Effective Training Through a Mobile App: Evidence from a Randomized Field Experiment

Kenn Chua, Qingxiao Li, Khandker Wahedur Rahman,

and Xiaoli Yang*

June 15, 2021

Abstract

Application of information and communication technologies could be a viable alternative to traditional agricultural extension services in developing countries. We develop a mobile application-based training module intended to improve the quality of grape and use a randomized controlled trial (RCT) to examine its effectiveness. We find that providing technical training through mobile app can improve farmers' knowledge and helps them enhance the quality of their produce. We also find that motivating farmers through mobile app is not effective and undermine the impact of increased knowledge. Bundling motivation with technical training can lead farmers to overestimate the quality of their product. It suggests that keeping training through mobile app focused on technical module is more desirable.

Keywords: Information and communication technologies, field experiment.

JEL Codes: O13, Q13.

Selected Paper prepared for presentation at the 2021 Agricultural & Applied Economics Association Annual Meeting, Austin, TX, August 1 – August 3

* Kenn Chua: Department of Applied Economics, University of Minnesota (chuax025@umn.edu); Qingxiao Li: Department of Applied Economics, University of Minnesota (lixx5376@umn.edu); Khandker Wahedur Rahman: Department of Applied Economics, University of Minnesota (kwrahman@gmail.com); Xiaoli Yang: College of Economics and Management, Shenyang Agricultural University (yangxiaoli@syau.edu.cn). We thank Xiaoyu Sun for providing excellent research assistance.

1 Introduction

Farmers in developing countries usually lack access to vital resources and services that facilitate the adoption of new technology and better farming practices. Agricultural extension services, including technical training, is an important method to overcome these deficiencies and reduce poverty by providing information and transferring knowledge to farmers (Anderson and Feder 2004; Nakasone et al. 2014). However, traditional extension service typically entails a great number of human resources as well as high fixed and recurrent financial costs (Quizon, et al. 2001; ICRAF 2018) that limit their scalability and efficiency. For instance, traditional extension services in the form of in-person trainings often involve low-frequency visits that occur outside the planting and harvest seasons due to constraints brought about by distance and time (Cole and Fernando 2021). While these factors limit farmers' access to timely and high-quality agricultural information and extension services (e.g., Ferroni and Zhou 2012), the rapid expansion of information and communication technologies (ICTs) in developing countries offers great potential to overcome the myriad challenges presented by knowledge delivery in the rural setting (Aker 2011).

ICTs include different types of technologies, including radio, television, computer, mobile phones, etc. The mobile phone is one of the fastest-growing and most widespread forms of ICTs.[2] The mode of delivering information through mobile phones is important, and voice messages and SMS messages are the popular methods that have been studied in the literature.

This paper studies the impact of providing technical training through an ICT, an easy-to-use mobile application, on farmers' technical knowledge and welfare. Our analysis is based on a sample of grape farmers in rural China. We develop a mobile app that contains and disseminates technical training videos for each farming stage. In addition, we provided aspirational videos via the same app which demonstrated success stories of farmers who had adopted the techniques being taught through the app. Access to the technical as well as the aspirational videos was randomized for a sample of 1,026 farmers who were interested in participating. We help farmers to install the app on their phones before the farming season and upload contents before each farming stage. Farmers in both treatment and control groups installed the mobile app, but only farmers in the treatment groups can access the technical training and aspirational contents.

[2] Based on Gallup World Poll, around 83 percent of adults in developing counties have a mobile phone in 2018. Source available at https://www.brookings.edu/blog/future-development/2019/04/10/mobile-phones-are-key-to-economic-development-are-women-missing-out/.

We find that providing training through mobile app is an effective alternative to traditional extension service for improving farmers' knowledge. We find evidence that farmers in both our treatment arms have improved technical know-how due to our intervention.

In addition, we find that providing focused training to farmers helps them achieve higher quality product. Farmers in our training only arm improves the sweetness of their product by 0.29 standard deviations (SD). When we look at the impact on grape sweetness for those farmers whose knowledge also improves due to the treatment, we find that sweetness increases by 0.55 SD.

However, bundling multiple learning objectives together does not yield desired outcome. We find that while the training and aspiration arm increases the knowledge of the farmers, it does not increase the sweetness of the grape. We find weak evidence of improvement of farmers' aspiration. Moreover, we find that famers in these arms have large overestimation of the quality of their product.

We contribute to the growing literature of using ICT in helping farmers improve welfare. Cole and Fernando (2021) conducted a randomized impact evaluation of a program in India that send unified voice messages to selected farmers with information on weather and crop conditions and provides a hotline for specific agricultural consulting. Their results show a weak impact on farming practices, and they argue that this may be due to the spillovers from treatment to the control group. Another study by Fafchamps and Minten (2012) investigates the impact of SMS messages that contain agricultural information advisory tips in India. This study finds small effects on crop grading but no effect on farmers' cultivation practice and harvest gains. In general, these results suggest that voice messages and SMS messages delivery mechanisms face limitations and generally lead to less desirable outcomes.

Fu and Akter (2016) argue that video images would be useful to address the problems in the previous methods. Their study investigates the impact of a program in India that assigns village assistants to travel across villages with mobile phones that can record short dialogue strips (SDs) and short videos of farming problems that farmers have. The village assistants will send the SDs and videos to an agricultural adviser to look for solutions, and then they will pass back to the farmers. Using a difference-in-difference approach, Fu and Akter (2016) find that farmers increased their awareness and knowledge of new agricultural practices and farmers' aspiration to try new technology. In another related study, Van Campenhout (2017) examines the impact of a project that uses a mobile app to provide agricultural information and extension services to smallholder farmers in Uganda. The project provides recruited village assistants with phones that contain a preloaded mobile app, which can be used to search agriculture-related information and extension. The recruited village assistants can search for information requested by farmers about farming and marketing to help the farmers. Van Campenhout (2017) shows that farmers impacted by the project changed crop choice and received higher average prices for the crops they sell but did not increase productivity. Both studies rely on village assistants to facilitate the project, which can be costly compared to directly providing the ICTs to the farmers.

The rest of the paper is organized as follows: we discuss the background in the following section. In section 3, we describe the experimental design and data description. We enumerate the empirical strategy in section 4, followed by a discussion of results in section 5. Section 6 concludes the paper.

2 Background

This study took place in Beizhen, one of the largest grape-producing cities in China. The economy of Beizhen is agriculture-oriented, and there are roughly 10,000 grape farming households.

Despite having more than 20 years of grape farming experience, farmers in Beizhen follow the traditional technique, which has the high-yield advantage but neglects the quality. As Chinese consumers are demanding greater food quality (Huang and Gale 2009), the market for low-quality grapes, mainly due to low sweetness, has been shrinking and the prices have been dropping in the past few years. Being aware of this market change, the local government of Beizhen has been trying different ways to help farmers improve their grape quality, such as offering in-person training sessions by experts. Nevertheless, even with the presence of training such as field demonstrations, most farmers are unable to acquire new farming techniques. In addition, traditional training methods are generally expensive, and thus this has become a pressing challenge for the local government.

In this study, we partner with the Beizhen government to develop a mobile app that can provide technical training to local grape farmers. Our goal is to increase farmers' technical skills, which can help them increase their grape quality and eventually increase the price of their grapes. Since lack of aspiration may be another reason for farmers not to adopt the new techniques, we also offer aspiration videos in our app to one of the treatment arm farmers.

In Beizhen, all farmers have mobile phones with access to the internet.[3] In fact, more than 98 percent of rural villages in China have internet coverage, and the cost of accessing the internet is low.[4] Furthermore, China has the most mobile app downloads in the world, and Chinese internet users spend more than 30 percent of total usage time on video apps.[5] Hence, the potential reach of our mobile app is large.

3 Experimental Design and Data Description

In this section, we describe our sample, intervention, study design, and data collection timeline.

3.1 Study Setting and Sample Frame

Our sample consists of farmers residing in the grape-growing regions of Beizhen in Liaoning, China. The criteria for inclusion in the sampling frame include: (1) the household engaged in grape farming in 2019; (2) the household resided within the seven townships with the largest concentration of grape farming to limit survey costs. In total, we successfully interviewed 1,026 farmers from 38 villages at baseline.

3.2 Intervention

This study evaluates the effectiveness of using a custom mobile application as a form of agricultural extension service. The mobile app released a series of videos aimed at boosting farmers' technical knowledge on farming practices that raise grape quality. All farmers in the study received the mobile application, but the content released varied across treatment and control groups. Videos were released throughout the planting season between May and September. Moreover, every release was accompanied by an SMS message alerting farmers to the update. The content automatically downloads to the user's phone upon accessing the app while connected to the internet. Figure 1 shows the interface of the mobile app.

Technical videos only (T1): The first set of interventions consist of a series of videos, one to three minutes in length, on grape farming techniques that can be employed to raise grape

[3] About 45 percent of the developing world has access to the internet (ITU 2019).
[4] See https://www.chinadaily.com.cn/a/202008/19/WS5f3c8e42a31083481726142d.html.
[5] See https://global.chinadaily.com.cn/a/201908/16/WS5d561e4ea310cf3e35566287.html.

quality. Each video was curated to be relevant to the farmers' particular needs at each stage of the grape-growing period, and include lessons on water management, fertilizer use, pest, and disease control, as well as fruit pruning techniques. A total of 60 videos were released in a timely manner beginning May 2020, the sprouting and leafing period, until mid-September 2020, the beginning of the harvest season. Figure 2 summarizes the quantity and timing of these video releases.

Technical videos and aspiration videos (T2): The second set of interventions includes both the 60 videos released to the first group plus an additional 15 aspirational videos promoting the practice of growing of high-quality grapes. These videos feature prominent speakers from the Beizhen Grape Association, a group of farmers charged with ensuring standards of high-quality grapes in the region as well as promoting the wider adoption of the Beizhen grape brand in markets across China. In these videos, speakers like the chairman and vice chairman of the association spoke about their own experience raising the quality of their grapes and selling them under the Beizhen brand.

Placebo videos: Apart from technical and aspiration videos, we released videos featuring the local history of the grape industry as well as natural landscapes of the region. These were released to all farmers at different points throughout the study period.

On top of videos released through the app, we also provided monetary incentives for farmers to watch the videos. Specifically, beginning the end of June we told farmers that we would provide 2 RMB (0.3 USD) per video watched. These were applied uniformly across all groups regardless of the type of video.

3.3 Randomization

Our experiment follows a cluster randomized design with two treatment arms and a control group. The unit of randomization is the sub-village (zu) of residence, which was chosen to minimize contamination across groups. In total, our sample contains 116 clusters with a median number of 7 households interviewed per sub-village. Thirty-nine clusters were assigned to receive the technical videos only (T1; N = 325); another 39 was assigned to receive both the technical videos and aspiration videos (T2; N = 332); while 38 control group clusters receive only placebo videos (C; N = 369).

3.4 Timeline and Data Collection

Our fieldwork took place from January 2020 to January 2021. The baseline data was collected in early January 2020 after the previous year's harvest season. Importantly, we were able to do this in-person as this preceded the outbreak of COVID-19 in China. We interviewed 1,026 farmers living in 38 villages of Beizhen, and collected information regarding their grape production, sales, self-assessments of own grape quality, as well as household demographics. We also conducted a short test of technical knowledge on grape farming and inquired about their aspired income and grape quality three and five years into the future.

After the baseline, we conducted two short midline follow-ups with the farmers via phone call. The first follow-up transpired in early May, in which we asked farmers whether they were impacted by the pandemic, and whether they were still planting grapes this season. We also ensured that the apps were installed by each farmer as we started releasing the videos on the same month. A second follow-up was conducted in late June, in which we informed the farmers about the monetary incentives associated with watching the videos.

A more detailed in-person midline survey was then conducted during the harvest period in October 2020. We inquired about their grape production for the year, including investments in inputs and farming practices adopted. To measure grape quality, we collected both self-assessments similar to those collected at baseline and a sample of the farmers' grapes which we use to obtain an objective measure of grape quality (our main outcome of interest).

Finally, in January 2021, we conducted an endline survey in which we inquire about the farmers' total grape sales for the year. We also collected information regarding their grape storage and feedback regarding the mobile application. Due to logistical constraints imposed by the COVID-19 pandemic, only the baseline and September midline were administered in-person while the endline was administered via phone call.

3.5 Measures of Farming Knowledge, Grape Quality, and Aspiration

In order to measure farmers' awareness and knowledge of farming practices that improve grape quality, we asked the farmers 10 questions on a range of topics including grapevine inflorescence, water and fertilizer use, disease prevention techniques, and pest control. We calculated the number of correct answers to these questions to calculate a knowledge score and standardized it with respect to the control group.

Meanwhile to measure the quality of farmers' grapes, we rely on both objective and subjective measures. Grape quality in our context can be judged along several dimensions including sweetness, the shape of a grape bunch, the roundness of the individual berries, and the color of the fruit. As the local grape market is segmented into low- and high-quality markets, grapes that are sold in the latter are typically sweeter, form a conically shaped bunch, and have berries that are spherical. Moreover, high-quality grapes are normally priced between 1.5 to 2 times higher than low-quality grapes.

Apart from using price, a useful proxy to capture the overall quality of the grape is its sweetness. Grape sweetness is measured on a scale of 8-24 with the highest quality grapes having a rating of 20 or higher. We obtain an objective sweetness rating of the farmers' grapes by collecting a sample from their harvest during the 2020 grape season. Placing the grapes in the machine allows us to obtain an objective measure of quality. Because this scale of rating of sweetness is widely known among the farmers, we ask them about their own rating of their harvest, which we use as a subjective assessment of quality. This self-report measure is asked at both the baseline and the September midline.

Finally, to measure the aspiration of farmers, we follow Bernard et al. (2014) and asked farmers what level of income from grape farming they would like to achieve within a 3-year and 5-year horizon. Similarly, we ask farmers what level of grape quality (sweetness) they would like to achieve within a three-year and five-year time frame.

3.6 Farmer Characteristics and Sample Balance

In Table 1, we report summary statistics and tests of balance of the baseline sample farmers. Our sample is balanced along several demographic and economic dimensions such as gender, age, health status, household size, years of grape planting, grape planting area, and grape yield. Key outcome variables such as technical knowledge test scores, self-rated sweetness, aspired income, and aspired sweetness are also balanced across groups. However, we do find that our technical videos only (T1) group has a greater proportion of farmers that have completed middle school or above, and higher revenue from grapes. To address potential imbalance along observables, we include these variables as control in robustness check and find that our main results are robust to the inclusion of these additional control variables.

3.7 Attrition

While we experience a large attrition, there is no systematic difference of attrition between experimental arms. Table 2 shows attrition in midline and endline. We did not find about 22% of baseline farmers at midline and 31% of baseline farmers at endline. As this table shows, there is no significant variation of attrition across treatment arms.

From an initial baseline sample of 1,026, our analytical sample consists of 687 grape farmers whom we were able to successfully interview in all rounds. Figure 3 provides a snapshot of the timeline of data collection as well as the number of farmers lost at each wave.

4 Empirical Strategy

Our preferred specification is as follows:

$$y_{iz} = \beta_0 + \beta_1 T1_z + \beta_2 T2_z + X'_{iz}\delta + \varepsilon_{iz} \tag{1}$$

where y_{iz} is the outcome of interest measured at endline for farmer i in zu z. $T1_z$ is a binary indicator variable that takes the value of 1 if zu z was randomly assigned to training only arm and $T2_z$ is a binary indicator variable that takes the value of 1 if zu z was randomly assigned to training and aspiration arm. X_{iz} includes baseline characteristics. In our preferred specification, we only include outcome variable measured at the baseline. If a baseline measurement of the outcome variable is unavailable, we do not include any baseline characteristics in the preferred specification. In alternate specifications, we control for farmer's gender, age, training status, education, health condition, total household income, years of experience, baseline planting area, inverse hyperbolic sine of baseline yield and baseline revenue from grape. All standard errors are clustered at the zu level. Since we assigned the treatment status randomly, estimates of β_1 and β_2 from equation (1) gives us the impact of *T1* and *T2*.

Through our treatment, we provide farmers the training to produce higher quality grapes. The immediate impact of this would be to increase farmers' knowledge. While we can measure the intent-to-treat (ITT) effect of the training on the quality of grape and other outcomes related to knowledge and aspiration through equation (1), we can also measure the impact of our intervention on these outcome variables for those farmers whose knowledge increased due to our intervention, i.e., the treatment-on-the-treated (TOT) impact. Our preferred specification for TOT estimation is as follows:

$$\text{First Stage: } k_{iz} = \alpha_0 + \alpha_1 D_z + X_{iz}' \lambda + \nu_{iz}$$

$$\text{Second Stage: } y_{iz} = \beta_0 + \beta_1 \hat{k}_{iz} + X_{iz}' \delta + \varepsilon_{iz}$$

where k_{iz} is farmer i's score on our test at endline. $D_z \epsilon \{T1_z, T2_z\}$ is an indicator variable for treatment status for the respective treatment group for which we estimate the TOT effect. Estimation of TOT is restricted only to a treatment group and the control group.

5 Results

We find that our treatment group farmers watched the videos we provide them. Table 3 shows that on average training arm farmers watch technical videos 22.2 percentage points more, while training and aspiration arm farmers watch those videos 26.6 percentage points more. Training and aspiration arm farmers watch aspirational videos 9.3 percentage points more.

While the share of videos watched was low, we find that providing training through mobile application is effective. Table 4 shows that training arm increases farmer's test score by 0.52 standard deviations, while training and aspiration arm increases test score by 0.45 SD. In our endline test, we repeated five questions from the baseline. We also find a significant increase in farmers' scores on these five questions (column 2). This shows that technical training on agricultural production technique can be provided through mobile applications as well.

Training only arm has a positive effect on increasing the sweetness of grapes. We find that grapes produced by training arm farmers were 0.297 SD sweeter than control group farmers (Table 5). We also estimate the TOT effects on the sweetness of grapes and find that training only arm farmers experience an increase of sweetness by 0.554 SD (Table 6). We do not find, however, any significant impact of training and aspiration arm on the sweetness of grapes. We also do not find any significant impact of either treatment arm on the count or weight of grapes. Training and aspiration arm farmers experience a slight increase on their aspired sweetness in three years, but no increase in their aspired income in 3 or 5 years (Table 7).

These results suggest that bundling multiple learning objectives when providing farmers training through mobile application is not as effective as keeping it focused. While training only arm and training and aspiration arm farmers had access to the same content and their share of watching technical videos were similar, only the earlier group farmers succeeded in translating the increase in knowledge to increase the quality of their products. In addition, training and aspiration group farmers only had a small increase in their aspiration.

Interestingly, we find that farmers of both arms believe that their grapes are sweeter. Table 8 shows that training only arm farmers assess their grapes to be 0.474 SD sweeter than control group farmers, while training and aspiration arm farmers assess their grapes as 0.510 SD sweeter. This suggests that while farmers overestimate how sweet their grapes are, when farmers saw technical videos and aspirational videos together, they overestimated more than the training only group farmers.

We do additional exploratory analysis and report them in Table 9. We do not find any impact of our intervention on choice of variety, planation area, yield, sales volume, sales revenue, or sales price. No increase in sales revenue or price indicates that while our intervention succeeded in increasing the quality of grapes, lack of demand side change (branding, connecting with the middlemen) hindered the farmers to obtain a price premium for their higher quality products.

6 Conclusion

Providing technical training is an important method to facilitate farmers to adopt new technology and better farming practices. We conduct an RCT to test whether technical training can be provided to farmers through mobile application. We find that while providing training through apps is an effective intervention, bundling technical modules with aspirational modules fail to achieve either increasing the quality of products or aspiration.

Our results show that trying to nudge farmers with aspirational videos lead to these farmers overestimates the quality of their products and contravene any potential increase in the actual quality of product.

Our findings suggest that using mobile-based training can be an effective alternative to reach many farmers with. Since farmers can watch videos in their own time, these trainings are flexible, does not require constant trainer involvement, and can be scaled-up quite easily.

Our findings further suggest that bundling multiple objectives on a digitally delivered training is not effective. It is, therefore, desirable that such training modules only focus on one learning objective.

References

Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics*, *42*(6), 631–647. https://doi.org/10.1111/j.1574-0862.2011.00545.x

Anderson, J. R., & Feder, G. (2004). Agricultural Extension: Good Intentions and Hard Realities. *The World Bank Research Observer*, *19*(1), 41–60. https://doi.org/10.1093/wbro/lkh013

Bernard, T., Dercon, S., Orkin, K., & Taffesse, A. S. (2014). The Future in Mind: Aspirations and Forward-Looking Behaviour in Rural Ethiopia. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2514590

Cole, S. A., & Fernando, A. N. (2021). 'Mobile'izing Agricultural Advice Technology Adoption Diffusion and Sustainability. *The Economic Journal*, *131*(633), 192–219. https://doi.org/10.1093/ej/ueaa084

Fafchamps, M., & Minten, B. (2012). Impact of SMS-Based Agricultural Information on Indian Farmers. *The World Bank Economic Review*, *26*(3), 383–414. https://doi.org/10.1093/wber/lhr056

Ferroni, M., & Zhou, Y. (2012). Achievements and Challenges in Agricultural Extension in India. *Global Journal of Emerging Market Economies*, *4*(3), 319–346. https://doi.org/10.1177/0974910112460435

Fu, X., & Akter, S. (2016). The Impact of Mobile Phone Technology on Agricultural Extension Services Delivery: Evidence from India. *The Journal of Development Studies*, *52*(11), 1561–1576. https://doi.org/10.1080/00220388.2016.1146700

Huang, K. S., & Gale, F. (2009). Food demand in China: Income, quality, and nutrient effects. *China Agricultural Economic Review*, *1*(4), 395–409. https://doi.org/10.1108/17561370910992307

Nakasone, E., Torero, M., & Minten, B. (2014). The Power of Information: The ICT Revolution in Agricultural Development. *Annual Review of Resource Economics*, *6*(1), 533–550. https://doi.org/10.1146/annurev-resource-100913-012714

Quizon, J., Feder, G., & Murgai, R. (2001). Fiscal Sustainability of Agricultural Extension: The Case of the Farmer Field School Approach. *Journal of International Agricultural and Extension Education*, *8*(1). https://doi.org/10.5191/jiaee.2001.08102

Van Campenhout, B. (2017). There is an app for that? The impact of community knowledge workers in Uganda. *Information, Communication & Society*, *20*(4), 530–550. https://doi.org/10.1080/1369118X.2016.1200644

Tables

Table 1 Baseline Balance Test

	(1) C Mean/(SD)	(2) T1 Mean/(SD)	(3) T2 Mean/(SD)	(4) *p-value* from test of (1)=(2)=(3)
Farmer Characteristics				
Male (=1)	0.67	0.72	0.70	0.532
	(0.47)	(0.45)	(0.46)	
Age (in years)	47.80	46.53	47.72	0.175
	(8.86)	(8.76)	(8.67)	
Completed middle school or above (=1)	0.62	0.67	0.58	0.069*
	(0.49)	(0.47)	(0.49)	
Has a good health (=1)	0.43	0.46	0.36	0.118
	(0.50)	(0.50)	(0.48)	
Household size	3.79	3.87	3.80	0.734
	(1.36)	(1.34)	(1.25)	
Has training experience (=1)	0.31	0.35	0.30	0.583
	(0.46)	(0.48)	(0.46)	
IHS(Total household income)	11.27	11.61	11.23	0.100*
	(2.00)	(1.43)	(2.02)	
Years of grape planting	21.50	21.45	21.48	0.999
	(8.36)	(7.94)	(7.26)	
Grape planting area (acre)	1.74	1.94	1.82	0.347
	(1.20)	(1.19)	(1.07)	
IHS(Grape yield)	10.92	11.00	11.09	0.617
	(1.55)	(1.41)	(1.24)	
IHS(Revenue from grape)	9.39	10.41	9.26	0.018**
	(4.03)	(3.16)	(4.14)	
IHS(Average grape sales price)	1.34	1.34	1.28	0.418
	(0.64)	(0.50)	(0.48)	
Outcomes Variables				
Test score (standardized)	0.00	-0.09	-0.11	0.523
	(1.00)	(1.03)	(1.07)	
Self assessed sweetness (standardized)	-0.00	0.07	0.11	0.595
	(1.00)	(0.82)	(0.96)	
Self assessed count (standardized)	-0.00	0.09	-0.01	0.552
	(1.00)	(1.06)	(0.99)	
Self assessed weight (standardized)	-0.00	0.23	-0.06	0.058*
	(1.00)	(0.90)	(0.95)	

IHS(Aspired income in 3 years)	11.37	11.78	11.91	0.119
	(3.13)	(2.66)	(2.35)	
Aspired sweetness in 3 years (standardized)	-0.00	-0.11	0.08	0.125
	(1.00)	(0.94)	(1.03)	
IHS(Aspired income in 5 years)	10.21	11.27	10.73	0.125
	(4.82)	(3.93)	(4.52)	
Aspired sweetness in 5 years (standardized)	-0.00	-0.06	0.08	0.322
	(1.00)	(0.94)	(1.01)	
Observations	370	324	332	
Cluster	38	39	39	

p-value from joint test of equality	
C=T1	0.007***
C=T2	0.148
T1=T2	0.016**

Table 2: Attrition

	(1)	(2)
	Missing at Midline	Missing at Endline
T1	0.053	0.016
	(0.037)	(0.038)
T2	0.049	0.045
	(0.039)	(0.038)
Observations	1,026	1,026
Control-group mean	0.222	0.311
T1=T2 (*p-value*)	0.931	0.515

Notes: Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 3: Share of Video Watched by Treatment Arm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Technical Video					Aspirational Video		
	Overall	May	June	July	August	Overall	May	June
T1	0.222***	0.077***	0.172***	0.295***	0.253***	0.000***	0.000***	-0.000***
	(0.019)	(0.012)	(0.017)	(0.026)	(0.027)	(0.000)	(0.000)	(0.000)
T2	0.266***	0.090***	0.188***	0.356***	0.314***	0.093***	0.095***	0.091***
	(0.019)	(0.012)	(0.020)	(0.026)	(0.022)	(0.012)	(0.013)	(0.015)
Observations	687	687	687	687	687	687	687	687
Control-group mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T1=T2 (*p-value*)	0.104	0.463	0.554	0.098	0.083	0.000	0.000	0.000

Notes: Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 4: Impact on Test Score

	(1) Standardized Test Score (All 10 questions)	(2) Standardized Test Score (Repeated 5 questions)
T1	0.520***	0.371***
	(0.097)	(0.095)
T2	0.451***	0.413***
	(0.102)	(0.083)
Observations	687	687
Control-group mean	0.000	0.000
T1=T2 (*p*-value)	0.492	0.572

Notes: All regressions include test score at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 5: Impact on Grape Quality

	(1) Sweetness	(2) Count	(3) Weight
T1	0.297**	0.138	-0.114
	(0.132)	(0.117)	(0.103)
T2	0.099	0.010	-0.154
	(0.109)	(0.121)	(0.116)
Observations	679	679	679
Control-group mean	0.000	0.000	0.000
T1=T2 (*p-value*)	0.150	0.364	0.720

Notes: All outcome variables are standardized with respect to control group. All regressions include self-assessed grape quality at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 6: TOT Effect on Sweetness

	(1) Sweetness (T1)	(2) Sweetness (T2)
T1	0.554*	0.218
	(0.294)	(0.241)
Observations	467	466
Control-group mean	0.000	0.000

Notes: All outcome variables are standardized with respect to control group. All regressions include self-assessed grape quality at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses.
*** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 7: Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year Aspiration		5-year Aspiration	
	IHS(Income)	Sweetness	IHS(Income)	Sweetness
T1	0.103	0.125	0.101	0.101
	(0.080)	(0.107)	(0.089)	(0.095)
T2	0.028	0.186*	0.034	0.095
	(0.094)	(0.107)	(0.094)	(0.096)
Observations	686	684	685	684
Control-group mean	12.215	0.000	12.392	0.000
T1=T2 (*p-value*)	0.404	0.562	0.475	0.946

Notes: All regressions include outcome variable measured at baseline. Outcome variables in columns (2) and (4) are standardized with respect to control group. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 8: Impact on Self-Assessed Grape Quality

	(1) Sweetness	(2) Count	(3) Weight
T1	0.474***	0.173*	0.213**
	(0.092)	(0.103)	(0.105)
T2	0.510***	0.039	0.149
	(0.086)	(0.093)	(0.106)
Observations	687	687	687
Control-group mean	0.000	0.000	0.000
T1=T2 (*p*-value)	0.666	0.202	0.576

Notes: All outcome variables are standardized with respect to control group. All regressions include self-assessed grape quality at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses.
*** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 9 Impact on Additional Grape Production-Related Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Jufeng Variety (=1)	Planting Area (Acre)	IHS(Yield)	IHS(Sale Volume)	IHS(Revenue)	IHS(Price)
T1	-0.004	-0.031	0.038	0.227	0.265	0.039
	(0.012)	(0.069)	(0.075)	(0.163)	(0.178)	(0.028)
T2	-0.000	0.064	0.032	-0.168	-0.135	0.035
	(0.007)	(0.068)	(0.081)	(0.214)	(0.227)	(0.027)
Observations	687	687	687	687	687	672
Control-group mean	0.988	1.790	11.10	10.74	11.63	1.646
T1=T2 (*p*-value)	0.742	0.252	0.944	0.0147	0.0194	0.857

Notes: All outcome variables are standardized with respect to control group. All regressions include baseline outcome as control variable. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Figures

Figure 1: App Interface

Figure 2: Study Timeline

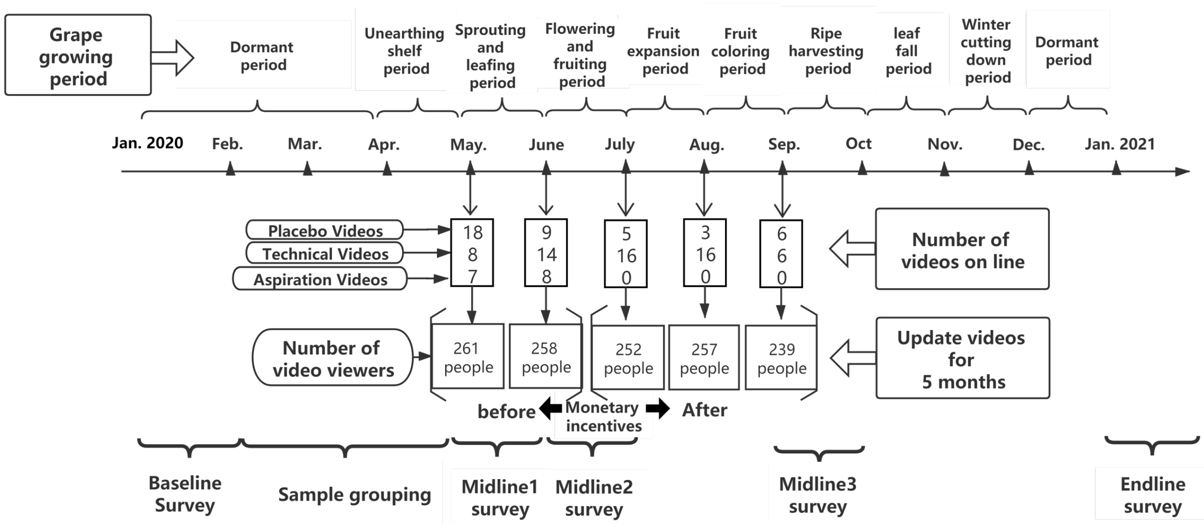

Figure 3: Sample Coverage and Attrition