The Grapes of App: Experimental Evidence on Training Farmers Using A Smartphone Application

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Abstract

We conduct a two-arm cluster-randomized controlled trial to study the impact of technical training via a mobile application for grape farmers in China. Our results show that farmers with access to technical videos on mobile devices significantly improved their knowledge and perceived their grapes to be of higher quality. Objective measurements support these claims, showing an increase in grape sweetness by 0.30 standard deviations. However, farmers who received aspirational videos in addition to technical content did not experience an increase in the sweetness of their grapes despite having improved knowledge. Farmers sustained their engagement with the app and retained higher knowledge levels two years after the intervention, during which those who received technical training also saw long-term improvements in yield, revenue, and prices. Our findings highlight the potential of mobile technology in improving agricultural practices at scale and offer insights for designing effective training programs for farmers in developing countries.

Keywords: Technology adoption, ICT in agriculture, training, product quality.

JEL Codes: O13, Q16, L86.

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1 Introduction

Farmers in developing countries typically lack access to vital resources and services that facilitate the adoption of new technology and better farming practices, with the lack of information and technical know-how being critical barriers (Foster and Rosenzweig, 2010; Magruder, 2018). Technical training provided by agricultural extension services is a key intervention to bridge these gaps, helping alleviate poverty through the dissemination of information and knowledge to farmers (Anderson and Feder, 2004; Nakasone, Torero and Minten, 2014). Such services are instrumental in enhancing technology adoption and boosting farmers' productivity (Bellemare, 2010; Davis, Nkonya, Kato, Mekonnen, Odendo, Miiro and Nkuba, 2012; Godtland, Sadoulet, Janvry, Murgai and Ortiz, 2004; Grimm and Luck, 2020; Magnan, Hoffmann, Opoku, Gajate Garrido and Kanyam, 2021; Pan, Smith and Sulaiman, 2018).

In the absence of a proper agriculture extension service, information transfer can be scant or ineffective (Takahashi, Muraoka and Otsuka, 2020). However, the traditional extension service is typically human resource intensive and entails high fixed and recurrent financial costs (Quizon, Feder and Murgai, 2001), limiting scalability and cost-efficiency, with in-person training often restricted to low-frequency visits outside the planting and harvest seasons due to distance and time constraints (Cole and Fernando, 2021). Consequently, farmers' access to timely and high-quality agricultural information and extension services is limited (Ferroni and Zhou, 2012).

The rapid expansion of information and communication technologies (ICTs) in developing countries, particularly mobile phones, offers significant potential to overcome these challenges and improve agricultural productivity (Aker, 2011; Fabregas, Kremer and Schilbach, 2019). Although ICTs include different types of technologies such as radio, television, computers, and mobile phones, mobile phones are the most widely accessible and, thus, may have the biggest potential to increase agricultural productivity.[1] For instance, voice and SMS messaging have been shown to be effective in delivering vital information to farmers (Cole and Fernando, 2021; Fu and Akter, 2016; Larochelle, Alwang, Travis, Barrera and Dominguez Andrade, 2019).[2] However, effective ICT usage in agriculture requires proper information provision, digital literacy, and monitoring of actual usage (Lele and Goswami, 2017).

We use a two-arm cluster-randomized controlled trial (RCT) to examine the effects of an easy-to-use mobile application or *app* — designed to deliver technical training — on the technical knowledge and technology adoption among grape farmers in rural China.[3] This mobile app is tailored to provide training videos covering each phase of grape production. It also features inspirational videos that highlight the success stories of farmers who have successfully implemented the techniques offered through the app. Since our app automatically records app usage, we can identify what, when, and how long the farmer watched each video in our app — a solution to the difficulty of observing whether farmers read the text and document which content the farmer asked for via voice calls. This notable feature may help extension agents or researchers better understand farmers' needs and make adjustments accordingly. Furthermore, a mobile app allows us to bundle additional interventions, such as offering aspiration videos.[4]

[1]Around 83 percent of adults in developing counties had a mobile phone in 2018 (Klapper, 2019).

[2]See Aker, Ghosh and Burrell (2016) for a detailed discussion.

[3]To the best of our knowledge, this is the first paper that uses a mobile application based video delivery of farmer training. While the use of apps has been studied in the context of agricultural extension (Giulivi, Harou, Gautam and Guereña, 2023; Tjernström, Lybbert, Hernández and Correa, 2021; Van Campenhout, 2017), these studies do not focus on extensive app-based training using videos. In addition, Fu and Akter (2016) studied audio-visual communication in solving farmers' problems, while Hörner, Bouguen, Frölich and Wollni (2022) screened movies that discussed adopting the said technology to help farmers. However, these interventions did not allow farmers to access knowledge at their own pace, a key feature of our study. We focus on providing training through one's mobile phone, making it available at the farmer's convenience so that they watch it on-demand.

[4]Prior work has shown that in addition to alleviating external constraints such as access to credit, technology, or information, relaxing internal constraints that hinder an individual's agency may not only enhance their psychological well-being (Ridley, Rao, Schilbach and Patel, 2020) but also open pathways out of poverty (Genicot and Ray, 2017; Lybbert and Wydick, 2018). In the context of agriculture, there exists a growing body of evidence showing that exposure to aspirational content may enhance agricultural output and investments (Bernard, Dercon, Orkin and Taffesse, 2014; Cecchi, Garcia, Lensink and Wydick, 2022).

We randomize access to both the technical and aspirational videos among a group of 1,026 interested farmers. The control group farmers received placebo videos, while one treatment group farmers (T1) additionally received technical videos and the other treatment group farmers (T2) received both technical and aspirational videos in addition to the placebo videos. We helped farmers install the app on their phones before the farming season and uploaded timely and relevant content throughout the grape growing season in 2020.

We find that farmers frequently use the app to watch the pre-recorded training videos, often during breaks in their workdays. This allows them to learn new techniques without having to take time away from their work hours or weekends. Further, our results suggest an effective increase in technical knowledge, with farmers in the treatment groups showing a 9.4 to 10.8 percent increase in total score on knowledge, i.e., 0.45 to 0.52 standard deviations (SDs) compared to the control group. These findings suggest that app-based training presents a viable alternative to conventional in-person training, which typically demands considerable fixed costs and extensive time commitments (Kondylis, Mueller and Zhu, 2017; Maertens, Michelson and Nourani, 2021).

The training delivered via our mobile application not only improves farmers' perceptions of their produce's quality but also leads to an enhancement in an objective measure of quality — machine-rated sweetness. We find that grape sweetness increases by 0.30 standard deviations (SDs) for T1 group, the farmers that only recieved technical videos. However, the T2 group, which received both technical and aspirational videos, does not show a similar statistically significant enhancement in sweetness. The training does not seem to affect other aspects of grape quality, including the number of grapes per bunch or the weight of the bunch. We also find that despite increasing farmers' knowledge, the intervention also leads farmers to overestimate the quality of their products.

Nevertheless, we do not find strong evidence suggesting any change in aspiration among our study farmers. Farmers in T2 show only a slight increase in their aspiration to produce sweeter grapes within three years—a two percent rise over the raw control mean, statistically significant at the 10 percent level—yet this result does not survive the multiple hypothesis adjustment. The intervention has no effect on the farmers' aspired income over three or five years, nor their aspirations regarding the sweetness of grapes in five years.

We find some evidence of behavioral changes through an analysis of cultivation expenses. Notably, there was a consistent increase in labor expenditures across both treatment groups. This suggests that farmers invested in additional labor in response to the enhanced technical knowledge. The increased hiring reflects an attempt to implement more labor-intensive practices crucial for improving grape quality such as fruit pruning.

The differential impact on grape sweetness can be explained by the varying engagement with the app for technical video content, which correlates with the farmers' baseline income aspirations over three years. We find that more aspirational T1 farmers use the app for technical videos more frequently and spend more time on the app than T2 farmers. This variation also translates into achieved grape quality; T1 farmers with more than median baseline aspiration experience a higher (and increasing with aspiration) sweetness than T2 farmers.

We find that the usage of the app and the increase in knowledge persist in the long run. We surveyed a share of farmers two years after the intervention and found that the farmers kept engaging with the app. We also find that treatment farmers have significantly more knowledge. While we do not see any change in aspirational sweetness or income, we find that yield, revenue, and prices increase for T1 farmers two years after the intervention.

Our main results survive several robustness checks. First, we deviate from our preferred specification by choosing control variables implementing using the double LASSO method of Chernozhukov, Chetverikov, Demirer, Duflo, Hansen and Newey (2017). Our main results remain qualitatively similar when we include these control variables. Second, we do multiple hypothesis testing by calculating adjusted sharpened-q values using the methods suggested by Anderson (2008) based on Benjamini, Krieger and Yekutieli (2006). While the sharpened q-values are higher than the p-values for a majority of our main outcome variables, they are within the threshold of statistical significance.

The intervention is relatively inexpensive. The total cost (development of the app and distribution of the incentive) per farmer was \$27.5 and \$31.7 for the T1 and T2 groups, respectively. The relatively low cost of the intervention indicates that app-based delivery of training can be a scalable solution in the right context.

The absence of significant improvement in quality among farmers who received both technical and aspirational videos suggests that when a decentralized training modality is applied for farmers, bundling multiple learning objectives together may not yield the desired outcome. As found in our analysis, underlying heterogeneity of the desired additional outcome can potentially dilute any impact on the main outcome. This finding implies that ICT-based training may need to be more targeted and tailored to specific learning outcomes to be effective. While ICT platforms offer the advantage of scalability, reaching a wide audience with ease, this scalability may come at the expense of the intensity and depth of learning. Effective digital training requires a strategic balance: maximizing the reach while ensuring that the depth of knowledge transfer is not compromised.

This paper contributes to four main strands of literature. It contributes to the emerging research on digital extension services (Arouna, Michler, Yergo and Saito, 2021; Hidrobo, Palloni, Gilligan, Aker and Ledlie, 2022; Oyinbo, Chamberlin, Abdoulaye and Maertens, 2021; Spielman, Lecoutere, Makhija and Campenhout, 2021; Tjernström et al., 2021). Identifying an effective mode of information delivery via mobile phones is crucial for enhancing the impact of such information. Voice messages (Cole and Fernando, 2021; Walter, Kremer, Reich, Sun, van Herwaarden and Yesigat, 2021) and SMS messages (Casaburi, Kremer, Mullainathan and Ramrattan, 2019; Fafchamps and Minten, 2012; Larochelle et al., 2019) are the popular methods that have been studied in the literature. But some information may be too complex to convey through text or voice (Fabregas et al., 2019), so there is a recent advancement of research using video to promote extension services (Baul, Karlan, Toyama and Vasilaky, 2024). However, the challenge of synchronizing farmers' schedules for collective video viewing remains, unless videos can be distributed in a personalized manner. Our mobile app addresses this issue by delivering pre-recorded videos while tracking app usage to assess technology adoption. It also contributes to the broad literature on information provision and technology adoption in agriculture (Bandiera and Rasul, 2006; Beg, Islam and Rahman, 2024; Bold, Kaizzi, Svensson and Yanagizawa-Drott, 2017; Campenhout, 2021; Conley and Udry, 2010; Emerick and Dar, 2021; Harou et al., 2022; Islam, Ushchev, Zenou and Zhang, 2019; Van Campenhout, Spielman and Lecoutere, 2021). Moreover, it contributes to the burgeoning literature relating aspirations with economic behavior (Genicot and Ray, 2020; Janzen, Magnan, Sharma and Thompson, 2017). Finally, it provides novel insights regarding the potential use of ICT in promoting economic development (Aker, 2010; Aker and Fafchamps, 2015; Fabregas et al., 2019; Jensen, 2007; Nakasone et al., 2014).

The rest of the paper is organized as follows: We discuss the background section 2 and describe the study design in section 3. In section 4, we discuss the data collection timeline and describe our data. We enumerate the empirical strategy in section 5, followed by a discussion of the results in section 6. Section 7 concludes the paper.

2 Background

This study takes place in Beizhen of the Liaoning province, a renowned grape-growing region with over 300 years of cultivation history. The economy of Beizhen is agriculture-oriented, and there are roughly 10,000 grape-farming households. As Chinese consumers are demanding greater food quality (Huang and Gale, 2009), the market for low-quality grapes, which are often characterized by low sweetness, has been shrinking and the prices have been dropping in recent years. However, most growers continue to prioritize yield over quality, using high-yield cultivation and management techniques that lead to poor fruit quality, including loose fruit clusters, large and small grains, poor coloring, and insufficient sugar content. Despite the increase in demand for high-quality grapes, growers in Beizhen have not yet adapted to this shift in market conditions.

The local government of Beizhen has been working to help farmers improve their grape quality in response to changes in market demand, including offering in-person training sessions from experts. Our baseline findings support the need for training, as only 50 percent of farmers were able to accurately identify the frequency and amount of watering during the fruit expansion period that impacts the shape, weight, and sugar content of the bunches and improves grape quality. These results highlight the importance of providing targeted training and support to help farmers adapt to changing market conditions and improve the quality of their products.

Despite the availability of local training options such as field demonstrations, many farmers are unable to effectively learn and apply new farming techniques. While they may understand the information presented on-site, they struggle to apply it to their own grape production. Traditional on-site training methods, like slide presentations and live demonstrations, may not effectively transfer information and may not meet the needs of growers throughout the production process. As a result, there is a pressing need for the local government to find innovative ways to help farmers improve the quality of their grapes.

With the goal of improving grape quality, we partnered with the Beizhen government to explore the use of modern information and communication technologies (ICTs) as a potential substitute for traditional extension services. Given the widespread accessibility of mobile internet in China, we developed a mobile app to provide technical training to local grape farmers.[5] We study whether the provision of technical training through short and accessible videos on this custom mobile app can be a viable alternative to traditional forms of agricultural extension service. With a mobile internet penetration rate of 67 percent, and

[5]A snapshot of the app interface is shown in Figure B1 in B.

99 percent of netizens accessing the internet via mobile phones (CNNIC, 2020), the potential reach of our mobile app is large. Additionally, China has the highest number of mobile app downloads in the world and Chinese internet users spend over 30 percent of their usage time on video apps (Zinan, 2019), making mobile apps an effective platform for delivering technical training to farmers.

3 Study Design

3.1 Content of the Videos

The app released a series of videos aimed at increasing farmers' technical knowledge of farming practices that improve grape quality. These videos were released throughout the planting season from May to September. Grape production in Beizhen can be divided into 5 stages: budding and leafing (May), flowering and fruiting (June), fruit expansion (July), fruit coloring (August), and ripening and harvesting (September). At key points during each stage, the app provided the necessary technical information on water management, fertilizer management, pest and disease management, and fruit pruning techniques, with different content relevant to each month.

The content is automatically downloaded to the user's phone upon accessing the app with an active internet connection. Our goal is to increase farmers' technical skills, which can help them improve their grape quality and potentially increase the price of their grapes. In addition to providing technical information, we included motivational videos in one of the two treatment arms of our study to address the potential issue of lack of motivation as a barrier to the adoption of new techniques.

We released three types of videos. The first set consisted of 60 technical videos ranging in length from one to three minutes, covering topics such as pruning and thinning techniques, water and fertilizer management, and pest and disease control, these technical videos focused on regulating grape yield in order to improve grape quality.[6] Each video was designed to be relevant to the farmers' needs at different stages of the grape-planting cycle and was explained by local leading farmers and large growers, who have significant influence in promoting planting methods and changing output patterns.[7]

The second set of videos consisted of 15 aspirational videos promoting the practice of growing high-quality grapes. These videos featured prominent speakers from the Beizhen Grape Association, a group of farmers responsible for ensuring standards of high-quality grapes in the region and promoting the wider adoption of the Beizhen grape brand in markets across China. In these videos, speakers such as the chairman and vice-chairman of the association shared their own experiences raising the quality of their grapes and selling them under the Beizhen brand. These videos outlined the standards of high-quality grapes in Beizhen for the majority of growers, discussed the development of the high-quality grape market in the next three years, and shared their own success stories with the Beizhen grape brand. We hypothesized that as motivational videos can potentially enhance the psychological well-being of farmers (Ridley et al., 2020) and facilitate learning among themselves (Fabregas et al., 2019), farmers who watched aspirational videos in addition to technical videos may experience greater learning and improved grape quality. We released these videos in May and June.[8]

In addition to the technical and aspirational videos, we also released 41 placebo videos featuring the local history of the grape industry and the natural landscapes of the region. These placebo videos were made available to all farmers at different points throughout the study period.

[6]We present a detailed discussion on the content of technical videos in C.

[7]The large farmers control a large amount of land and have increasingly focused on fruit quality, risk avoidance, and innovation in recent years. They use local climatic conditions, farming habits, and land level to make targeted production material input combinations, explore changes in planting patterns, and apply modern means to production.

[8]We decided to provide all aspirational videos before the start of the planting season when farmers become too busy.

3.2 Experimental Design

Our sample consists of farmers residing in the grape-growing regions of Beizhen. The criteria for inclusion in the sampling frame include: (i) the household engaged in grape farming in 2019; (ii) the household resided within the seven townships with the highest concentration of grape farming to limit survey costs.

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 from 38 villages with a median number of 7 households interviewed per zu.

All farmers in the study received the mobile application, but the content released varied across treatment and control groups. All farmers received the placebo videos. Thirty-nine clusters were assigned to receive additional technical videos (Treatment Arm 1, or T1; N = 325). Another 39 were assigned to receive in addition both the technical videos and aspiration videos (Treatment Arm 2, or T2; N = 332). Thirty-eight control group clusters received only placebo videos (Control Group, or C; N = 369). Figure 1 presents the experimental design of the study.

We started releasing videos in May 2020 (the sprouting and leafing period) and continued to do so until mid-September 2020 (the beginning of the harvest season). Figure 2 summarizes the number and timing of these video releases. Each release was accompanied by an SMS message alerting farmers to the update. We sent SMS alerts of video updates to growers every day at noon or in the evening when they returned home after a break from farming.

In addition to the videos released through the app, we also provided monetary incentives for farmers to watch the videos. Specifically, beginning at 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.[9] We issued a 2-yuan red envelope through WeChat for each video fully watched.[10] We made it clear that the reward would only be given if the video was completed on the day it was uploaded, preventing farmers from simply opening the video to claim the reward without viewing it.

4 Data Description

4.1 Data Collection

Our main 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.

The sample frame of growers surveyed in this study is the census database of grape growers in Beizhen, Liaoning province, which includes 9,767 grape growers in 52 villages in 10 townships of the city with grape cultivation. We first randomly selected seven townships, then randomly selected 38 villages, and finally randomly selected 1,840 respondents from the sample frame to conduct a one-on-one household survey. We interviewed 1,042 farmers living in 38 villages of Beizhen and collected information regarding their grape production, sales, self-assessments of their 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 screening, we had a baseline sample of 1,026 farmers from 38 villages.

During the baseline survey, our enumerators installed the app we developed on the mobile

[9] After we implemented the monetary incentive, the number of people watching the videos was significantly higher in both experimental groups than before the monetary incentive, which indicates that our monetary incentive was effective.

[10] Sending red envelopes through WeChat is a common practice in China, widely regarded as a symbol of good fortune.

phones of the farmers and explained how to use the app to the farmers.[11] Farmers were also informed that instructional videos would be made available at the onset of the farming season, and they would receive notifications when these videos were uploaded. Farmers were randomly assigned to treatment after the baseline survey.

We conducted two short follow-up surveys with the farmers via phone call. The initial follow-up, termed midline 1, and conducted in May 2020, collected information about their experiences with the pandemic and their grape planting plans for the season. Additionally, we verified the installation of the apps necessary for disseminating videos to them. The subsequent follow-up, midline 2, carried out in June, informed the farmers about the monetary incentives associated with watching the videos.

In September 2020, the harvest month, we conducted a more detailed *in-person* survey (endline 1). This survey inquired about the farmers' grape production, including their investments in inputs and farming practices. Additionally, we administered a quiz comprising 10 technical questions related to our training. To evaluate grape quality, we garnered self-assessments akin to those at the baseline and collected grape samples from the farmers to obtain an objective quality metric (our main outcome of interest).[12]

In January 2021, we conducted a phone survey (endline 2) to gather data on farmers' total grape sales and the average prices at which they sold their grapes. This timing allowed farmers sufficient opportunity to complete their grape sales. We also collected information on their grape storage practices and feedback on the mobile application. Due to logistical constraints from the COVID-19 pandemic, the baseline and endline 1 surveys were conducted in person, while endline 2 was administered via phone.

Finally, in March 2023, after China relaxed its COVID-19 policies, we conducted an additional follow-up survey. This data enables us to measure longer-term outcomes, just

[11] All farmers in our sample are experienced in using mobile phone apps for watching videos and their phones have access to the internet.

[12] Our enumerators visited the farms of the participants and purchased a bunch of grapes from each. These grapes were meticulously bagged, labeled, and subsequently transported to a laboratory for measurement.

over two years after the completion of the experiment.

4.2 Tracking App Usage

We collected app login data to track farmer's usage patterns of the app. Since the app automatically records the login time, stay time, and exit time of each farmer, we can observe whether the farmer has accessed the app, the number of times they have logged into the app, and the total amount of time they have spent on the app. We also track the frequency and total time spent watching each video. To ensure the integrity and security of our app database, we have dedicated technical staff responsible for its maintenance. This includes performance analysis and transformation, object reorganization, historical data migration, and other tasks. Depending on changes in the application environment, we readjust the app model to improve and enhance the growers' experience of using the app.

4.3 Measures of Farming Knowledge, Grape Quality, and Aspiration

Since farmers are likely to misreport knowledge and adoption of technology (Kondylis, Mueller and Zhu, 2015), we relied on objective measures of these outcomes. In order to measure farmers' awareness and knowledge of farming practices that improve grape quality, at the endline 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.

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 measuring the sweetness of their produce using a sweetness measuring machine (See Figure B2). We collected a sample from their harvest during the 2020 grape season and placed the grapes in the machine to obtain an objective measure of quality. Because this scale of rating 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 first endline. In addition to the sweetness measures, we also used a weighing machine to collect the weight of the grapes along with the count of grapes per bunch.

Finally, to measure the aspirations of farmers, we follow Bernard, Dercon, Orkin and Taffesse (2014) and ask 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.

4.4 Farmer Characteristics and Sample Balance

In Table 1, we report summary statistics and tests of the 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. Our sample is about 70 percent male and on average 47 years old. The average household size in our sample is 3.8. Roughly 62 percent of the farmers completed middle school or above. Only 42 percent of the farmers report to have a good health. About 32 percent of the farmers reported to have previous training experience. Our sample farmers are highly experienced: on average they have been producing grapes for 21.5 years. An average farmer plants on about 1.8 acres of land. We apply the inverse hyperbolic sine (IHS) transformation of yield, revenue, and prices. The average IHS yield of our baseline farmers was 11, while the IHS revenue and prices were 9.7 and 1.3, respectively.

Key outcome variables such as technical knowledge test scores, self-rated sweetness, aspired income, and aspired sweetness are also balanced across groups. We standardize test scores, measures of quality, and measures of aspired quality with respect to the mean and standard deviation of the control group values. We IHS transform 3- and 5-year aspired income—the average baseline IHS values of them are 11.7 and 10.7, respectively.

We 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 control variables chosen using the double LASSO method of Chernozhukov et al. (2017) in robustness checks.

4.5 Analytical Sample and Attrition

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 B3 provides a snapshot of the timeline of data collection as well as the number of farmers lost at each wave.

While we experience large attrition, we find no systematic difference in attrition rates between experimental arms (Table A1). Attrition farmers were more likely to own larger grape farms (insert table here), but were not statistically different across groups. Finally, we assess balance in our analytical sample and report summary statistics in Table A2. Consistent with what we find in our baseline sample, endline farmers are balanced along most demographic and economic dimensions including our key outcomes of interest.

5 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 the training-only arm and $T2_z$ is a binary indicator variable that takes the value of 1 if zu z was randomly assigned to the training and aspiration arm. X_{iz} includes baseline characteristics. In our preferred specification, we only include outcome variables measured at the baseline when available. As a robustness check, in an alternate specification, we additionally control for variables chosen following the post-double selection methods suggested by Chernozhukov et al. (2017). We feed the algorithm the following variables: farmer's gender, training status, completing middle school or above, having good health; age, total household income, years of experience, baseline planting area, inverse hyperbolic sine of baseline yield and baseline revenue from grape, baseline knowledge, baseline aspiration variables, baseline self-reported sweetness of grape, and first-order interaction between each variable. 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 give us the impact of T1 and T2. Thus, all reported estimates are intent-to-treat (ITT) effects.

6 Results

We present three primary analyses. First, we assess farmer engagement with the mobile app. Second, we examine the intervention's effectiveness in improving the farmers' technical knowledge. Third, we delve into the intervention's impact on grape quality. Complementing these, we investigate two secondary outcomes: changes in the farmers' aspirations and an array of other grape-related outcomes.

6.1 Video Watching Using the App

The treatment farmers spent more time using the app than the control group farmers. To assess the extent of video viewership, we employ three metrics: initial app usage, frequency of app interactions, and total hours spent on the app. For each of these outcomes, we calculate overall usage and usage by each type of video (placebo, technical, aspirational) as the outcome variable. Table 2 reports the results.

We find that farmers in the treatment group are over twice as likely to engage with the app compared to their counterparts, with 36 to 39 percentage points higher usage than the control group's 31 percent. While treatment farmers are more likely to watch technical videos by design, we find that they are also more likely to watch placebo videos than the control group.

Moreover, treatment farmers exhibit more frequent app usage throughout the study. They interact with the app an additional 59.3 to 63.8 times on average, significantly more than the control group's mean of 4.2 times during the same period.

This higher app usage translates into more time spent on the app.[13] Both T1 and T2 group farmers spend significantly more time than the control group farmers watching the placebo videos, with 7.8 and 10.2 additional minutes respectively. As expected, treatment group farmers also dedicated more time to watching the technical videos, with 75.5 and 72.9 extra minutes respectively, given that control group farmers lack access to these videos.[14] Notably, there is no significant difference in time spent watching placebo and technical videos between the two treatment groups. However, T2 farmers spend significantly more time

[13] This is unsurprising given that 91% of farmers who used the app said it is helpful or partially helpful.

[14] One control group farmer managed to watch the technical and aspirational videos due to a bug in the app.

viewing the aspirational videos, aligning with expectations as these videos were exclusively available to them.

We further analyze the proportion of total technical and aspirational videos watched by farmers. Table A3 indicates that on average, farmers in the training arm watch technical videos 22.2 percentage points more, while training and aspiration arm farmers view these videos 26.6 percentage points more. Meanwhile, on average, T2 farmers watched only 9.3 percent of the aspiration videos.

The proportion of videos watched increases following the introduction of incentives to view them. Columns 2-5 of Table A3 illustrate that technical videos released in the latter half of the study are viewed more frequently than those in the first half. Figure B4 depicts a stark increase in farmers' interactions with the app after the introduction of incentives in June.

Importantly, farmers do not reduce their working hours or leisure time during weekends to use the app. Most activity on the app occurs mid-week, particularly from Tuesday to Thursday, as shown in Figure B5. Regarding the time of day, peak activity is observed in the evening—when they were resting after work—and at noon—during lunch hours (Figure B6).

6.2 Farmers' Knowledge

Though the proportion of videos watched was modest, our findings indicate that delivering training via the mobile application effectively enhances farmers' knowledge. During the endline survey, we administered a 10-question test, which included five questions repeated from the baseline. To assess the training's impact on farmers' knowledge, we developed two outcome variables based on the endline test results. Firstly, we calculated the total number of questions each farmer answered correctly. Secondly, we employed item response theory (IRT) to generate test scores, which we then standardized relative to the control group's mean and standard deviation. We constructed each outcome using two approaches: (i) incorporating all 10 questions, and (ii) focusing solely on the five repeated questions from the baseline.

Table 3 shows that the training arm enhances the farmer's overall test score by 0.796 points, translating to a 10.8 percent increase from the raw means. The training and aspiration arm elevates the test score by 0.691 points, or a 9.4 percent increase from the raw means. In terms of standardized IRT score, T1 and T2 farmers exhibit increases of 0.541 and 0.474 standard deviations in their knowledge, respectively. Despite the relatively high raw mean of the control group, which moderates the magnitude of the increase, the training's positive impact on augmenting farmers' knowledge is evident.

Furthermore, there is a significant increase in test scores when focusing solely on the five repeated questions from the baseline test (Columns 2 and 4). Here, test scores ascend by 0.299 points (0.377 SD) for the T1 group and 0.333 points (0.420 SD) for the T2 group. We interpret this as evidence that mobile applications may be an effective means of providing technical training, at least insofar as it can materially raise farmers' knowledge.

6.3 Grape Quality

6.3.1 Impact on Sweetness

After establishing that the farmers watched the videos and enhanced their knowledge, we assess the intervention's impact on grape quality. We use two quality measures: self-assessed and machine-measured sweetness. We standardize these measures with respect to the control group's means and standard deviations.

We find that farmers in both arms believe that their grapes are sweeter. Table 4 shows that farmers in the training-only arm assess their grapes to be 0.47 SD sweeter than control group farmers, while training and aspiration arm farmers assess their grapes as 0.51 SD sweeter.

However, only the T1 group farmers show a statistically significant change in the actual quality of their product based on the objectively measured quality of the product. The grapes of T1 farmers are 0.30 SD sweeter than those of control group farmers. The T2 farmers do not experience any significant improvement in the sweetness of their grapes. These findings suggest that although farmers receiving the treatments tend to overestimate the sweetness of their grapes, those exposed to both technical and aspirational videos exhibit a greater propensity for overestimation than those who received only the training videos.

We do not find any significant changes when we analyze other characteristics of the grapes produced by the study farmers. There is no significant difference from the control group in the count of grapes in a bunch or their overall weight in either treatment arm. Table A4 presents these results. While T1 farmers believe their grape counts are higher and their grapes weigh more, these perceptions do not correspond with the machine-measured data.

6.3.2 Variation in Sweetness Between T1 and T2

We explore whether the difference in the increase of grape sweetness between T1 and T2 farmers is related to baseline aspired income. We examine app usage for technical videos and machine-measured grape sweetness at the endline as a function of baseline aspired income over three years, using a non-parametric approach. By calculating residuals from a regression of using the app at the endline on farmer and grape controls and then determining the percentile of residual baseline aspired income in three years, we create plots for the control and two treatment groups, as depicted in Figure 3.

We find that T1 farmers with higher aspirations tend to use the app more for technical videos compared to T2 farmers. The app usage for technical videos among T1 farmers remains relatively consistent across the spectrum of baseline aspired income over three years. In contrast, T2 farmers exhibit high app usage for those with lower aspirations, but this usage diminishes among those with higher aspirations.

Specifically, T1 farmers in the higher aspiration brackets (70th percentile and above) engage with the app for technical videos more than their T2 counterparts. T1 farmers above the 20th aspiration percentile dedicate more minutes to technical videos compared to T2 farmers.[15]

The more extensive engagement with technical videos by T1 farmers correlates with a higher grape quality achieved in the endline. T1 farmers' grapes exhibit higher sweetness across various levels of baseline aspired income. Notably, this difference becomes more marked among farmers with higher aspirations and progressively increases for those above the median aspiration level.

These observations imply that a focused approach in mobile application-based training may be more effective than a bundled approach with multiple learning objectives. While the training-only arm and training-and-aspiration arm farmers had access to the same technical content and their share of watching technical videos was similar, there is heterogeneity in the usage of apps for technical videos. This heterogeneity also translates into variation in the increase of grape sweetness because of the intervention.

6.4 Farmers' Aspiration

We next assess whether the farmers' aspirations increased after participating in the program. During the endline, we collected farmers' aspired income and grape sweetness in three- and five-years-time. We use the IHS of aspired income and standardized aspired sweetness as the outcome variables to measure farmer aspirations. We report results in Table 5.

We find, at best, only weak evidence suggesting an impact of the aspirational videos on farmers' aspirations. No significant change is observed in the farmers' aspirations as

[15] Based on the literature, one potential explanation for this behavior is attention cost (Lipnowski, Mathevet and Wei, 2020). Bundling multiple issues can lead to farmers restricting their attention to one over the other.

measured through income. Farmers in the training and aspiration arm show a modest increase in their aspired sweetness for three years, registering a 0.19 standard deviation (SD) increase in aspired sweetness (a two percent increase relative to the control group's mean). However, there is no significant difference in the aspired sweetness of farmers for five years.

Further examination into whether the treatment affects aspiration differently pre- and post-intervention reveals no substantial evidence. Table A5 presents that the point estimates for changes in income aspiration are negative for treated farmers, with magnitudes larger than a positive control mean, indicating that treated farmers' endline income aspiration was lower than their baseline income aspiration. Nonetheless, these estimates are not statistically significant.[16] The change in aspired sweetness over three years is negative for all study groups, and no significant evidence suggests a differential change across groups. While treatment farmers exhibit an increased aspired sweetness over five years compared to control farmers, these differences are not statistically significant either.

6.5 Additional Outcomes

In the subsection on additional outcomes, we conduct further analyses on various grape-related outcomes, as detailed in Table 6.

Our initial analysis investigates whether farmers opted for different grape varieties, particularly in comparison to the commonly grown Jufeng variety. We observe that the treatment does not influence the choice of grape variety. We also examine changes in the amount of land cultivated by treatment group farmers and find no alteration in the planting area.

We lack direct measures of farming practices but can test whether the farmers' expenditure patterns in the cultivation process changed. Our findings show that our intervention does not alter expenditures on fertilizer, biofertilizer, or pesticides. However, farmers in both treatment arms increased their labor expenditure, implying that they engaged more labor to

[16]Income aspiration gaps are Winsorized at the 1 and 99 percentiles.

implement certain practices learned through our intervention. These results are presented in Table A6.

Further exploration into the intervention's effects on grape yield, revenue, and price also reveals no significant impact on these outcomes. While revenue for T1 and T2 do not differ significantly from the control group, we can reject the null hypothesis of equality between T1 and PT2 at a five percent significance level. Notably, the point estimates for revenue for T1 are positive, in contrast to negative estimates for T2.

The absence of significant effects on revenue and prices across the treatment groups, despite the expectation that sweeter grapes would provide an advantage, is related to the timing of the sales season from September 2020 to February 2021, a period significantly impacted by the COVID-19 pandemic. During the pandemic, consumer behavior and market dynamics underwent substantial changes. Economic uncertainties and health concerns led to shifts in purchasing patterns, with many consumers prioritizing essential goods over specialty items. Grapes, even higher quality varieties, may not have been considered essential, leading to stable demand and prices across grapes of varying sweetness. This stabilization may explain why sweeter grapes did not result in higher revenues or prices.

Additionally, the pandemic disrupted supply chains and market operations (Aday and Aday, 2020). Lockdowns, transportation restrictions, and labor shortages affected the ability of farmers to market and distribute their produce effectively. Even if the sweeter grapes had a quality advantage, logistical challenges and reduced market access could have negated this benefit, resulting in no significant differences in sales volume, revenue, or prices among the treatment groups. For example, transport restrictions were particularly obstructive for fresh food supply chains, leading to increased levels of food loss and waste and affecting farmers' access to markets (Food and Organization, 2020). Retail environments also adapted to the pandemic by altering their stocking and sales strategies. Many markets focused on maintaining inventory levels of staple foods rather than promoting specialty items. As a result, sweeter grapes might not have received the promotional push needed to differentiate them from other grape varieties, contributing to the uniformity in market outcomes (OECD, 2020).

6.6 Long-Term Outcomes

The evidence so far shows that the app intervention had significant impacts on immediate outcomes such as app usage and knowledge test scores. Our last analysis considers whether these effects translated into long-term impacts on various metrics, as measured two years after the intervention. Table 7 details these long-term outcomes, including app usage, knowledge test scores, aspiration sweetness and income, yield, revenue, and price.

Our analysis of app usage reveals that both treatment groups continued to engage with the app over the two-year period, despite not receiving any alerts or financial incentives to sustain this usage. Specifically, T1 and T2 participants were significantly more likely to use the app compared to the control group. This sustained engagement, even without additional incentives, suggests that the app provided ongoing value and utility to the users.

We find that the significantly higher knowledge test scores for both T1 and T2 persist in the long term. This suggests that the app not only facilitated immediate learning but also contributed to sustained knowledge gains. The consistent use of the app likely reinforced learning outcomes, leading to higher knowledge retention over time.

However, the effects on aspiration sweetness and income were not statistically significant. This suggests that while the app may have impacted practical knowledge and usage behaviors, it did not significantly alter farmers' aspirations regarding the sweetness of their grapes or their income goals even in the long run.

In terms of agricultural outcomes, T1 showed a significant positive impact on yield and revenue, suggesting that the app helped improve agricultural productivity and financial outcomes for these farmers. In contrast, while T2's impacts on yield and revenue were positive, they were not statistically significant. Additionally, T1 participants achieved better prices for their grapes over the long term. This indicates that the app's sustained use likely contributed to better agricultural practices and market outcomes, especially for T1, highlighting the importance of continued engagement and possible differences in how each treatment group utilized training videos through the app.

6.7 Robustness

As a robustness check, we present the main results where we include control variables in our preferred specification chosen using the double LASSO method of Chernozhukov et al. (2017). We also conduct multiple hypothesis tests and present adjusted q-values calculated for all our outcomes using the method suggested by Anderson (2008) based on Benjamini et al. (2006).[17]

6.7.1 Selecting Controls with LASSO

We feed the machine with the following baseline variables and their interactions: gender, age, whether the farmer received training before, completion of middle school, having good health, total household income (IHS), years of experience, baseline knowledge score (standardized IRT score), plantation area, yield, grape sales revenue, an indicator variable for cultivating Jufeng variety, total grape sales, prices received, and aspired income and sweetness in 3- and 5-years. We also include their squared and cubed terms.

Our main results remain qualitatively similar when we include these control variables. These results are presented in Tables A7-A11.

One additional insight from estimating the main results with machine-chosen controls is that for the repeated five questions, the knowledge of T2 farmers increased significantly

[17] In addition, we run a battery of heterogeneity tests with respect to baseline characteristics, but we do not find any significant heterogeneity of results from any of these analyses. These tables are presented in D.

more than T1 farmers. The magnitude of point estimates for all 10 questions is also larger for T2 farmers, but they are not significantly different than T1 farmers. However, we do not find any qualitatively different results for measures of grape qualities.

6.7.2 Multiple Hypothesis Testing

Our main results survive multiple hypothesis tests. We present multiple hypothesis tests in Table A12. We compare the following outcomes together: use of the app, app usage frequency, minutes spent on the app, total test sores and standardized IRT test score (all 10 questions and repeated 5 questions), machine- and self-reported sweetness, aspired income (IHS) and sweetness in 3- and 5-years, cultivating Jufeng variety, total planing area, yield, sale volume, revenue, and price. Our main results remain unchanged after multiple hypothesis adjustments.

6.8 Cost of the Intervention

The total cost of the experiment, encompassing both the development of the application and the distribution of viewing bonuses as incentives, averaged \$27.5 per farmer for the T1 group and \$31.7 per farmer for the T2 group. These relatively low costs highlight the feasibility of scaling up mobile-app-based interventions. The cost-effectiveness per farmer also suggests that our approach is replicable and sustainable, particularly when considering its potential to boost agricultural productivity and sustainability. Furthermore, although no incentives were provided to encourage ongoing app use over a two-year period, many farmers have continued to use it. This suggests that the app holds a "shadow price" for farmers—representing its inherent value—whereas in-person training, with its associated human and time costs, would likely be far more expensive.

The intervention's affordability and effectiveness suggest it has strong potential as a scalable solution for improving farming practices, particularly in contexts where resources are constrained.

7 Conclusion

Technical training is a critical avenue to facilitate farmers' adoption of new technology and improved farming practices. In this study, we conducted an RCT to evaluate the effectiveness of providing technical training to farmers through a mobile application.

We show that using mobile-app-based training offers an efficient way to disseminate timely information to a broad base of farmers at a relatively low cost. The flexibility of mobile app-based training allows farmers to engage with content at their convenience, reducing the need for continuous trainer involvement and consequently saving significant costs in human resources.

Moreover, our intervention successfully enabled participants to apply their enhanced knowledge to improve product quality. Farmers who received only the training component of the study were able to produce noticeably sweeter grapes within a short period. While we did not observe an immediate increase in farmers' financial outcomes, there is evidence of long-term improvements in yield, revenue, and price. The intervention was also cost-effective, with low overall costs and no need for incentives to keep farmers using the app.

Nevertheless, our findings suggest that bundling multiple objectives on digitally delivered training programs can be ineffective, potentially driven by underlying heterogeneity. When we bundled technical modules with aspirational ones, we did not observe an increase in either product quality or aspiration levels. There is a significant difference in the usage of the app for technical videos between training only and training with aspiration arm farmers. We find that training only farmers with high aspirations use the app more for technical videos, which translates into variation in grape sweetness across the two treatment arms.

This indicates that when training is provided using ICTs, it is desirable that such training modules only focus on the primary learning objective. Given the relative ease in scaling up such intervention, the apparent necessity to keep a sharper focus poses a tension between the breadth and depth when considering the delivery of extension services to farmers through this modality—an issue that merits further exploration.

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Tables

Table 1
Balance Test at Baseline

	(1)	(2)	(3)	(4)
	C	T1	T2	p-value from test of (1)=(2)=(3)
Farmer Characteristics				
Male (=1)	0.673	0.719	0.696	0.530
Age (in years)	47.797	46.531	47.723	0.171
Completed middle school or above (=1)	0.619	0.673	0.584	0.065*
Has a good health (=1)	0.430	0.457	0.358	0.113
Household size	3.792	3.870	3.798	0.734
Has training experience (=1)	0.311	0.346	0.301	0.581
Total household income (IHS)	11.271	11.610	11.228	0.095*
Years of grape planting	21.497	21.451	21.480	0.999
Grape planting area (acre)	1.738	1.937	1.817	0.329
IHS of grape yield (jin)	10.921	11.004	11.095	0.616
IHS of revenue from grape (yuan)	9.392	10.406	9.260	0.016**
IHS of average grape sales price (yuan)	1.119	1.216	1.050	0.058*
Outcomes Variables				
IRT Test Score (standardized)	-0.000	-0.086	-0.112	0.525
Self assessed sweetness (standardized)	-0.000	0.055	0.079	0.637
Self assessed count (standardized)	-0.000	0.082	-0.006	0.549
Self assessed weight (standardized)	-0.000	0.231	-0.062	0.054*
Aspired income in 3 years (IHS)	10.907	11.201	11.442	0.257
Aspired sweetness in 3 years (standardized)	-0.000	-0.100	0.073	0.117
Aspired income in 5 years (IHS)	9.877	10.611	10.309	0.408
Aspired sweetness in 5 years (standardized)	-0.000	-0.056	0.066	0.316
N	370	324	332	
Cluster	38	39	39	

Notes: The first three columns report variable means for each experimental arm at baseline. Column (4) reports p-values from a joint test of difference in means. Significance tests are based on standard errors clustered by zu. *** p<0.01 ** p<0.05 * p<0.1

Table 2

App Usage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Used the App (=1)				*App Usage Frequency*				*Minutes Spent*			
	Overall	Placebo Videos	Technical Videos	Aspirational Videos	Overall	Placebo Videos	Technical Videos	Aspirational Videos	Overall	Placebo Videos	Technical Videos	Aspirational Videos
T1	0.360***	0.245***	0.638***	0.000	59.273***	7.401***	51.880***	-0.008	82.989***	7.793***	75.206***	-0.010
	(0.051)	(0.050)	(0.042)	-	(7.516)	(1.716)	(6.761)	(0.008)	(10.124)	(1.573)	(9.075)	(0.010)
T2	0.391***	0.246***	0.669***	0.426***	63.828***	8.881***	50.745***	4.202***	85.335***	10.202***	72.900***	2.233***
	(0.036)	(0.039)	(0.029)	(0.036)	(5.883)	(1.779)	(4.407)	(0.968)	(8.801)	(1.588)	(7.813)	(0.433)
Observations	687	687	687	687	687	687	687	687	687	687	687	687
Control-group mean	0.310	0.310	0.004	0.004	4.176	4.012	0.157	0.008	2.960	2.294	0.656	0.010
T1=T2 (p-value)	0.553	0.985	0.549	0.000	0.632	0.514	0.888	0.000	0.861	0.255	0.847	0.000

Notes: These regressions do not include any control variables. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 3
Impact on Test Score

	(1)	(2)	(3)	(4)
	Total Test Score		Standardized IRT Score	
	All 10 questions	Repeated 5 questions	All 10 questions	Repeated 5 questions
T1	0.796***	0.299***	0.541***	0.377***
	(0.149)	(.077)	(0.100)	(0.096)
T2	0.691***	0.333***	0.474***	0.420***
	(0.156)	(0.067)	(0.104)	(0.084)
Observations	687	687	687	687
Control-group mean	7.380	4.388	0.000	0.000
T1=T2 (p-value)	0.492	0.574	0.527	0.577

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

Table 4

Impact on Grape Quality

	(1) Self-Assessed Sweetness	(2) Machine-Measured Sweetness
T1	0.474***	0.297**
	(0.092)	(0.132)
T2	0.510***	0.099
	(0.086)	(0.109)
Observations	687	679
Control-group mean	0.000	0.000
Raw Control-group mean	17.377	15.920
Raw Control-group SD	1.897	1.327
T1=T2 (*p*-value)	0.666	0.150

Notes: All outcome variables are standardized with respect to the 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 5

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
Raw Control-group mean		18.375		19.197
Raw Control-group SD		1.884		2.230
T1=T2 (*p*-value)	0.404	0.562	0.475	0.946

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

Table 6

Impact on Additional Production-Related Outcomes

	(1) Jufeng Variety (=1)	(2) Planting Area (Acre)	(3) IHS(Yield)	(4) IHS(Revenue)	(5) Price
T1	-0.004	-0.031	0.038	0.265	0.039
	(0.012)	(0.069)	(0.075)	(0.178)	(0.028)
T2	-0.000	0.064	0.032	-0.135	0.035
	(0.007)	(0.068)	(0.081)	(0.227)	(0.027)
Observations	687	687	687	687	672
Control-group mean	0.988	1.790	11.10	11.63	1.646
T1=T2 (*p*-value)	0.742	0.252	0.944	0.019	0.857

Notes: All regressions include baseline outcome as the control variable. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 7

Impact on Outcomes After 2 Years

	(1) Used the App (=1)	(2) Knowledge Test Score	(3) Aspiration Sweetness	(4) Aspiration Income	(5) IHS(Yield)	(6) IHS(Revenue)	(7) Price
T1	0.287***	0.438***	0.377	1.712	0.202*	0.272*	0.360*
	(0.047)	(0.105)	(0.388)	(1.377)	(0.103)	(0.149)	(0.182)
T2	0.245***	0.505***	-0.079	-0.236	0.119	0.086	0.196
	(0.049)	(0.111)	(0.395)	(1.184)	(0.111)	(0.147)	(0.136)
Observations	550	550	544	540	550	550	550
Control-group mean	0.159	3.238	17.519	12.682	10.434	10.631	1.556
T1=T2 (p-value)	0.379	0.550	0.263	0.117	0.423	0.164	0.334

Notes: All regressions include baseline outcome as the control variable. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Figures

Figure 1
Experimental Design

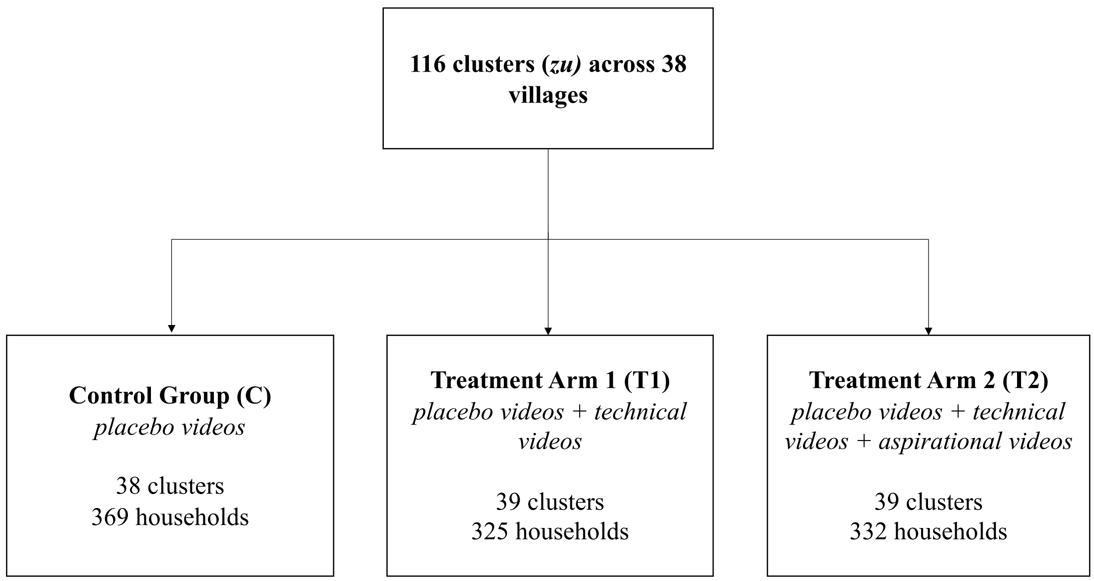


Figure 2
Study Timeline

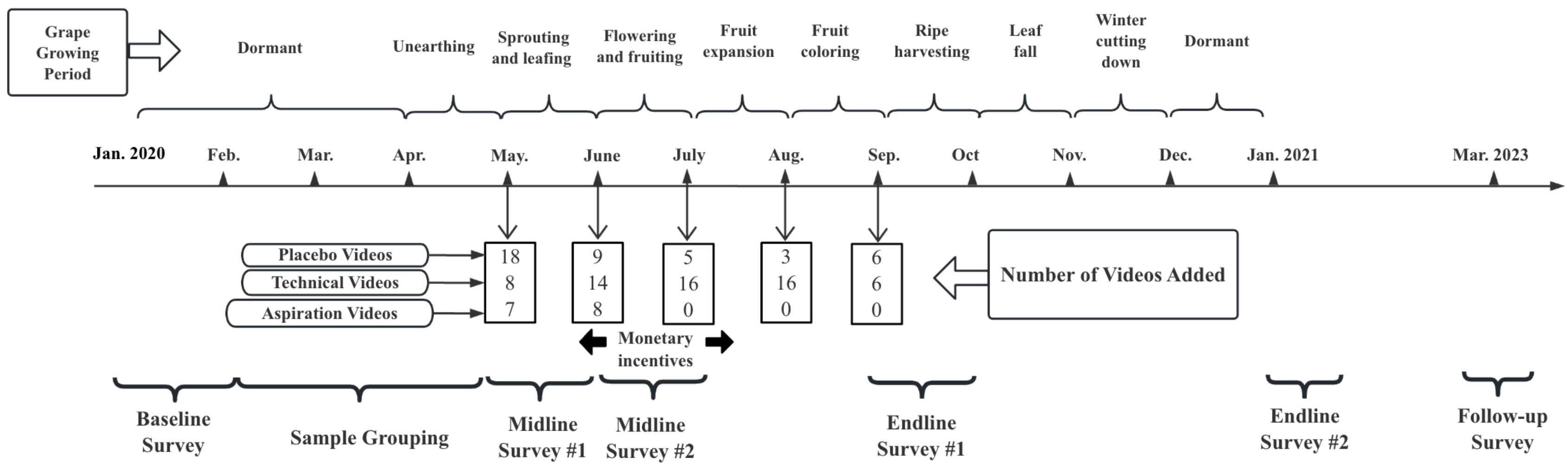
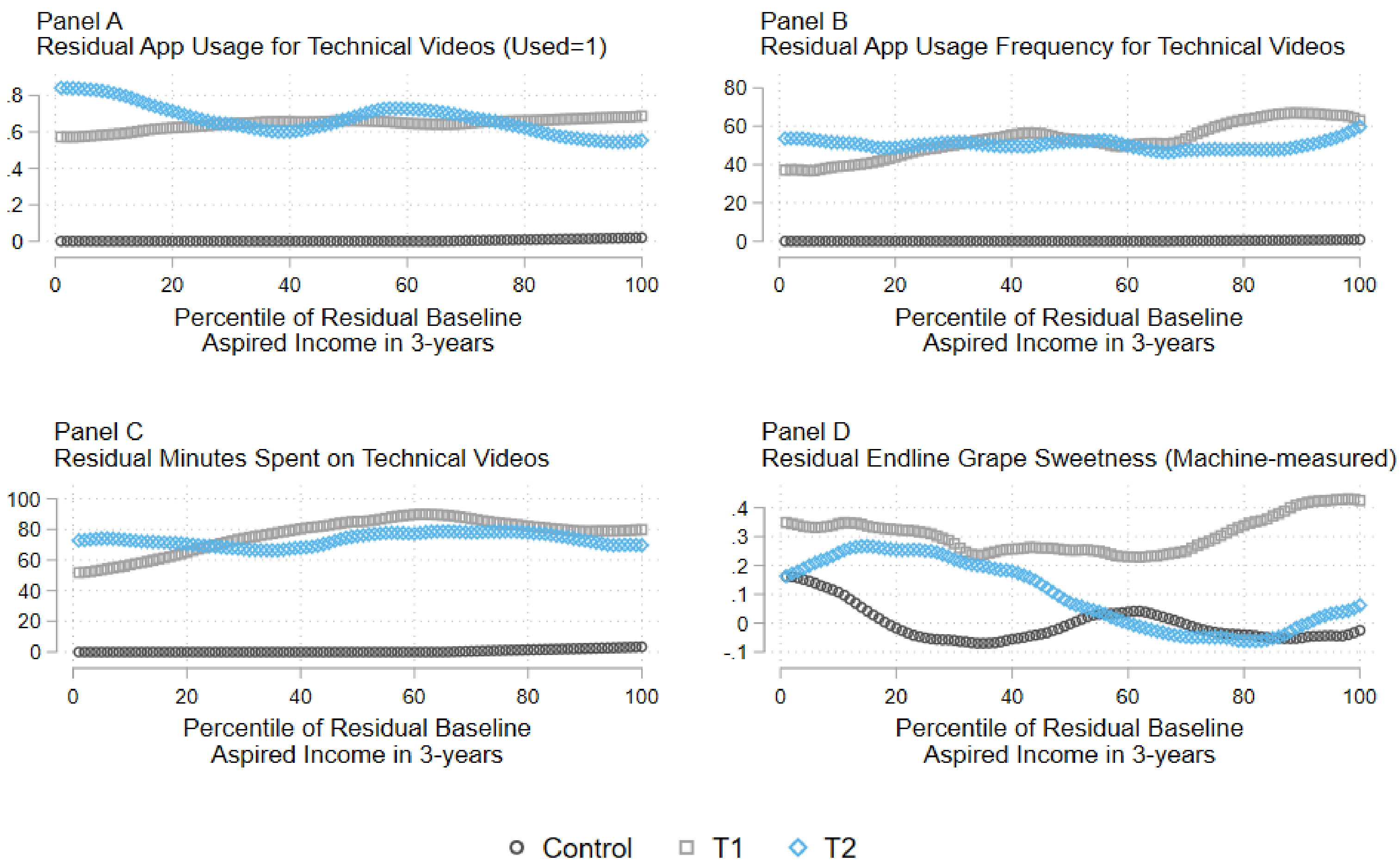


Figure 3

App Usage for Technical Videos and Grape Sweetness by Baseline Aspirations



Notes: This figure shows residual endline app usage outcomes over the percentile of residual baseline aspired income in 3 years. Outcome variables are: whether used app for technical videos (Panel A), app usage frequency for technical videos (Panel B), minutes spent on the app for technical videos (Panel C), and machine-measured grape sweetness (Panel D).

A Appendix Tables

Table A1
Attrition

	(1) Missing at Midline	(2) 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 A2
Balance Test: Non-attriters at Endline

	(1)	(2)	(3)	(4)
	C	T1	T2	p-value from test of (1)=(2)=(3)
Farmer Characteristics at Baseline				
Male (=1)	0.681	0.725	0.668	0.484
Age (in years)	47.854	46.101	47.751	0.092*
Completed middle school or above (=1)	0.631	0.670	0.562	0.085*
Has a good health (=1)	0.438	0.468	0.373	0.184
Household size	3.819	3.977	3.894	0.584
Has training experience (=1)	0.327	0.390	0.304	0.230
Total household income (IHS)	11.336	11.608	11.300	0.315
Years of grape planting	21.677	21.394	21.829	0.900
Grape planting area (acre)	1.817	2.056	1.846	0.159
IHS of grape yield (jin)	10.923	11.172	11.090	0.382
IHS of revenue from grape (yuan)	9.755	10.584	9.303	0.025**
IHS of average grape sales price (yuan)	1.181	1.243	1.045	0.046**
Baseline Outcome Levels				
IRT Test Score (standardized)	0.017	-0.071	-0.049	0.723
Self assessed sweetness (standardized)	0.014	0.091	0.090	0.661
Self assessed count (standardized)	0.019	0.048	-0.018	0.816
Self assessed weight (standardized)	-0.019	0.174	-0.072	0.209
Aspired income in 3 years (IHS)	11.087	11.205	11.341	0.799
Aspired sweetness in 3 years (standardized)	0.014	-0.063	0.088	0.334
Aspired income in 5 years (IHS)	9.961	10.743	10.333	0.427
Aspired sweetness in 5 years (standardized)	0.010	-0.038	0.087	0.400
N	260	218	217	
Cluster	38	38	39	

Notes: The first three columns report variable means for each experimental arm at endline. Column (4) reports p-values from a joint test of equality. Significance tests are based on standard errors clustered by zu. *** p<0.01 ** p<0.05 * p<0.1

Table A3
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)	-	-	-
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: These regressions do not include any control variables. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A4

Impact on Other Grape Outcome Measures

	(1)	(2)	(3)	(4)
	Self-Assessed		Machine-Measured	
	Count	Weight	Count	Weight
T1	0.173*	0.213**	0.138	-0.114
	(0.103)	(0.105)	(0.117)	(0.103)
T2	0.039	0.149	0.010	-0.154
	(0.093)	(0.106)	(0.121)	(0.116)
Observations	687	687	679	679
Control-group mean	0.000	0.000	0.000	0.000
Raw Control-group mean	81.784	1.865	68.173	1.659
Raw Control-group SD	20.617	0.439	20.272	0.510
T1=T2 (*p*-value)	0.202	0.576	0.364	0.720

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

Table A5
Impact on Difference in Aspiration Pre- and Post-Intervention

	(1)	(2)	(3)	(4)
	3-year aspiration difference		5-year aspiration difference	
	Income	Sweetness	Income	Sweetness
T1	-11,077.2	0.330	-15,870.0	0.335
	(10,488.4)	(0.272)	(16,439.2)	(0.277)
T2	-12,801.4	0.316	-20,896.6	0.230
	(10,146.9)	(0.267)	(16,578.5)	(0.296)
Observations	658	613	658	580
Control-group mean	9,077	-0.750	15,476	-0.256
T1=T2 (*p*-value)	0.894	0.952	0.800	0.675

Notes: Outcomes in this table are the difference between follow-up and baseline self-reported aspired income (columns (1) and (3)) or sweetness (columns (2) and (4)) in respective years. Income differences are Winsorised at 1 and 99 percentile levels. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table A6
Impact on Agricultural Investments

	(1) Fertilizer Expenditure (IHS))	(2) Biofertilizer Expenditure (IHS)	(3) Labor Expenditure (IHS)	(4) Pesticide Expenditure (IHS)
T1	0.112	-0.158	0.649*	-0.046
	(0.129)	(0.404)	(0.373)	(0.100)
T2	0.042	-0.337	0.754**	-0.039
	(0.134)	(0.377)	(0.349)	(0.125)
Observations	687	687	687	687
Control-group mean	9.225	4.923	6.098	8.736
T1=T2 (p-value)	0.525	0.650	0.777	0.944

Notes: All regressions include baseline outcome as the control variable. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A7

App Usage (Control Variables Picked Using LASSO)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Used the App (=1)				*App Usage Frequency*				*Minutes Spent*			
	Overall	Placebo Videos	Technical Videos	Aspirational Videos	Overall	Placebo Videos	Technical Videos	Aspirational Videos	Overall	Placebo Videos	Technical Videos	Aspirational Videos
T1	0.385***	0.269***	0.660***	0.000	61.467***	6.968***	53.905***	0.595	83.582***	8.015***	75.341***	0.227
	(0.059)	(0.058)	(0.049)	(0.018)	(9.228)	(1.943)	(8.041)	(0.489)	(11.759)	(1.867)	(10.410)	(0.231)
T2	0.409***	0.255***	0.693***	0.430***	59.234***	7.700***	47.207***	4.328***	76.632***	8.778***	65.603***	2.251***
	(0.046)	(0.046)	(0.036)	(0.041)	(7.723)	(1.831)	(6.491)	(1.167)	(10.279)	(1.924)	(9.427)	(0.406)
Observations	687	687	687	687	687	687	687	687	687	687	687	687
Control-group Mean	0.310	0.310	0.004	0.004	4.176	4.012	0.157	0.008	2.960	2.294	0.656	0.010
T1=T2 (*p*-value)	0.703	0.816	0.569	0.000	0.837	0.741	0.472	0.000	0.615	0.767	0.438	0.000

Notes: These regressions do not include any control variables. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table A8

Impact on Test Score (Control Variables Picked Using LASSO)

	(1)	(2)	(3)	(4)
	Total Test Score		Standardized IRT Score	
	All 10 questions	Repeated 5 questions	All 10 questions	Repeated 5 questions
T1	0.605***	0.285***	0.418***	0.360***
	(0.133)	(.080)	(0.090)	(0.101)
T2	0.757***	0.406***	0.524***	0.513***
	(0.147)	(0.081)	(0.100)	(0.102)
Observations	687	687	687	687
Control-group mean	7.380	4.388	0.000	0.000
T1=T2 (p-value)	0.289	0.074	0.288	0.074

Notes: These regressions include control variables picked by implementing the post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A9

Impact on Grape Quality (Control Variables Picked Using LASSO)

	(1) Self-Assessed Sweetness	(2) Machine-Measured Sweetness
T1	0.499***	0.292**
	(0.095)	(0.127)
T2	0.553***	0.115
	(0.103)	(0.117)
Observations	687	679
Control-group mean	0.000	0.000
T1=T2 (p-value)	0.634	0.179

Notes: All outcome variables are standardized with respect to the control group. All regressions include control variables picked by implementing the post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A10

Impact on Aspiration (Control Variables Picked Using LASSO)

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS(Income)	Sweetness	IHS(Income)	Sweetness
T1	0.074	0.157	0.099	0.147
	(0.065)	(0.109)	(0.078)	(0.092)
T2	0.024	0.200*	0.024	0.096
	(0.066)	(0.118)	(0.076)	(0.104)
Observations	686	684	685	684
Control-group mean	12.215	0.000	12.392	0.000
T1=T2 (p-value)	0.445	0.668	0.327	0.574

Notes: Outcome variables in Columns (2) and (4) are standardized with respect to the control group. All regressions include control variables picked by implementing the post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A11

Impact on Additional Production-Related Outcomes (Control Variables Picked Using LASSO)

	(1) Jufeng Variety (=1)	(2) Planting Area (Acre)	(3) IHS(Yield)	(4) IHS(Sale Volume)	(5) IHS(Revenue)	(6) IHS(Price)
T1	-0.007*	-0.041	-0.068	-0.088	-0.064	0.017
	(0.004)	(0.064)	(0.047)	(0.135)	(0.150)	(0.022)
T2	-0.000	0.019	0.026	-0.248	-0.228	0.028
	(0.004)	(0.062)	(0.052)	(0.195)	(0.213)	(0.023)
Observations	687	687	687	687	687	672
Control mean	0.988	1.790	11.10	10.74	11.63	1.646
T1=T2 (p-value)	0.287	0.408	0.0544	0.407	0.434	0.606

Notes: All regressions include control variables picked by implementing the post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A12

Multiple Hypothesis Testing

	T1			T2		
	Effect	*p*-value	Sharpened q-value	Effect	*p*-value	Sharpened q-value
Used Upp (=1)	0.360***	0.000	0.001	0.391***	0.000	0.001
App Usage Frequency	59.273***	0.000	0.001	63.828***	0.000	0.001
Minutes Spent	82.980***	0.000	0.001	85.335***	0.000	0.001
Total Test Score (All 10 questions)	0.796***	0.000	0.001	0.691***	0.000	0.001
Total Test Score (Repeated 5 questions)	0.299***	0.000	0.001	0.333***	0.000	0.001
Standardized Test Score (All 10 questions)	0.541***	0.000	0.001	0.474***	0.000	0.001
Standardized Test Score (Repeated 5 questions)	0.377***	0.000	0.001	0.420***	0.000	0.001
Sweetness (Machine Reported)	0.297**	0.027	0.037	0.099	0.368	0.341
Sweetness (Self Reported)	0.474***	0.000	0.001	0.510***	0.000	0.001
3-year Aspiration IHS(Income)	0.103	0.201	0.219	0.028	0.766	0.516
3-year Aspiration Sweetness	0.125	0.243	0.254	0.186*	0.085	0.111
5-year Aspiration IHS(Income)	0.101	0.260	0.263	0.034	0.720	0.516
5-year Aspiration Sweetness	0.101	0.291	0.289	0.095	0.326	0.319
Jufeng Variety (=1)	-0.004	0.712	0.516	0.000	0.965	0.616
Planting Area (Acre)	-0.031	0.656	0.511	0.064	0.346	0.329
IHS(Yield)	0.038	0.619	0.490	0.032	0.694	0.516
IHS(Sale Volume)	0.227	0.167	0.201	-0.168	0.434	0.389
IHS(Revenue)	0.265	0.140	0.184	-0.135	0.552	0.435
IHS(Price)	0.039	0.160	0.201	0.035	0.206	0.219

Notes: Adjusted sharpened q-values calculated for all outcomes using the method suggested by Anderson (2008) based on Benjamini et al. (2006). *** p<0.01 ** p<0.05 * p<0.1

B Appendix Figures

Figure B1
App Interface

Figure B2
Sweetness Measurement Machine

Figure B3
Sample Coverage and Attrition

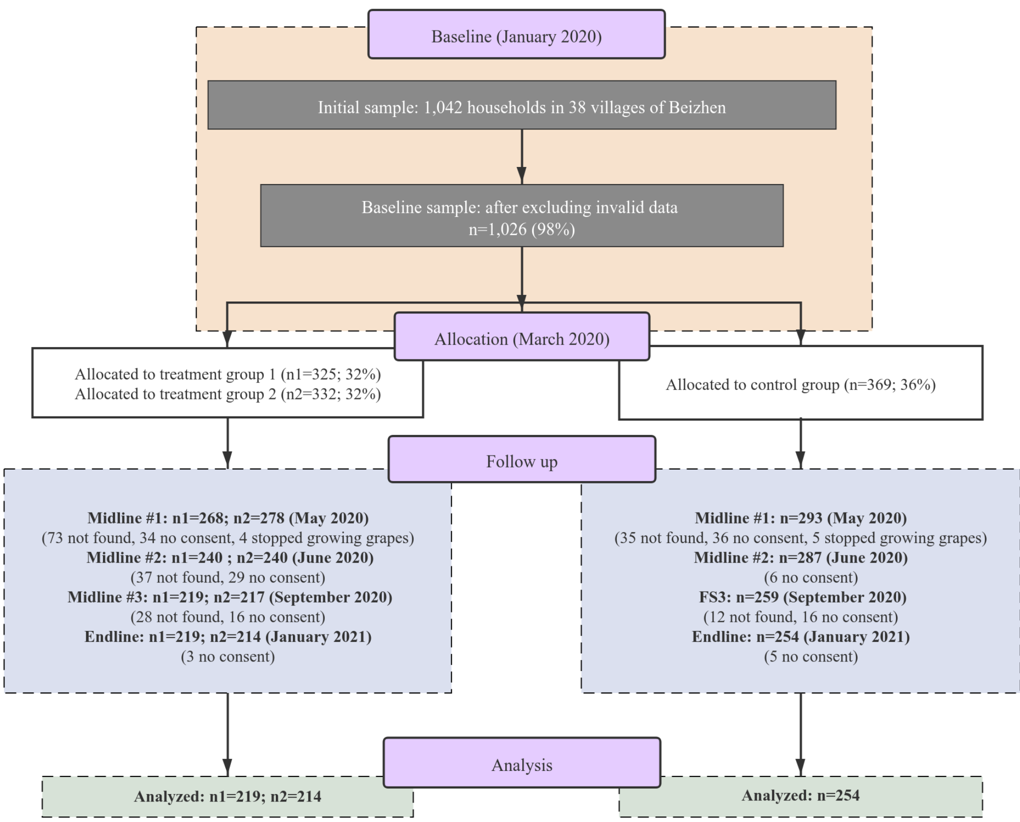
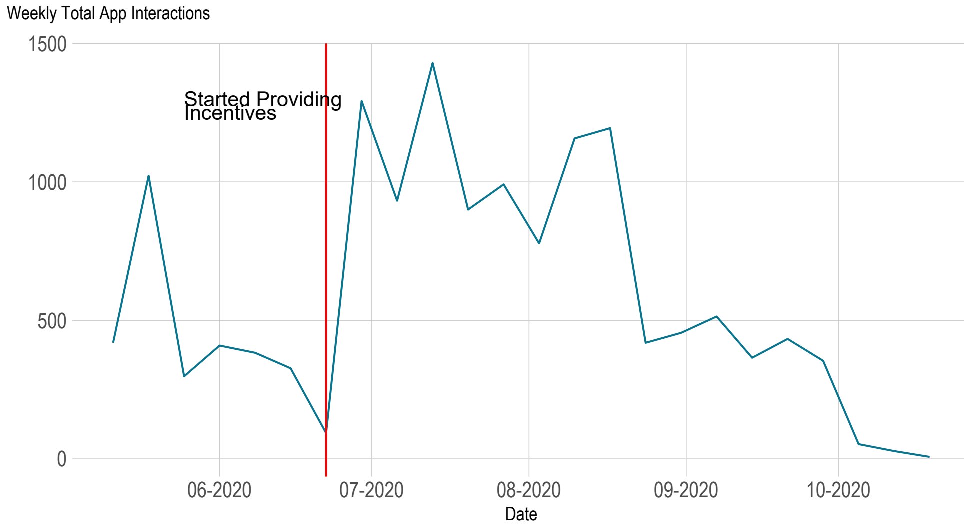
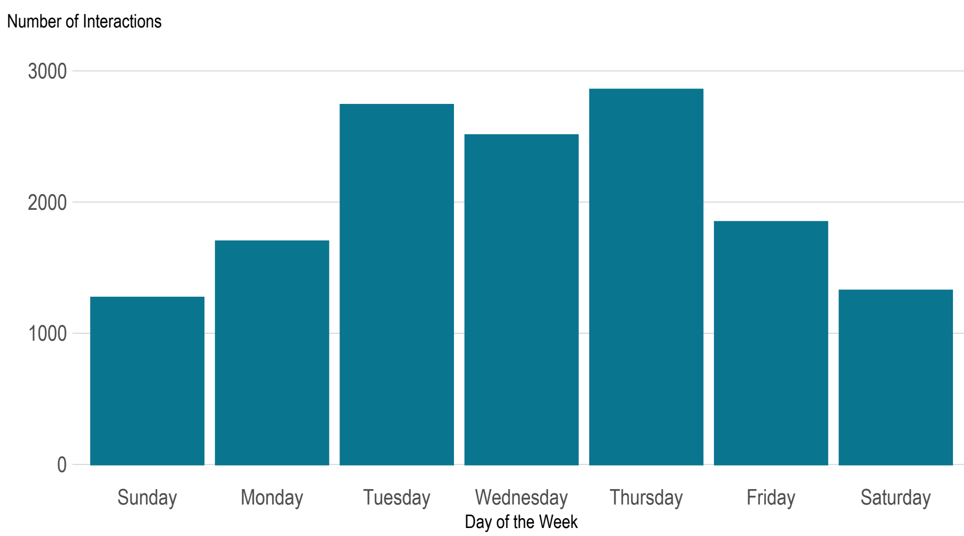


Figure B4
App Interaction Frequency During the Study Period



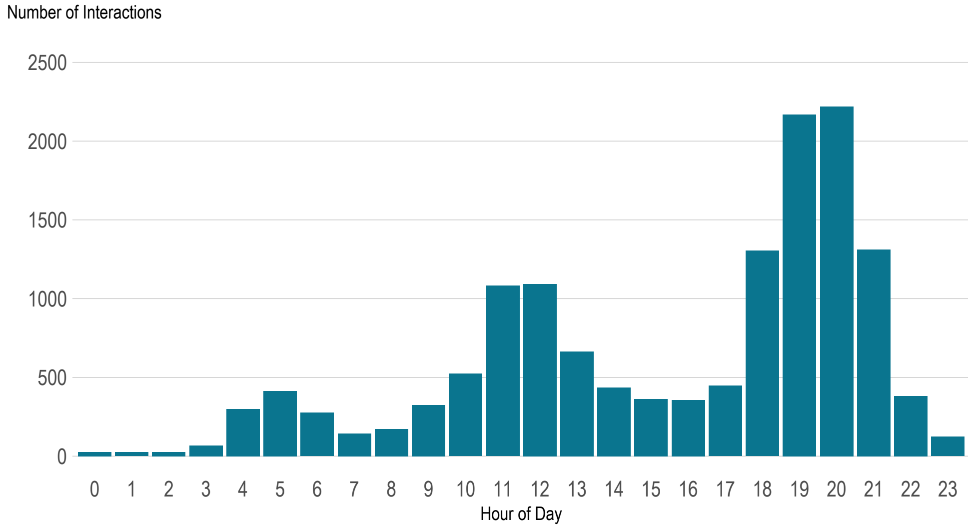
Note: Each interaction is a video click by the user.

Figure B5
App Interaction Frequency by the Day of the Week



Note: Each interaction with the app is a video click by the user.

Figure B6
App Interaction Frequency by the Time of the Day



Note: Each interaction with the app is a video click by the user.

C Topics of Technical Videos

Pruning spike thinning fruit

- In order to improve grape quality, inflorescence thinning is performed to regulate the number of bunches. Subsequently, the inflorescence is modified and shaped, and bunch adjustments are made. These steps aim to manage yield, elevate quality, achieve bunch uniformity, and fine-tune the shape of the bunches.

- If the farmers in the experimental group follow the technical video instruction, they will perform bud blotting and branch setting in spring when new shoots are sprouting, and picking, inflorescence thinning and spike pruning when grapes are flowering, which will result in sufficient supply of nutrients needed for grapes, well-proportioned and ventilated fruit clusters, uniform sunlight, satisfying fruit growth, and promoting sugar accumulation under photosynthesis, which will eventually lead to higher grape sweetness and improved grape quality and sales price.

Water and fertilizer management

The crucial "five fertilizations" and "six waterings" of the grape year, along with the growing process, were explained and demonstrated.

- *Five fertilizer applications*

  - Pre-Budbreak Fertilization: Administered before grape buds emerge, this nitrogen-based fertilizer aims to promote even bud sprouting, vigorous leaf development, and strong, sizable inflorescences.

  - Expansion Phase Fertilization: Occurring post-grape setting when berries reach the size of green beans, this fertilizer is primarily nitrogen-based with added phosphorus and potassium. Options include high-nitrogen or standard N-P-K compound fertilizers, supplemented as needed with extra nitrogen sources like urea. The dosage at this stage constitutes about 50% of the annual fertilizer use.

  - Ripening Fertilizer: Applied in two stages, 20-30 days before grape ripening, this is a high-potassium, water-soluble fertilizer. A second application is made as the grapes begin to soften but haven't yet changed color.

- Post-Harvest Fertilizer: After the grape harvest, an immediate application of approximately 15 kg of high-nitrogen, water-soluble fertilizer is made. The goal is not only to replenish the vine's vitality but also to encourage bud differentiation and set the stage for better yields the following year.
- Overwintering Fertilizer: Traditionally applied during grape dormancy, our video recommends an August-September timeframe after harvest while leaves are still green. This period aligns with a second peak in grape root growth, stimulating the production of fibrous roots to bolster the plant and improve overwintering. The fertilizer at this stage is predominantly organic, optionally augmented with calcium or a minor quantity of N-P-K elements.

The timing of fertilizer application should be intricately aligned with the grapevine's growth and developmental phases. For farmers in the experimental group who adhere to the technical video guidelines on the proper use of nitrogen, phosphorus, potassium, and calcium fertilizers, the benefits are multi-fold. During the budding stage, the budding rate is enhanced, inflorescences grow larger, and new shoots strengthen. In the early fruit phase, the grape enlargement accelerates, the rate of small, undeveloped fruits decreases, and flower bud differentiation is encouraged. Lastly, in the fruit ripening stage, grapes achieve full coloration, the flesh firms up, and sugar content becomes uniform. These changes contribute to a thicker grape cell wall and higher cell sap concentration, ultimately boosting the grape's final sweetness level.

- *Six irrigation applications*
  - Pre-budding: This stage, occurring before grape sprouting, marks the first critical period for irrigation. New shoots and inflorescences will develop rapidly, and the root system becomes highly active. In northern China, where spring droughts are common, immediate watering is critical to prevent poor budding and branch draining due to dry winds.
  - Pre-flowering: Approximately 10 days prior to flowering, new shoots and inflorescences experience rapid growth and root systems start generating new roots. Given the rising transpiration and nutrient assimilation rates, additional water is essential. Proper watering during dry spells enhances fruit set rate.
  - Post-flowering: The second critical period is about 10 days after the flower drop. Shoots thicken, leaves proliferate, and new lateral roots form at this stage. This period also coincides with the first peak of grape growth, making it vital for both fertilizer and water supply.

- Fruit coloring: During this stage, grapes grow quickly and sugar accumulation begins. Adequate fertilizer at this juncture improves not just the current year's grape quality but also has a favorable impact on the yield for the following year.
- Fruit ripening: In moisture-rich areas, soil usually retains enough water. However, in drier regions or when large amounts of fertilizer have been applied, irrigation becomes necessary. Proper soil moisture results in high yields and sugar content, whereas excessive moisture can lead to fruit cracking and diminished fragrance.
- Soil burial for cold protection: In northern China's winter and spring drought-prone areas, a small amount of watering is required to moisten dry soil before burying the grapes to protect them from cold weather.

Grapes have specific water needs and should not be inundated. The early growth and nutritional stages demand more water, while the later growth and fruit-bearing stages require less, with an avoidance of rain and dew. In the instructional video, we specify that irrigation should occur 5-7 times during key periods: budding, before and after flowering, and before and after grape expansion. Additional irrigation may follow the harvest, with adjustments based on soil conditions. If farmers in the experimental group adhere to the video guidelines and adjust irrigation based on the grape's developmental stages, they can achieve optimal water content for grape growth, fruit expansion, and ripening. This practice will likely lead to healthier plants, minimized risks of fruit cracking, rotting, and dropping, as well as favorable fruit development, higher yields, and increased sugar content.

Pest control

Pests and diseases significantly affect grape growth, development, and yield quality. The impact is particularly severe in regions with frequent rainfall. The diverse array of grape pests and diseases, along with their complex patterns of occurrence, complicates management efforts. For this reason, our technical videos also emphasize crucial strategies for pest and disease control.

In the training videos, we advocate for a "proactive and integrated" approach as the cornerstone for managing grape pests and diseases. Close monitoring of potential outbreaks is key, and precautionary spraying is advised even in the absence of evident issues. To optimize yield and quality while safeguarding both environmental and human health, we recommend a diverse set of control measures, including chemical, biological, and physical methods, for effective and economical pest management.

The videos delve into four specific types of control measures.

- Biological Control: Predominantly involves the utilization of insects, bacteria, and fungi to manage pests. This approach is non-toxic to both plants and mammals, environmentally friendly, and maintains the natural ecological balance. Current applications include the use of Agricultural Anti 402 biopesticides, particularly effective in root tumor management post-excision.
- Physical Control: Leverages the specific susceptibilities of pests to variables like temperature, light spectrum, and sound to either kill or repel them. For instance, heat treatment techniques are currently used to de-virus non-toxic seedlings.
- Chemical Control: Employs chemical pesticides as the primary tool for pest mitigation. While effective and convenient, this approach carries drawbacks such as environmental pollution and the potential eradication of beneficial organisms.
- Agricultural Control: Entails field sanitation measures like the removal and proper disposal of diseased branches, leaves, and fruits. Additionally, vine tying, heart picking, and secondary tip removal are advocated for better light and air circulation. Improved fertilizer and water management also strengthen the plant's disease resistance. Organic, phosphorus, and potassium fertilizers are preferred over chemical nitrogen-based ones. Timely weed removal minimizes pest habitats.

Integrated pest and disease control is crucial for sustainable grape cultivation. Therefore, farmers in the experimental group should familiarize themselves with common grape pests and diseases to implement targeted treatments. Soil and environmental management need reinforcement, including regular orchard maintenance and soil amendments. Actions such as filling in soil gaps, burning diseased plant matter, and pruning unhealthy branches contribute to optimal grape development, larger fruit sizes, and enhanced fruit quality.

D Heterogeneity Tables

D.1 Gender

Table D1
Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.616***	0.359**
	(0.148)	(0.155)
T1 x Male	-0.198	0.016
	(0.169)	(0.179)
T2	0.541***	0.353**
	(0.168)	(0.153)
T2 x Male	-0.031	0.090
	(0.189)	(0.183)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x Male	0.419	0.375
T1 + T1 x Male (SE)	0.114	0.111
T1 + T1 x Male (*p*-values)	0.000	0.001
T2 + T2 x Male	0.509	0.443
T2 + T2 x Male (SE)	0.113	0.100
T2 + T2 x Male (*p*-values)	0.000	0.000

Notes: All regressions include test scores at baseline and an indicator variable for the farmer being male. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D2

Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.306*
	(0.163)
T1 x Male	0.006
	(0.244)
T2	0.001
	(0.178)
T2 x Male	0.104
	(0.221)
Observations	691
Control mean	0.021
T1 + T1 x Male	0.313
T1 + T1 x Male (SE)	0.176
T1 + T1 x Male (p-values)	0.079
T2 + T2 x Male	0.105
T2 + T2 x Male (SE)	0.131
T2 + T2 x Male (p-values)	0.425

Notes: All regressions include test scores at baseline and an indicator variable for the farmer being male. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D3
Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.136	0.111	0.229	0.088
	(0.257)	(0.187)	(0.297)	(0.163)
T1 x Male	0.001	-0.004	-0.054	0.019
	(0.254)	(0.214)	(0.276)	(0.196)
T2	1.494	-0.004	1.476	-0.112
	(1.488)	(0.181)	(1.483)	(0.159)
T2 x Male	0.254	-1.297	0.004	-0.008
	(0.211)	(1.410)	(0.176)	(0.221)
Observations	694	692	693	692
Control mean	-0.018	0.006	-0.015	0.000
T1 + T1 x Male	0.137	0.107	0.175	0.107
T1 + T1 x Male (SE)	0.196	0.116	0.206	0.107
T1 + T1 x Male (p-values)	0.485	0.360	0.397	0.321
T2 + T2 x Male	0.211	0.250	0.179	0.183
T2 + T2 x Male (SE)	0.223	0.123	0.223	0.102
T2 + T2 x Male (p-values)	0.345	0.045	0.424	0.075

Notes: All regressions include test scores at baseline and an indicator variable for the farmer being male. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.2 Age

Table D4
Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.492***	0.353***
	(0.099)	(0.097)
T1 x Age (in Years)	0.006	-0.004
	(0.011)	(0.008)
T2	0.450***	0.419***
	(0.103)	(0.084)
T2 x Age (in Years)	0.001	-0.012
	(0.011)	(0.008)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x Age	0.498	0.350
T1 + T1 x Age (SE)	0.101	0.099
T1 + T1 x Age (p-values)	0.000	0.001
T2 + T2 x Age	0.451	0.407
T2 + T2 x Age (SE)	0.104	0.085
T2 + T2 x Age (p-values)	0.000	0.000

Notes: All regressions include test scores at baseline and age (in years). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D5

Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.303**
	(0.131)
T1 x Age (in Years)	-0.001
	(0.010)
T2	0.103
	(0.107)
T2 x Age (in Years)	-0.007
	(0.011)
Observations	679
Control mean	0.000
T1 + T1 x Age	0.302
T1 + T1 x Age (SE)	0.131
T1 + T1 x Age (p-values)	0.023
T2 + T2 x Age	0.096
T2 + T2 x Age (SE)	0.111
T2 + T2 x Age (p-values)	0.387

Notes: All regressions include test scores at baseline and age (in years). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D6
Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.068	0.114	0.074	0.095
	(0.082)	(0.108)	(0.090)	(0.096)
T1 x Age (in Years)	0.008	-0.017*	0.011	-0.010
	(0.007)	(0.009)	(0.008)	(0.010)
T2	0.025	0.196*	0.025	0.099
	(0.096)	(0.107)	(0.094)	(0.096)
T2 x Age (in Years)	0.004	-0.016	0.004	-0.008
	(0.008)	(0.012)	(0.009)	(0.011)
Observations	686	684	685	684
Control mean	12.215	0.000	12.392	0.000
T1 + T1 x Age	0.076	0.098	0.085	0.085
T1 + T1 x Age (SE)	0.083	0.107	0.090	0.095
T1 + T1 x Age (p-values)	0.360	0.365	0.350	0.375
T2 + T2 x Age	0.029	0.180	0.029	0.092
T2 + T2 x Age (SE)	0.097	0.106	0.095	0.095
T2 + T2 x Age (p-values)	0.764	0.094	0.760	0.338

Notes: All regressions include test scores at baseline and age (in years). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.3 Training

Table D7
Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.396***	0.296***
	(0.121)	(0.098)
T1 x Has Training Experience	0.361**	0.239
	(0.174)	(0.170)
T2	0.325***	0.351***
	(0.118)	(0.084)
T2 x Has Training Experience	0.392*	0.186
	(0.199)	(0.174)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x Has Training Experience	0.757	0.536
T1 + T1 x Has Training Experience (SE)	0.138	0.163
T1 + T1 x Has Training Experience (p-values)	0.000	0.001
T2 + T2 x Has Training Experience	0.718	0.537
T2 + T2 x Has Training Experience (SE)	0.171	0.162
T2 + T2 x Has Training Experience (p-values)	0.000	0.001

Notes: All regressions include test scores at baseline and whether a farmer has training experience. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D8

Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.312**
	(0.146)
T1 x Has Training Experience	-0.047
	(0.196)
T2	0.069
	(0.138)
T2 x Has Training Experience	0.101
	(0.208)
Observations	679
Control mean	0.000
T1 + T1 x Has Training Experience	0.265
T1 + T1 x Has Training Experience (SE)	0.188
T1 + T1 x Has Training Experience (p-values)	0.160
T2 + T2 x Has Training Experience	0.169
T2 + T2 x Has Training Experience (SE)	0.163
T2 + T2 x Has Training Experience (p-values)	0.301

Notes: All regressions include test scores at baseline and whether a farmer has training experience. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D9

Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.224	0.150	0.280*	0.185*
	(0.139)	(0.123)	(0.166)	(0.107)
T1 x Has Training Experience	-0.115	-0.091	-0.210	-0.255
	(0.256)	(0.209)	(0.264)	(0.196)
T2	0.886	0.270**	0.867	0.168
	(0.822)	(0.126)	(0.826)	(0.106)
T2 x Has Training Experience	-0.883	-0.264	-0.849	-0.222
	(0.816)	(0.196)	(0.826)	(0.177)
Observations	686	684	685	684
Control mean	0.000	0.000	0.000	0.000
T1 + T1 x Has Training Experience	0.109	0.059	0.070	-0.070
T1 + T1 x Has Training Experience (SE)	0.248	0.181	0.244	0.169
T1 + T1 x Has Training Experience (p-values)	0.662	0.746	0.774	0.678
T2 + T2 x Has Training Experience	0.003	0.006	0.018	-0.055
T2 + T2 x Has Training Experience (SE)	0.199	0.166	0.208	0.159
T2 + T2 x Has Training Experience (p-values)	0.989	0.974	0.932	0.732

Notes: All regressions include test scores at baseline and whether a farmer has training experience. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.4 Middle School

Table D10
Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.559***	0.431**
	(0.193)	(0.187)
T1 x Completed Middle School or Above	-0.085	-0.103
	(0.211)	(0.201)
T2	0.425**	0.488***
	(0.192)	(0.161)
T2 x Completed Middle School or Above	0.116	-0.101
	(0.223)	(0.179)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x Completed Middle School or Above	0.474	0.329
T1 + T1 x Completed Middle School or Above (SE)	0.094	0.098
T1 + T1 x Completed Middle School or Above (p-values)	0.000	0.001
T2 + T2 x Completed Middle School or Above	0.541	0.388
T2 + T2 x Completed Middle School or Above (SE)	0.106	0.090
T2 + T2 x Completed Middle School or Above (p-values)	0.000	0.000

Notes: All regressions include test scores at baseline and whether a completed middle school or above. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D11
Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.350*
	(0.187)
T1 x Completed Middle School or Above	-0.082
	(0.201)
T2	0.073
	(0.180)
T2 x Completed Middle School or Above	0.054
	(0.213)
Observations	679
Control mean	0.000
T1 + T1 x Completed Middle School or Above	0.268
T1 + T1 x Completed Middle School or Above (SE)	0.150
T1 + T1 x Completed Middle School or Above (p-values)	0.077
T2 + T2 x Completed Middle School or Above	0.127
T2 + T2 x Completed Middle School or Above (SE)	0.129
T2 + T2 x Completed Middle School or Above (p-values)	0.326

Notes: All regressions include test scores at baseline and whether a completed middle school or above. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D12

Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.271	0.318*	0.248	0.230
	(0.219)	(0.175)	(0.236)	(0.154)
T1 x Completed Middle School or Above	-0.131	-0.296	-0.060	-0.201
	(0.233)	(0.184)	(0.228)	(0.187)
T2	0.210	0.215	0.070	0.088
	(0.130)	(0.182)	(0.145)	(0.163)
T2 x Completed Middle School or Above	0.760	-0.024	0.976	0.036
	(1.023)	(0.218)	(1.036)	(0.195)
Observations	686	684	685	684
Control mean	0.000	0.000	0.000	0.000
T1 + T1 x Completed Middle School or Above	0.140	0.022	0.189	0.029
T1 + T1 x Completed Middle School or Above (SE)	0.155	0.113	0.155	0.114
T1 + T1 x Completed Middle School or Above (p-values)	0.367	0.846	0.225	0.800
T2 + T2 x Completed Middle School or Above	0.970	0.191	1.046	0.124
T2 + T2 x Completed Middle School or Above (SE)	1.018	0.129	1.026	0.116
T2 + T2 x Completed Middle School or Above (p-values)	0.343	0.142	0.310	0.287

Notes: All regressions include test scores at baseline and whether a completed middle school or above. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.5 Experience

Table D13

Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.521***	0.368***
	(0.097)	(0.094)
T1 x Years of Experience	0.001	-0.003
	(0.011)	(0.010)
T2	0.454***	0.417***
	(0.101)	(0.084)
T2 x Years of Experience	-0.018*	-0.014
	(0.010)	(0.009)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x Years of Experience	0.522	0.365
T1 + T1 x Years of Experience (SE)	0.099	0.093
T1 + T1 x Years of Experience (p-values)	0.000	0.000
T2 + T2 x Years of Experience	0.436	0.403
T2 + T2 x Years of Experience (SE)	0.103	0.082
T2 + T2 x Years of Experience (p-values)	0.000	0.000

Notes: All regressions include test scores at baseline and years of experience. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D14
Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.296**
	(0.132)
T1 x Years of Experience	0.007
	(0.011)
T2	0.099
	(0.108)
T2 x Years of Experience	0.001
	(0.011)
Observations	679
Control mean	0.000
T1 + T1 x Years of Experience	0.303
T1 + T1 x Years of Experience (SE)	0.130
T1 + T1 x Years of Experience (*p*-values)	0.021
T2 + T2 x Years of Experience	0.100
T2 + T2 x Years of Experience (SE)	0.110
T2 + T2 x Years of Experience (*p*-values)	0.366

Notes: All regressions include test scores at baseline and years of experience. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D15

Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.104	0.124	0.109	0.100
	(0.079)	(0.107)	(0.088)	(0.095)
T1 x Years of Experience	-0.003	-0.014	-0.002	-0.006
	(0.009)	(0.010)	(0.009)	(0.009)
T2	0.030	0.190*	0.031	0.099
	(0.093)	(0.106)	(0.091)	(0.095)
T2 x Years of Experience	-0.015	-0.022**	-0.018*	-0.019**
	(0.010)	(0.010)	(0.010)	(0.009)
Observations	686	684	685	684
Control mean	12.215	0.000	12.392	0.000
T1 + T1 x Years of Experience	0.100	0.111	0.107	0.094
T1 + T1 x Years of Experience (SE)	0.080	0.108	0.089	0.096
T1 + T1 x Years of Experience (p-values)	0.212	0.309	0.233	0.328
T2 + T2 x Years of Experience	0.015	0.168	0.013	0.080
T2 + T2 x Years of Experience (SE)	0.095	0.108	0.093	0.097
T2 + T2 x Years of Experience (p-values)	0.877	0.120	0.889	0.413

Notes: All regressions include test scores at baseline and years of experience. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.6 BL Self-Assessed Sweetness

Table D16

Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.468***	0.305***
	(0.102)	(0.097)
T1 x Self-Assessed Sweetness	0.017	-0.065
	(0.106)	(0.122)
T2	0.446***	0.413***
	(0.112)	(0.087)
T2 x Self-Assessed Sweetness	-0.015	-0.131
	(0.116)	(0.099)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x Self-Assessed Sweetness	0.485	0.240
T1 + T1 x Self-Assessed Sweetness (SE)	0.158	0.157
T1 + T1 x Self-Assessed Sweetness (p-values)	0.003	0.130
T2 + T2 x Self-Assessed Sweetness	0.430	0.281
T2 + T2 x Self-Assessed Sweetness (SE)	0.182	0.130
T2 + T2 x Self-Assessed Sweetness (p-values)	0.020	0.032

Notes: All regressions include test scores at baseline and self-assessed sweetness. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D17
Impact on Grape Quality

	(1)
	Machine-Measured Sweetness
T1	0.297*
	(0.150)
T1 x Self-Assessed Sweetness	-0.002
	(0.124)
T2	0.167
	(0.112)
T2 x Self-Assessed Sweetness	-0.122
	(0.109)
Observations	679
Control mean	0.000
T1 + T1 x Self-Assessed Sweetness	0.295
T1 + T1 x Self-Assessed Sweetness (SE)	0.158
T1 + T1 x Self-Assessed Sweetness (*p*-values)	0.064
T2 + T2 x Self-Assessed Sweetness	0.045
T2 + T2 x Self-Assessed Sweetness (SE)	0.157
T2 + T2 x Self-Assessed Sweetness (*p*-values)	0.777

Notes: All regressions include test scores at baseline and self-assessed c sweetness. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D18

Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.119	0.160	0.102	0.111
	(0.091)	(0.122)	(0.097)	(0.107)
T1 x Self-Assessed Sweetness	-0.061	0.123	-0.067	0.147
	(0.084)	(0.117)	(0.102)	(0.117)
T2	-0.004	0.311**	-0.010	0.201*
	(0.105)	(0.121)	(0.101)	(0.104)
T2 x Self-Assessed Sweetness	-0.081	-0.132	-0.038	-0.095
	(0.072)	(0.123)	(0.084)	(0.118)
Observations	686	684	685	684
Control mean	12.215	0.000	12.392	0.000
T1 + T1 x Self-Assessed Sweetness	0.058	0.283	0.035	0.258
T1 + T1 x Self-Assessed Sweetness (SE)	0.118	0.180	0.126	0.163
T1 + T1 x Self-Assessed Sweetness (p-values)	0.623	0.120	0.783	0.118
T2 + T2 x Self-Assessed Sweetness	-0.086	0.179	-0.048	0.106
T2 + T2 x Self-Assessed Sweetness (SE)	0.140	0.166	0.136	0.157
T2 + T2 x Self-Assessed Sweetness (p-values)	0.541	0.285	0.727	0.502

Notes: All regressions include test scores at baseline and self-assessed sweetness. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.7 BL Revenue

Table D19
Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.510***	0.355***
	(0.103)	(0.098)
T1 x IHS(Revenue from grape)	-0.003	0.032
	(0.028)	(0.027)
T2	0.460***	0.426***
	(0.106)	(0.085)
T2 x IHS(Revenue from grape)	0.004	0.028
	(0.022)	(0.019)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x IHS(Revenue from grape)	0.507	0.387
T1 + T1 x IHS(Revenue from grape) (SE)	0.098	0.100
T1 + T1 x IHS(Revenue from grape) (p-values)	0.000	0.000
T2 + T2 x IHS(Revenue from grape)	0.463	0.454
T2 + T2 x IHS(Revenue from grape) (SE)	0.111	0.093
T2 + T2 x IHS(Revenue from grape) (p-values)	0.000	0.000

Notes: All regressions include test scores at baseline and household grape sales revenue. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D20

Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.326**
	(0.135)
T1 x IHS(Revenue from grape)	-0.024
	(0.023)
T2	0.082
	(0.109)
T2 x IHS(Revenue from grape)	-0.019
	(0.017)
Observations	679
Control mean	0.000
T1 + T1 x IHS(Revenue from grape)	0.302
T1 + T1 x IHS(Revenue from grape) (SE)	0.134
T1 + T1 x IHS(Revenue from grape) (p-values)	0.026
T2 + T2 x IHS(Revenue from grape)	0.063
T2 + T2 x IHS(Revenue from grape) (SE)	0.114
T2 + T2 x IHS(Revenue from grape) (p-values)	0.582

Notes: All regressions include test scores at baseline and household grape sales revenue. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D21

Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.095	0.128	0.109	0.118
	(0.085)	(0.105)	(0.094)	(0.098)
T1 x IHS(Revenue from grape)	-0.015	0.014	-0.031	-0.018
	(0.020)	(0.016)	(0.022)	(0.025)
T2	0.031	0.190*	0.024	0.100
	(0.094)	(0.107)	(0.093)	(0.097)
T2 x IHS(Revenue from grape)	-0.012	0.020	-0.027	0.012
	(0.023)	(0.019)	(0.023)	(0.019)
Observations	686	684	685	684
Control mean	12.215	0.000	12.392	0.000
T1 + T1 x IHS(Revenue from grape)	0.080	0.142	0.077	0.100
T1 + T1 x IHS(Revenue from grape) (SE)	0.082	0.107	0.088	0.096
T1 + T1 x IHS(Revenue from grape) (p-values)	0.330	0.186	0.385	0.303
T2 + T2 x IHS(Revenue from grape)	0.019	0.210	-0.003	0.112
T2 + T2 x IHS(Revenue from grape) (SE)	0.094	0.113	0.094	0.103
T2 + T2 x IHS(Revenue from grape) (p-values)	0.840	0.065	0.976	0.280

Notes: All regressions include test scores at baseline and household grape sales revenue. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.8 BL Knowledge

Table D22

Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.522***	0.373***
	(0.095)	(0.094)
T1 x Test score (standardized)	-0.205**	-0.199**
	(0.081)	(0.076)
T2	0.457***	0.418***
	(0.102)	(0.083)
T2 x Test score (standardized)	-0.135	-0.129*
	(0.088)	(0.072)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x Test score (standardized)	0.317	0.174
T1 + T1 x Test score (standardized) (SE)	0.113	0.106
T1 + T1 x Test score (standardized) (p-values)	0.006	0.103
T2 + T2 x Test score (standardized)	0.322	0.289
T2 + T2 x Test score (standardized) (SE)	0.120	0.096
T2 + T2 x Test score (standardized) (p-values)	0.009	0.003

Notes: All regressions include test scores at baseline and baseline test scores (standardized) from repeated 5 questions. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D23
Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.292**
	(0.128)
T1 x Test score (standardized)	0.287***
	(0.090)
T2	0.083
	(0.106)
T2 x Test score (standardized)	-0.005
	(0.097)
Observations	679
Control mean	0.000
T1 + T1 x Test score (standardized)	0.579
T1 + T1 x Test score (standardized) (SE)	0.167
T1 + T1 x Test score (standardized) (p-values)	0.001
T2 + T2 x Test score (standardized)	0.078
T2 + T2 x Test score (standardized) (SE)	0.131
T2 + T2 x Test score (standardized) (p-values)	0.552

Notes: All regressions include test scores at baseline and baseline test scores (standardized) from repeated 5 questions. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D24
Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.104	0.123	0.109	0.098
	(0.079)	(0.107)	(0.087)	(0.095)
T1 x Test score (standardized)	-0.184***	-0.002	-0.183**	-0.032
	(0.061)	(0.085)	(0.071)	(0.081)
T2	0.033	0.185*	0.033	0.094
	(0.093)	(0.107)	(0.092)	(0.096)
T2 x Test score (standardized)	-0.048	0.094	-0.039	0.057
	(0.066)	(0.077)	(0.067)	(0.074)
Observations	686	684	685	684
Control mean	12.215	0.000	12.392	0.000
T1 + T1 x Test score (standardized)	-0.080	0.121	-0.074	0.066
T1 + T1 x Test score (standardized) (SE)	0.091	0.133	0.101	0.117
T1 + T1 x Test score (standardized) (p-values)	0.378	0.366	0.467	0.573
T2 + T2 x Test score (standardized)	-0.015	0.279	-0.006	0.151
T2 + T2 x Test score (standardized) (SE)	0.108	0.136	0.108	0.116
T2 + T2 x Test score (standardized) (p-values)	0.893	0.042	0.957	0.197

Notes: All regressions include test scores at baseline and baseline test scores (standardized) from repeated 5 questions. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.9 BL Aspiration 3-yr Income

Table D25
Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.506***	0.349***
	(0.098)	(0.097)
T1 x IHS(Aspired income in 3 years)	0.019	-0.008
	(0.028)	(0.022)
T2	0.464***	0.413***
	(0.105)	(0.085)
T2 x IHS(Aspired income in 3 years)	0.017	-0.010
	(0.029)	(0.022)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x IHS(Aspired income in 3 years)	0.525	0.340
T1 + T1 x IHS(Aspired income in 3 years) (SE)	0.101	0.107
T1 + T1 x IHS(Aspired income in 3 years) (p-values)	0.000	0.002
T2 + T2 x IHS(Aspired income in 3 years)	0.482	0.403
T2 + T2 x IHS(Aspired income in 3 years) (SE)	0.111	0.095
T2 + T2 x IHS(Aspired income in 3 years) (p-values)	0.000	0.000

Notes: All regressions include test scores at baseline and baseline household aspired income in 3 years. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D26
Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.271*
	(0.137)
T1 x IHS(Aspired income in 3 years)	0.055*
	(0.033)
T2	0.024
	(0.113)
T2 x IHS(Aspired income in 3 years)	0.073**
	(0.034)
Observations	679
Control mean	0.000
T1 + T1 x IHS(Aspired income in 3 years)	0.326
T1 + T1 x IHS(Aspired income in 3 years) (SE)	0.137
T1 + T1 x IHS(Aspired income in 3 years) (p-values)	0.019
T2 + T2 x IHS(Aspired income in 3 years)	0.097
T2 + T2 x IHS(Aspired income in 3 years) (SE)	0.110
T2 + T2 x IHS(Aspired income in 3 years) (p-values)	0.379

Notes: All regressions include test scores at baseline and baseline household aspired income in 3 years. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D27

Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.075	0.107	0.074	0.102
	(0.081)	(0.105)	(0.086)	(0.092)
T1 x IHS(Aspired income in 3 years)	0.033	0.025	0.031	-0.001
	(0.025)	(0.024)	(0.026)	(0.024)
T2	0.022	0.171	0.029	0.088
	(0.097)	(0.105)	(0.094)	(0.098)
T2 x IHS(Aspired income in 3 years)	0.013	0.067***	0.001	0.042
	(0.026)	(0.023)	(0.024)	(0.026)
Observations	686	684	685	684
Control mean	12.215	0.000	12.392	0.000
T1 + T1 x IHS(Aspired income in 3 years)	0.108	0.132	0.105	0.101
T1 + T1 x IHS(Aspired income in 3 years) (SE)	0.089	0.110	0.094	0.096
T1 + T1 x IHS(Aspired income in 3 years) (p-values)	0.230	0.230	0.265	0.297
T2 + T2 x IHS(Aspired income in 3 years)	0.035	0.238	0.030	0.130
T2 + T2 x IHS(Aspired income in 3 years) (SE)	0.101	0.113	0.099	0.101
T2 + T2 x IHS(Aspired income in 3 years) (p-values)	0.728	0.037	0.766	0.202

Notes: All regressions include test scores at baseline and baseline household aspired income in 3 years. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.10 BL Aspiration 5-yr Income

Table D28

Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.548***	0.370***
	(0.095)	(0.094)
T1 x IHS(Aspired income in 5 years)	-0.023	-0.029*
	(0.021)	(0.015)
T2	0.459***	0.398***
	(0.103)	(0.086)
T2 x IHS(Aspired income in 5 years)	-0.006	-0.023
	(0.024)	(0.016)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x IHS(Aspired income in 5 years)	0.525	0.340
T1 + T1 x IHS(Aspired income in 5 years) (SE)	0.094	0.100
T1 + T1 x IHS(Aspired income in 5 years) (p-values)	0.000	0.001
T2 + T2 x IHS(Aspired income in 5 years)	0.453	0.375
T2 + T2 x IHS(Aspired income in 5 years) (SE)	0.105	0.090
T2 + T2 x IHS(Aspired income in 5 years) (p-values)	0.000	0.000

Notes: All regressions include test scores at baseline and baseline household aspired income in 5 years. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D29

Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.277**
	(0.135)
T1 x IHS(Aspired income in 5 years)	0.033
	(0.023)
T2	0.085
	(0.104)
T2 x IHS(Aspired income in 5 years)	0.013
	(0.019)
Observations	679
Control mean	0.000
T1 + T1 x IHS(Aspired income in 5 years)	0.310
T1 + T1 x IHS(Aspired income in 5 years) (SE)	0.133
T1 + T1 x IHS(Aspired income in 5 years) (*p*-values)	0.022
T2 + T2 x IHS(Aspired income in 5 years)	0.098
T2 + T2 x IHS(Aspired income in 5 years) (SE)	0.104
T2 + T2 x IHS(Aspired income in 5 years) (*p*-values)	0.348

Notes: All regressions include test scores at baseline and baseline household aspired income in 5 years. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D30

Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.069	0.106	0.062	0.117
	(0.082)	(0.103)	(0.086)	(0.091)
T1 x IHS(Aspired income in 5 years)	0.024	0.017	0.026	-0.001
	(0.016)	(0.019)	(0.017)	(0.019)
T2	0.032	0.170	0.030	0.092
	(0.098)	(0.105)	(0.096)	(0.093)
T2 x IHS(Aspired income in 5 years)	0.013	0.025	0.012	0.022
	(0.019)	(0.018)	(0.018)	(0.016)
Observations	686	684	685	684
Control mean	12.215	0.000	12.392	0.000
T1 + T1 x IHS(Aspired income in 5 years)	0.093	0.122	0.087	0.116
T1 + T1 x IHS(Aspired income in 5 years) (SE)	0.085	0.105	0.091	0.093
T1 + T1 x IHS(Aspired income in 5 years) (p-values)	0.277	0.246	0.337	0.214
T2 + T2 x IHS(Aspired income in 5 years)	0.045	0.195	0.042	0.114
T2 + T2 x IHS(Aspired income in 5 years) (SE)	0.097	0.105	0.096	0.097
T2 + T2 x IHS(Aspired income in 5 years) (p-values)	0.648	0.066	0.664	0.242

Notes: All regressions include test scores at baseline and baseline household aspired income in 5 years. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

D.11 Household Income

Table D31

Impact on Test Score

	(1)	(2)
	Standardized IRT Score	
	All 10 questions	Repeated 5 questions
T1	0.513***	0.360***
	(0.098)	(0.096)
T1 x IHS(Total household income)	0.021	0.013
	(0.055)	(0.050)
T2	0.453***	0.416***
	(0.102)	(0.084)
T2 x IHS(Total household income)	0.011	0.017
	(0.052)	(0.047)
Observations	687	687
Control mean	0.000	0.000
T1 + T1 x IHS(Total household income)	0.534	0.373
T1 + T1 x IHS(Total household income) (SE)	0.101	0.110
T1 + T1 x IHS(Total household income) (p-values)	0.000	0.001
T2 + T2 x IHS(Total household income)	0.464	0.433
T2 + T2 x IHS(Total household income) (SE)	0.112	0.102
T2 + T2 x IHS(Total household income) (p-values)	0.000	0.000

Notes: All regressions include test scores at baseline and total household income at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D32
Impact on Grape Quality

	(1) Machine-Measured Sweetness
T1	0.299**
	(0.134)
T1 x IHS(Total household income)	0.018
	(0.053)
T2	0.095
	(0.108)
T2 x IHS(Total household income)	-0.024
	(0.033)
Observations	679
Control mean	0.000
T1 + T1 x IHS(Total household income)	0.317
T1 + T1 x IHS(Total household income) (SE)	0.138
T1 + T1 x IHS(Total household income) (p-values)	0.024
T2 + T2 x IHS(Total household income)	0.071
T2 + T2 x IHS(Total household income) (SE)	0.112
T2 + T2 x IHS(Total household income) (p-values)	0.528

Notes: All regressions include test scores at baseline and total household income at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table D33

Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS (Income)	Sweetness	IHS (Income)	Sweetness
T1	0.099	0.122	0.103	0.098
	(0.083)	(0.106)	(0.090)	(0.096)
T1 x IHS(Total household income)	-0.056	0.050	-0.056	0.025
	(0.052)	(0.031)	(0.053)	(0.041)
T2	0.022	0.184*	0.020	0.092
	(0.093)	(0.106)	(0.092)	(0.095)
T2 x IHS(Total household income)	-0.069	-0.009	-0.083	-0.023
	(0.077)	(0.027)	(0.076)	(0.039)
Observations	686	684	685	684
Control mean	12.215	0.000	12.392	0.000
T1 + T1 x IHS(Total household income)	0.044	0.173	0.047	0.123
T1 + T1 x IHS(Total household income) (SE)	0.082	0.109	0.089	0.097
T1 + T1 x IHS(Total household income) (p-values)	0.595	0.116	0.596	0.209
T2 + T2 x IHS(Total household income)	-0.047	0.175	-0.064	0.069
T2 + T2 x IHS(Total household income) (SE)	0.108	0.114	0.107	0.106
T2 + T2 x IHS(Total household income) (p-values)	0.662	0.128	0.553	0.518

Notes: All regressions include test scores at baseline and total household income at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$