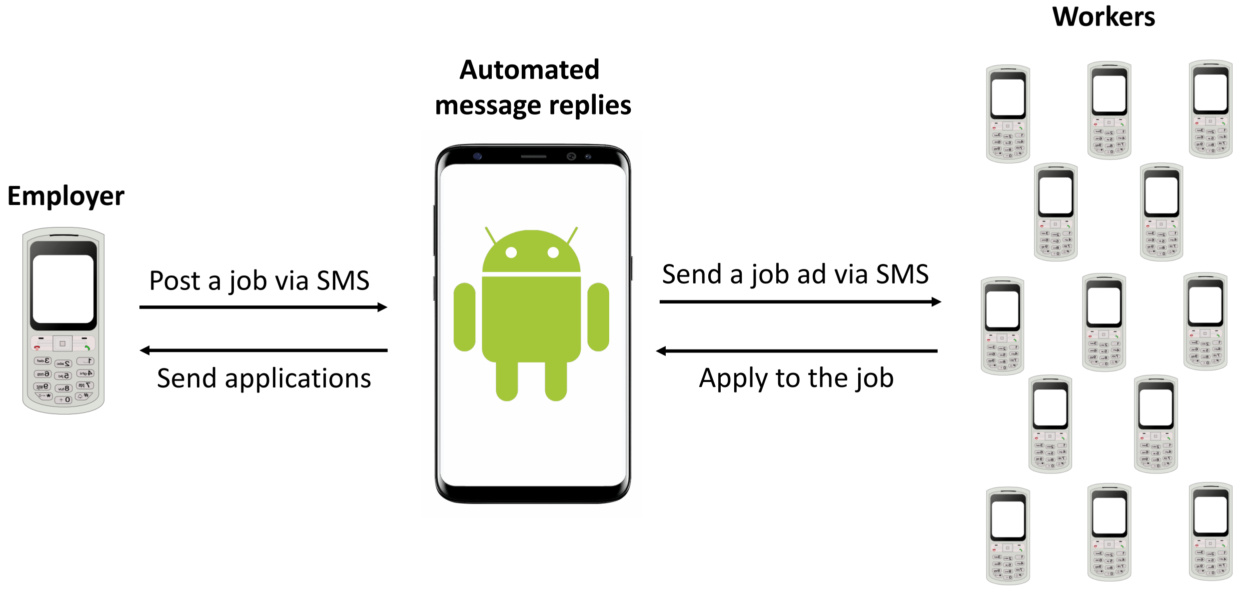


Figure A4: Message Interactions of The Messaging App

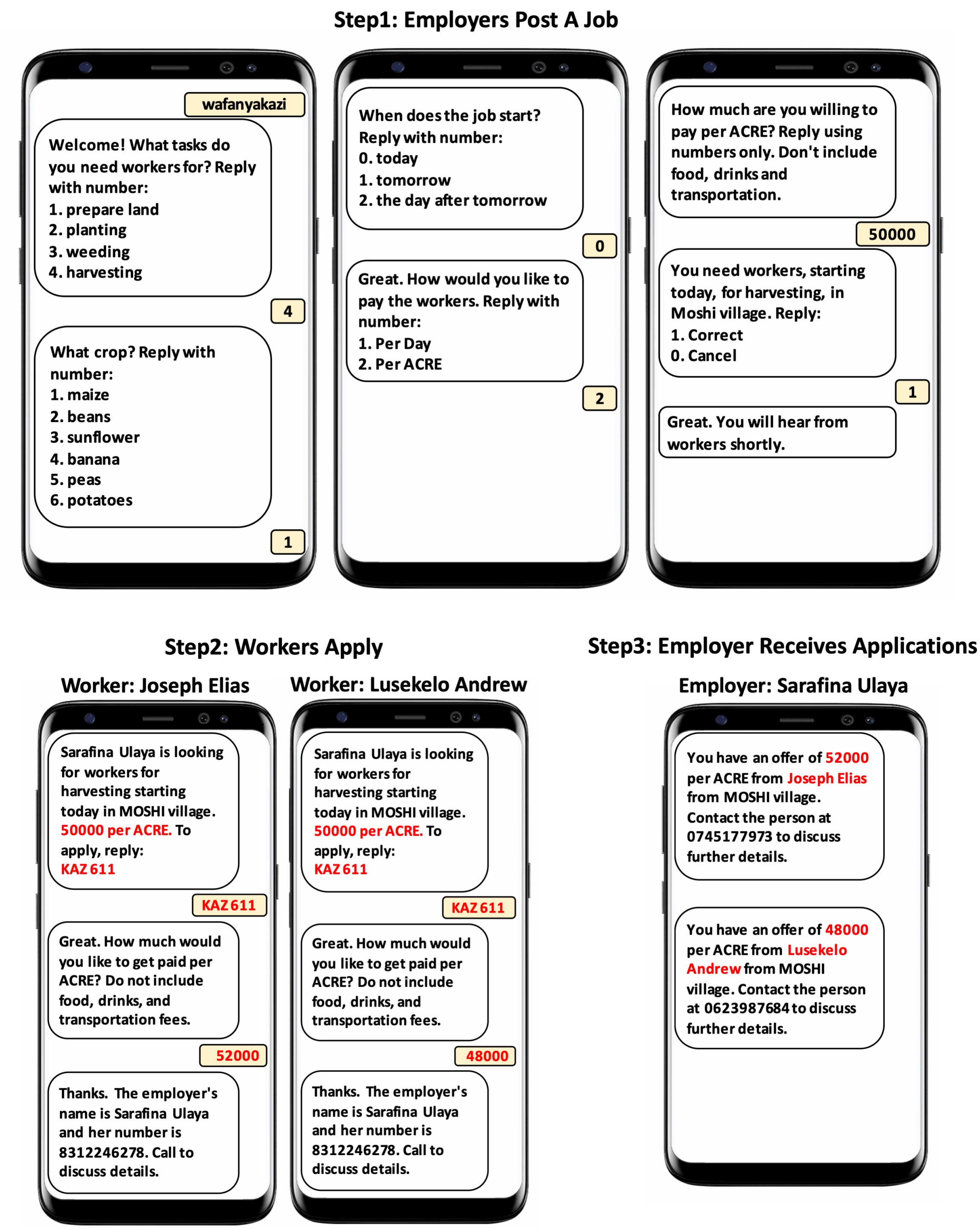
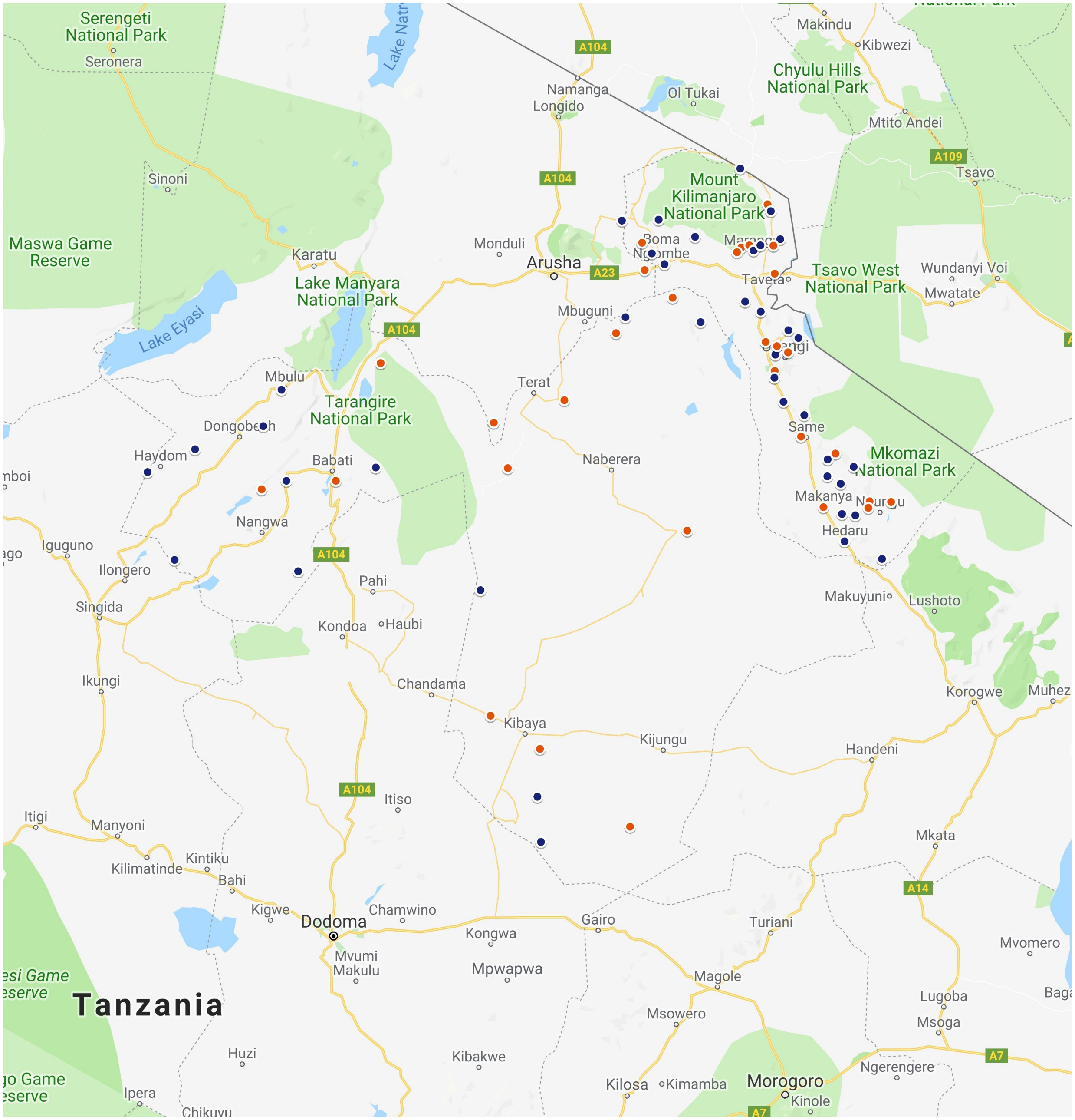


Figure A5: Map of Study Villages



Notes: Orange dots represent 30 control villages and blue dots represent 40 treatment villages in Kilimanjaro and Manyara Region of Tanzania.

Figure A6: Study Timeline

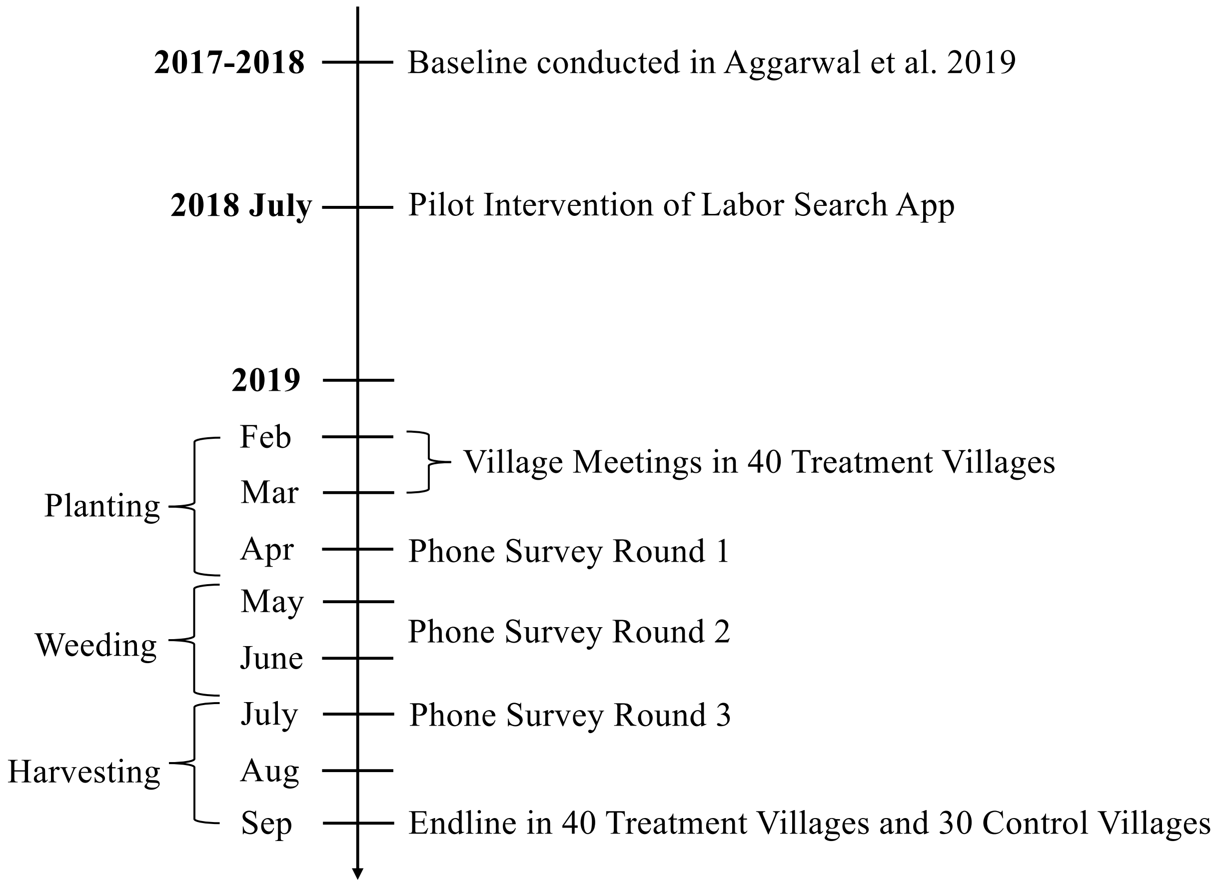


Figure A7: An Example of Village Meeting

Figure A8: Flyer Used For Village Meeting (1)

INNOVATIONS FOR POVERTY ACTION

SIMPLE WAY TO HIRE WORKERS FOR FARM ACTIVITIES

USE SMS SERVICE TO FIND WORKERS AND JOBS EASILY

REGISTRATION:

- Text **SAJILI** to **0746 217 484**
- You will receive text messages and follow the instructions.
- Registration and service is free of charge.

TO FIND CASUAL WORKERS

Once registered, text

WAFANYAKAZI

to

0746 217 484

and follow the instructions

TO FIND JOBS

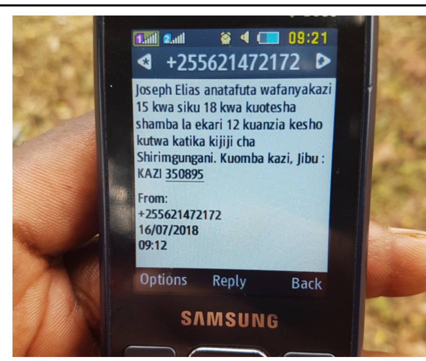
Once registered, to see if there are available jobs in your area, text:

KAZI

to

0746 217 484

Also, you will instantly receive job announcements whenever they are requested by employers.



FOR REGISTRATION AND OTHER QUESTIONS:

- **Call** Joseph Kissiri **0745 177973** or **0785 043635**
- **Do not call 0746 217484**. This number is not answerable.

Figure A9: Flyer Used For Village Meeting (2)

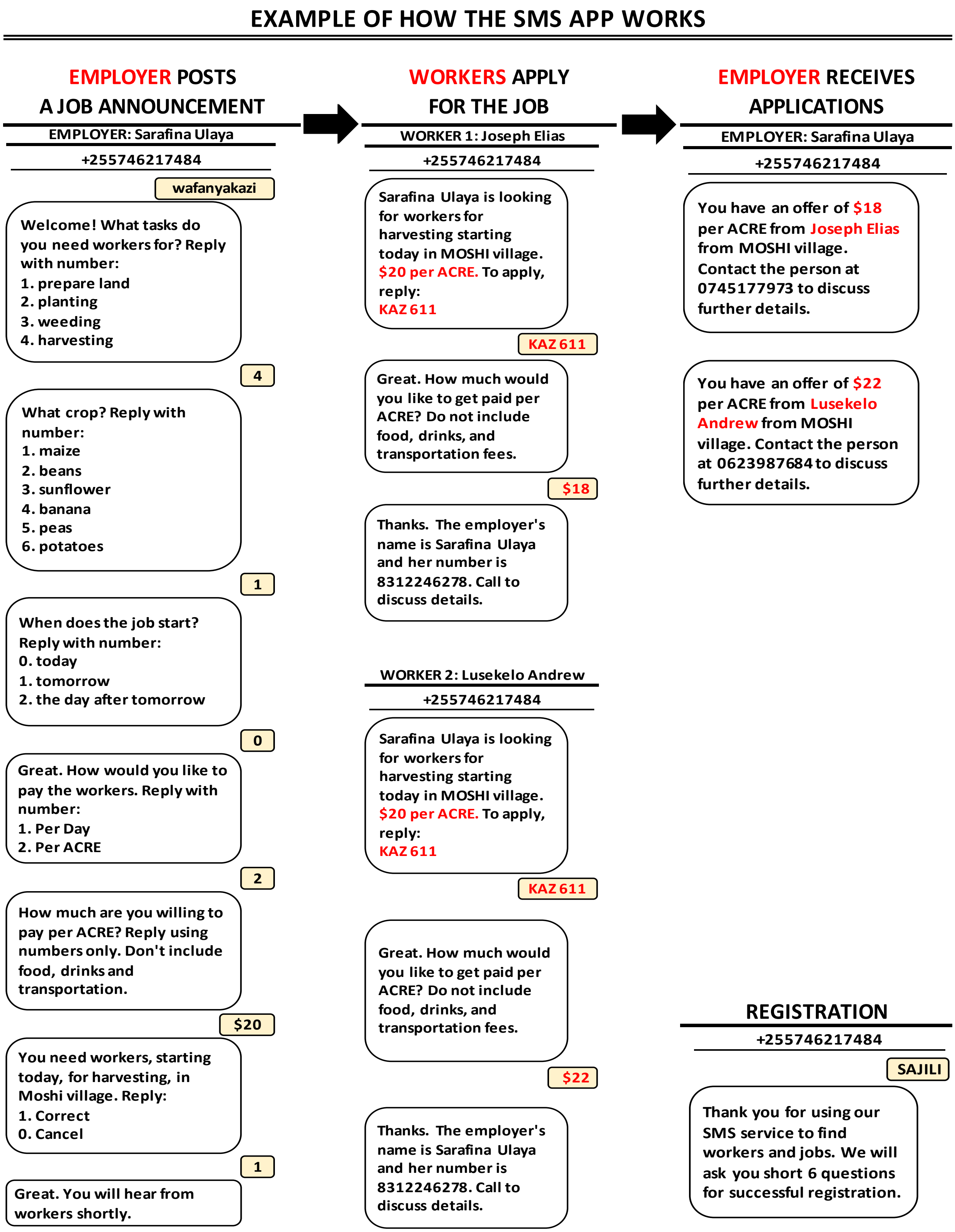
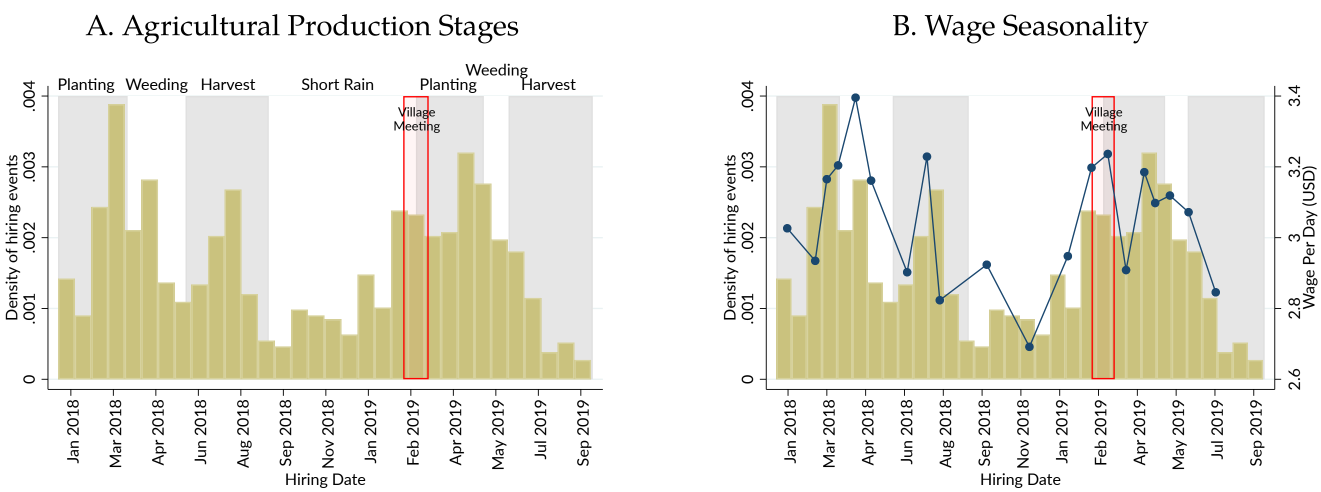


Figure A10: Production Stages and Seasonality



Notes: Panel A is a binned scatter plot with 66 hiring events per bin on average.

Figure A11: Wage Trajectory By Initial Wage Level

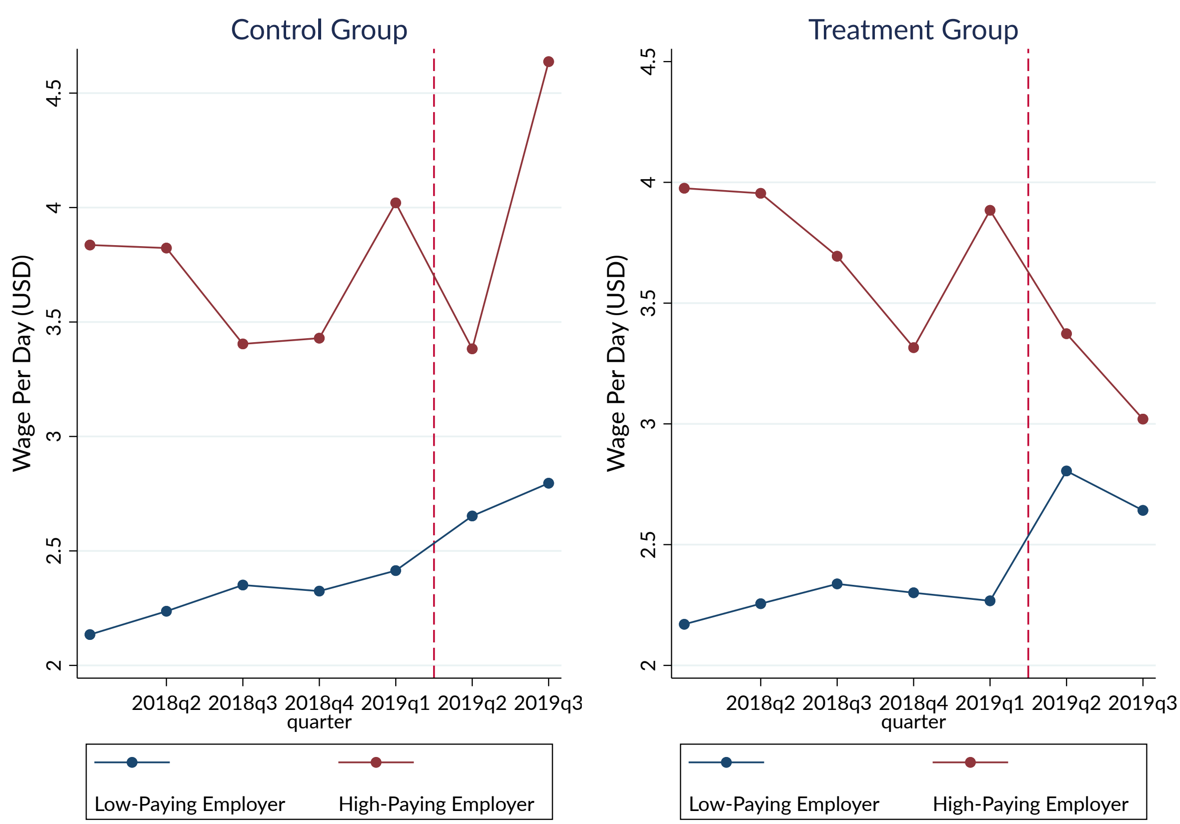


Figure A12: Telerivet Usage

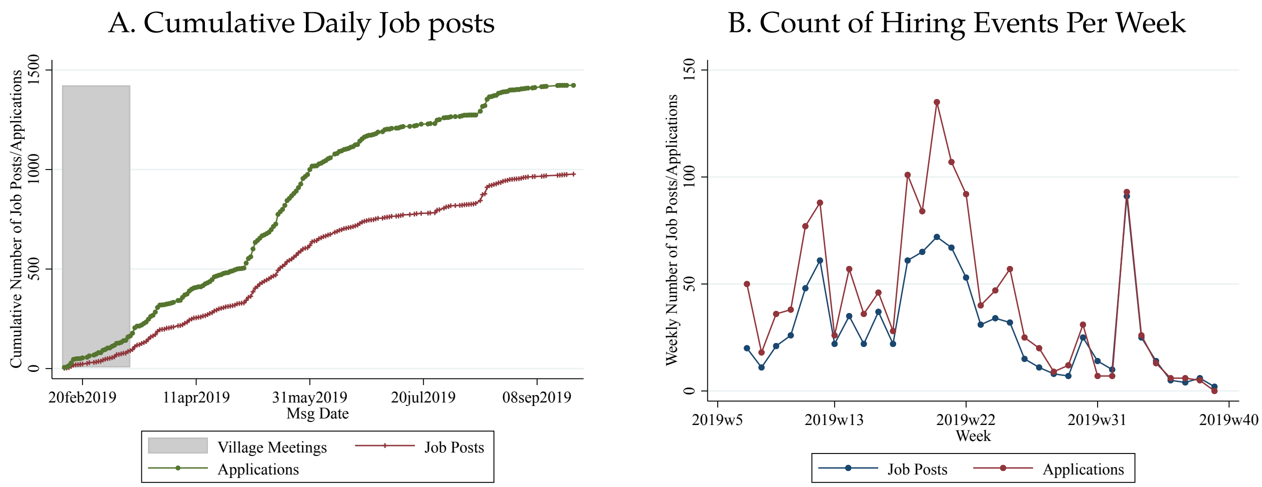


Figure A13: Telerivet Job Post Performance

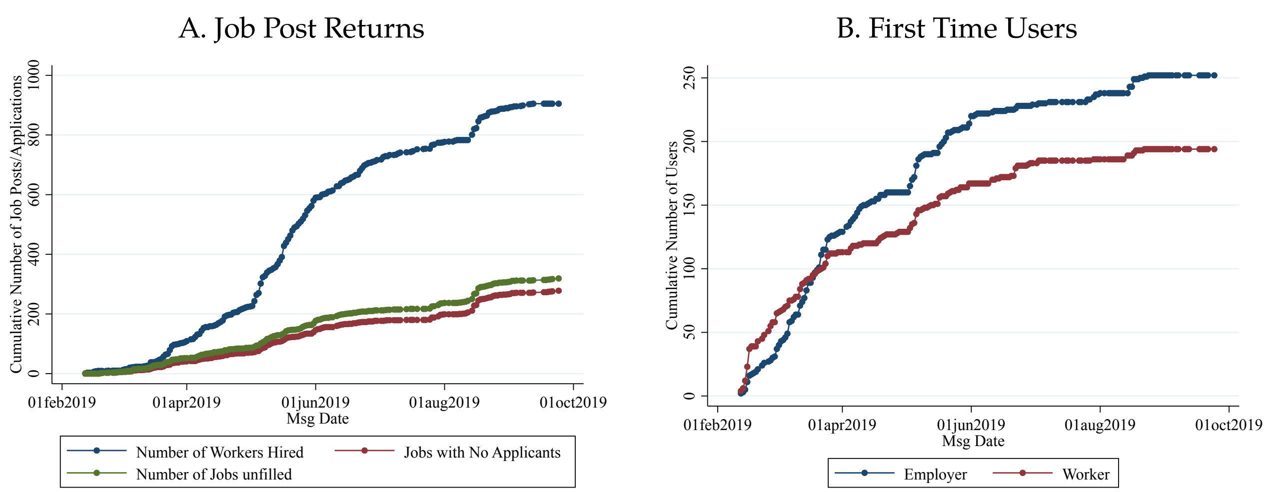


Table A1: Within Treatment, Wage Display Is Cross-Randomized

	Show Wage	Message Example
Job AD	No	*Jennifer is looking for workers for weeding for beans, starting tomorrow in village MOSHI. To apply for the job, reply: Job 805*
	Yes	*Jennifer is looking for workers for weeding for beans, starting tomorrow in village MOSHI.* ***$4 per Day****. To apply for the job, reply: Job 805*
Worker Application	No	*Joseph from village MOSHI applied to your job post. Call 8312246278 to discuss details.*
	Yes	*Joseph from village MOSHI applied to your job post with a wage* ***$5 per Day****. Call 8312246278 to discuss details.*

Table A2: Randomization Balance Check: Farmer Level

	(1) Control		(2) Treatment		T-test P-value
Variable	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	(1)-(2)
Abs. Percent Deviation From Village Avg Wage	136	1.989	201	-0.182	0.166
	[29]	(1.514)	[36]	(0.381)	
Standardized Wage	136	-0.054	201	0.037	0.592
	[29]	(0.093)	[36]	(0.142)	
Fraction of Households with Mobile Ownership	279	0.932	344	0.922	0.639
	[30]	(0.017)	[36]	(0.014)	
Respondent is Female	280	0.371	346	0.402	0.487
	[30]	(0.035)	[36]	(0.026)	
HH Hired Workers	280	0.689	346	0.671	0.705
	[30]	(0.038)	[36]	(0.032)	
HH Worked As A Casual Worker	280	0.421	344	0.430	0.872
	[30]	(0.042)	[36]	(0.035)	
Plot Size in Acreage	271	5.687	334	3.957	0.321
	[30]	(1.167)	[36]	(1.295)	
Total Labor Person Days	275	72.782	338	63.533	0.182
	[30]	(5.428)	[36]	(4.279)	
Labor Input Per Acre	271	31.478	334	36.926	0.182
	[30]	(3.048)	[36]	(2.690)	
Family Person Days	270	56.670	322	48.676	0.192
	[30]	(5.030)	[36]	(3.479)	
Hired Labor Person Days	275	24.015	338	20.556	0.578
	[30]	(4.505)	[36]	(4.303)	
Fraction of Hired Labor Person Days	274	0.222	334	0.232	0.818
	[30]	(0.031)	[36]	(0.029)	
Main Farming Season is Long Rainy Season	280	0.671	346	0.650	0.837
	[30]	(0.080)	[36]	(0.066)	
Used Chemical Fertilizer	271	0.247	334	0.266	0.813
	[30]	(0.057)	[36]	(0.058)	
Used Hybrid Seeds	270	0.578	334	0.614	0.639
	[30]	(0.059)	[36]	(0.050)	
Maize Harvest Quantity (Kg)	234	1209.718	293	900.638	0.221
	[30]	(215.943)	[36]	(129.626)	
Sold Maize	262	0.321	322	0.304	0.793
	[30]	(0.048)	[36]	(0.040)	

Notes: The balance test is shown for 650 study farmers based on the baseline survey collected *before* the intervention. The number of control villages is 30 and the number of treatment villages is 40. See Appendix Table A3 for the balance table at village level using phone survey and endline survey data. Last column shows the p-value of the t-test for the equality of the two means.

Table A3: Randomization Balance Check: Village Level

Variable	N	(1) Control Mean/SE	N	(2) Treatment Mean/SE	T-test P-value (1)-(2)
HH Worked as Casual Worker(s)	30	0.099	36	0.117	0.491
		(0.019)		(0.018)	
HH Hired Casual Workers	30	0.611	36	0.535	0.140
		(0.034)		(0.036)	
Average Wage	29	2.929	35	3.089	0.293
		(0.106)		(0.106)	
SD in Wage	29	1.130	35	1.101	0.813
		(0.080)		(0.089)	
CV in Wage	29	0.380	35	0.354	0.493
		(0.025)		(0.026)	
P50-p10 Wage Ratio	29	1.612	35	1.602	0.915
		(0.068)		(0.067)	
Mean-Min Wage Ratio	29	1.810	35	1.747	0.541
		(0.075)		(0.070)	
SD Log (Labor Per Acre)	30	0.831	36	0.777	0.527
		(0.065)		(0.054)	
CV Labor Per Acre	30	0.762	36	0.691	0.286
		(0.043)		(0.049)	
P50-p10 Labor Per Acre Ratio	30	3.529	36	3.587	0.942
		(0.662)		(0.491)	
Mean-Min Labor Per Acre Ratio	30	4.993	36	4.482	0.599
		(0.738)		(0.632)	
Number of Hired Workers	29	7.391	35	6.203	0.074*
		(0.501)		(0.427)	
Number of Prospective Workers Per Position	29	1.608	35	1.543	0.394
		(0.053)		(0.053)	
On-Farm Labor Days	30	82.135	36	76.368	0.539
		(8.326)		(4.956)	
On-Farm Family Days	30	48.442	36	46.323	0.736
		(5.235)		(3.677)	
On-Farm Hired Labor Days	30	24.612	36	18.567	0.137
		(3.435)		(2.287)	
On-Farm Exchange Labor Days	30	2.518	36	3.917	0.186
		(0.540)		(0.842)	
Used Fertilizer	30	0.226	36	0.254	0.698
		(0.051)		(0.049)	
Used Hybrid Seeds	30	0.524	36	0.545	0.748
		(0.047)		(0.042)	
Total Harvest Value (USD)	30	170.693	36	206.652	0.192
		(17.929)		(19.904)	

Notes: The balance test is done using the phone survey and endline survey. These surveys were implemented *after* the intervention, but the data for the pre-intervention period was also collected by recall as part of the surveys. See Appendix Table A2 for the balance table using the baseline data implemented *before* the intervention. Last column shows the p-value of the t-test for the equality of the two means.

Table A4: Attrition: Phone Survey

	Compliance: Phone Survey Completed			
	(1)	(2)	(3)	(4)
	Round1	Round2	Round3	All 3 Rounds
TREAT	-0.0318	-0.0182	-0.0254	-0.00921
	(0.0387)	(0.0378)	(0.0399)	(0.0396)
Constant	0.621***	0.611***	0.618***	0.579***
	(0.0281)	(0.0266)	(0.0301)	(0.0299)
Farmers	626	626	626	626
Villages	66	66	66	66

Notes: The attrition table includes those farmers for which we do not have a phone number. They are coded as non-compliance. Phone numbers of some treatment farmers were updated during the recent village meetings. In other words, we would have not been able to reach them if we did not hold village meetings. Since control villages did not have village meetings, I assume that those whose phone numbers got updated during the meetings are also non-compliant to ensure the balance between control and treatment villages. Round 2 and 3 asked farmers' all hiring/working events from the most recent survey date. For example, if a farmer participated in Round 1 but not in Round 2, then Round 3 asked their hiring/working events since the completed date of Round 1 survey. Standard errors are clustered at the village level.

Table A5: Attrition

		Reasons of Non-Compliance					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Interviewed	Refused	Moved	Unidentified	Travelling	Work Away	Sick/Died
Treatment	-0.01	0.01	-0.00	-0.00	0.01	-0.00	0.01
	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Constant	0.91***	0.02**	0.02**	0.02**	0.01	0.01*	-0.00***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Farmers	626	626	626	626	626	626	626
Villages	66	66	66	66	66	66	66

Table A6: Test for Equality of Two Variances of Wage Distributions in Figure 3.

Test	Outcome	Control SD	Treatment SD	P-value
Levene (1960)	Raw Wage (Pre)	1.377	1.371	0.966
Brown and Forsythe (1974)	Raw Wage (Pre)	1.377	1.371	0.835
Levene (1960)	Raw Wage (Post)	1.439	1.271	0.007
Brown and Forsythe (1974)	Raw Wage (Post)	1.439	1.271	0.008
Levene (1960)	Residualized Wage (Pre)	1.316	1.226	0.155
Brown and Forsythe (1974)	Residualized Wage (Pre)	1.316	1.226	0.169
Levene (1960)	Residualized Wage (Post)	1.292	1.141	0.006
Brown and Forsythe (1974)	Residualized Wage (Post)	1.292	1.141	0.007

Notes: Standard deviations of Control and Treatment group are reported in Columns 3 and 4. Column 5 reports the p-value from the test results with the null hypothesis of equal variances using the STATA command *robvar*. Brown and Forsythe (1974) replaces the mean in Levene (1960)'s formula with the median.

Table A7: ANCOVA Estimation of the Main Regression Results

	p50-p10 Ratio		Mean-Min Ratio	
	(1)	(2)	(3)	(4)
	p5010	p5010	meanmin	meanmin
TREAT	-0.182*	-0.139	-0.256**	-0.183**
	(0.101)	(0.0888)	(0.0995)	(0.0847)
Baseline p50-p10 Ratio		0.546***		
		(0.118)		
Baseline Mean-Min Ratio				0.544***
				(0.102)
Observations	68	68	68	68
Villages	68	68	68	68
Control Mean	1.562	1.562	1.707	1.707

Notes: This regression is at a village-level and controls for baseline outcome measures. Two villages out of 70 villages are dropped because they do not have any hiring events data after the intervention.

Table A8: Wage Dispersion Is Not Driven By Bidding Feature (Village Level)

	No Winsorization		Winsorized at p5 and p95	
	(1)	(2)	(3)	(4)
	Wage	Wage&B	Wage	Wage&B
TREAT	-0.0291	-0.0239	-0.0212	-0.0151
	(0.0302)	(0.0297)	(0.0259)	(0.0258)
TREAT $\times$ Post	-0.0596	-0.0595*	-0.0516	-0.0513
	(0.0379)	(0.0352)	(0.0349)	(0.0321)
TREAT_BID	0.0181	0.0199	0.0122	0.00940
	(0.0325)	(0.0339)	(0.0271)	(0.0279)
TREAT_BID $\times$ Post	-0.00708	-0.0159	-0.0153	-0.0160
	(0.0386)	(0.0361)	(0.0341)	(0.0308)
Stage FE	X	X	X	X
Task FE	X	X	X	X
Crop FE	X	X	X	X
Observations	1613	1613	1613	1613
Farmers	439	439	439	439
Villages	66	66	66	66
Control Mean	0.323	0.319	0.300	0.293

Notes: This regression is at a farmer-hiring event level data. Outcomes are individual percent deviation from the village mean wage and/or benefits in USD. The results are robust to using median wage as opposed to mean wage. Standard errors clustered at the village level.

Table A9: Treatment Effect on Skipping Meals Controlling For Winning A Raffle

	Dep.Var: Skip A Meal (HH Level)			
	(1)	(2)	(3)	(4)
	Past6m	Past3m	Past6m	Past3m
TREAT	-0.035*	-0.032*	-0.034*	-0.032*
	(0.020)	(0.017)	(0.020)	(0.017)
Won A Raffle Prize of 10 USD	-0.043***	-0.020*		
	(0.016)	(0.011)		
Won A Raffle Prize of 10 USD Or A Feature Phone			-0.049***	-0.026**
			(0.014)	(0.010)
Observations	566	566	566	566
Households	566	566	566	566
Villages	66	66	66	66
HH Endowment	X	X	X	X
Control Mean	0.075	0.051	0.075	0.051

Notes: This table replicates columns 5 and 6 in Table 13 controlling for winning a raffle prize. During the village meetings, one randomly selected person was given a feature phone to motive the training session. Throughout the agricultural season, two person was randomly selected from each village to get 10 USD if they used the app. Note that the random selection includes all users (not just study farmers who were interviewed). Among the study sample, six farmers won the phone during the village meeting, and seven farmers won the 10 USD. This is the 2 percent of the study sample (13/584 = 0.02).

Table A10: Feedback On The Search App (Treatment Villages Only)

	Mean	SD	N
The App Service Was Useful	0.93	0.25	44
Plan To Use The App in Future	0.50	0.50	274
I Am Willing To Contribute For The Service	0.74	0.44	129
Willingness To Pay Per Month	0.40	0.26	89
Willingness To Pay Per Ag. Season	1.49	2.84	86