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LETTER

Economic benefits of small-scale irrigation are associated with prevalence of irrigation nearby

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Supplementary material for this article is available online

Abstract

Small-scale irrigation can significantly increase household agricultural revenues. We explore the extent to which these earnings vary based on the share of farmers irrigating nearby. Using primary data collected from 985 smallholder farmers in rural Ethiopia, we demonstrate that irrigating in villages with high irrigation prevalence is associated with greater agricultural revenues and more commercialization opportunities, particularly in the dry season. The revenue gains associated with high-prevalence irrigators largely accrue to those who use mechanized irrigation technologies. Supporting low-prevalence irrigators with policies that improve market access can greatly amplify their ability to generate financial returns.

Main text

Climate change presents severe threats to sub-Saharan Africa, a region where households depend heavily on rainfed agriculture for food and income [1, 2]. As a result of climate change, agricultural productivity growth in Africa has declined by 34% since 1961 [3, 4]. This decline, the largest of any world region, has in turn fuelled substantial increases in food insecurity, malnutrition, and poverty [5–8].

A widely promoted strategy to increase climate resilience in sub-Saharan Africa (SSA) is investing in irrigation [9]. Irrigation is the use of any non-rainfall water source to cultivate crops. Irrigation technologies can help households adapt to changing precipitation patterns and withstand recurring droughts. Over the past six decades, national governments in SSA and their development partners worked to expand irrigation access through large-scale, centralized projects, but these investments have largely yielded disappointing results [10]. This experience has contributed to the growing interest in small-scale irrigation technologies that are adopted and operated by individual smallholder farmers [11, 12]. Small-scale irrigation can be more profitable, more easily expanded, and better adapted to local agroecological and hydrological conditions [13].

Billions of dollars have been committed to expand access to irrigation infrastructure in sub-Saharan Africa [14, 15]. For example, the World Bank has pledged to work with the African Development Bank to give national governments US$9 billion to improve irrigation access [16]. Other ongoing projects include a US$200 million investment to expand small-scale irrigation in Uganda and a US$265 million project to establish six new irrigation schemes in Malawi [17, 18].

A growing body of evidence suggests that such investments have the potential to meaningfully increase smallholder agricultural revenues [19]. At the same time, the increasing emphasis on small-scale, decentralized irrigation technologies raises important project design questions. For example, how might the prevalence of irrigation adoption at the community level impact the financial returns of individual farmers? In theory, a

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farmer's experience with irrigation could significantly vary depending on the share of farmers irrigating nearby. A relatively early adopter might find it difficult to source both information (e.g., about which crops to grow and how much to sell them for) and complementary inputs (e.g., fertilizer and improved seeds) that translate their irrigation efforts into meaningful financial returns. By contrast, widespread adoption of irrigation within a village may foster peer-to-peer learning, strengthen supply chains, and create economies of scale that help each farmer grow and sell their crops successfully. Understanding how much household earnings vary with village irrigation prevalence can thus guide decisions about where to prioritize irrigation infrastructure investments and how to bundle them with programs and policies that amplify their positive impact.

In this cross-sectional study we use primary data collected from 985 smallholder farmers in rural Ethiopia to measure the extent to which reported village irrigation prevalence moderates the relationship between irrigation and annual crop revenue. Ethiopia is a strategic setting for this study because it is well-poised for irrigation investments. Ethiopia's agricultural sector generates 35% of its gross domestic product and employs 85% of its labor force, but less than 1% of farmland in Ethiopia is irrigated (depending on the methodology used, irrigation prevalence can range between 1%–5%) [20–22]. Ethiopia also has a long history of droughts and erratic rainfall, both of which have contributed significantly to unemployment, sharp reductions in agricultural yields, and chronic food insecurity [23, 24]. Eliminating dependency on rainfed agriculture is thus a core focus of Ethiopia's Ten Year Development Plan (2021–2030) [25]. The Ethiopian government has indeed invested heavily in small-scale community irrigation schemes, but several studies demonstrate that the performance of these irrigation projects have been constrained by limited market availability, weak local institutions, and poor extension services [26].

Our study focuses on farmers who cultivate small plots of land (median landholding of 1.9 acres) for both self-consumption needs and local market sales. These smallholder farmers rely on a single water source to irrigate their crops in the dry season. The majority (85%) rely on surface water sources such as lakes, ponds, and rivers. A smaller subset (15%) use groundwater to irrigate. Irrigation practices in our study area are predominantly non-mechanized; 73% of farmers depend on gravity-fed systems (e.g., canals and furrows) or manual labor (e.g., watering cans) to irrigate (60% use canals and furrows, 10% use watering cans, and 3% use gravity piped systems). The remaining 27% of farmers use mechanized technology (i.e., diesel irrigation pumps and a flexible pipe) to water their crops.

We begin by comparing the crop revenue differential between irrigators and non-irrigators among households living in villages with different levels of irrigation prevalence. Next, we model the association between irrigation and annual crop revenue using multivariate linear regression, including an interaction term to assess the extent to which village irrigation prevalence moderates the association between irrigation and annual crop revenue. We operationalize the village irrigation prevalence variable using survey responses to the following multiple-choice question: '*As far as you know, what share of farmers in your village PLANTED during the DRY season last year between June* 2021 *and May* 2022*?*' (we deliberately used 'planted during the dry season' instead of 'irrigating' in our survey wording because respondents who used small-scale irrigation methods did not consider themselves to be the same as 'irrigators' who used large-scale water infrastructure like drip irrigation). Households that reported 'Very few (<10%)' or 'Less than half (25%–33%)' were classified as living in villages with low irrigation prevalence whereas households that reported 'About half (~50%)', 'More than half (66%–75%)', and 'Almost all (90%+)' were classified as living in villages with high irrigation prevalence. To test for the possibility of a dose–response relationship, we also operationalized reported village irrigation prevalence as a 5-level categorical variable (i.e., in its original form).

To test for differential effects among farmers using different types of irrigation technologies, we operationalize the irrigation variable in two ways: (i) as a binary variable (i.e., irrigator *versus* non-irrigator), and (ii) as a 3-level categorical variable (i.e., non-mechanized irrigator, mechanized irrigator, and non-irrigator). To explore potential mechanisms underpinning our results, we test whether 'high-prevalence irrigators' (i.e., irrigators living in villages where at least half of the households are reportedly irrigating) adopt different agricultural practices than 'low-prevalence irrigators' with respect to their crop timing, input use, and harvest commercialization strategies. Due to the cross-sectional nature of this study, estimates reported in the results section describe associations and should not be interpreted as causal effects. We conclude by discussing the implications of our findings for policy and practice.

Results

Among the farmers in our study, the differential in annual crop revenue between irrigators and non-irrigators is larger in villages where irrigation is more prevalent. On average, in villages with high irrigation prevalence, irrigators earn 260% more than non-irrigators (figure 1, panel A). By contrast, in villages with low irrigation prevalence, irrigators only earn 40% more than non-irrigators on average (figure 1, panel A).

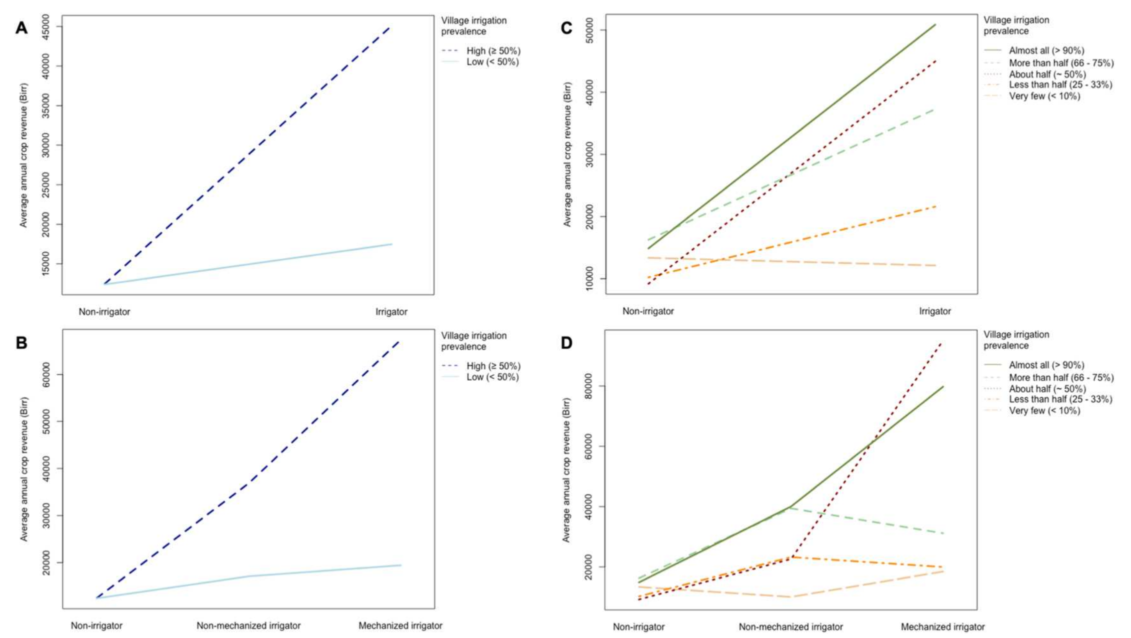

Figure 1. Comparing the average annual crop revenue of irrigators and non-irrigators living in villages with different levels of irrigation prevalence (n = 985 in panels A and B, n = 981 in panels C and D).

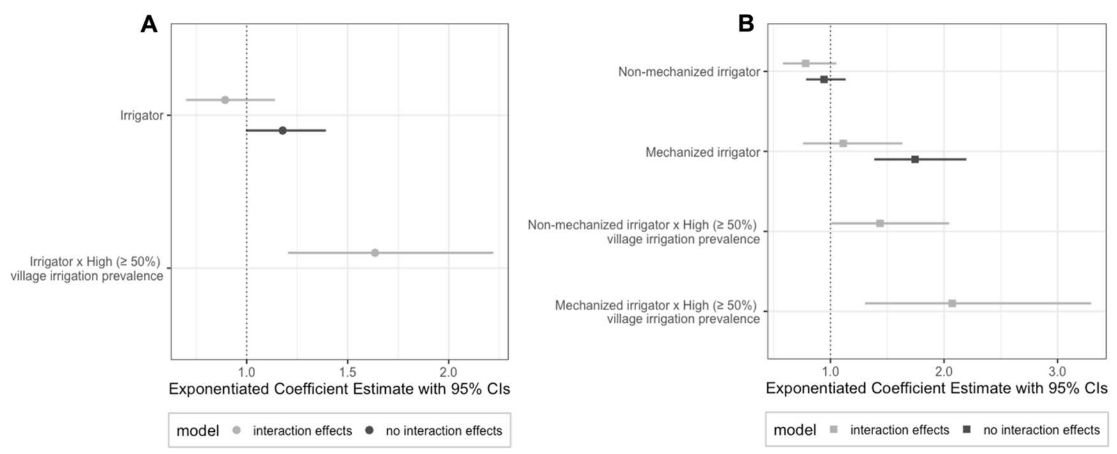

Figure 2. Exponentiated coefficients for multivariate linear regressions between log-transformed annual crop revenue (outcome) and irrigation (explanatory variable). Irrigation is modeled (i) as a binary variable (irrigator, non-irrigator) in panel A (n = 985) and (ii) as a 3-level categorical variable (irrigator using mechanized technologies, irrigator using non-mechanized technologies, non-irrigator) in panel B (n = 981). Both models have the same set of covariates.

The influence of irrigation prevalence on agricultural revenue is robust across several model specifications and after controlling for total area cultivated and other relevant household, agricultural, and contextual covariates (beta = 1.6 implying a 5X revenue differential, $p = 0.002$, panel A in figure 2 and table S2). The association also holds when we model the outcome of annual crop revenue as a per-capita metric (table S3) and per-acre cultivated metric (table S4); when we incorporate additional covariates (to control for each household's poverty status and the global agro-ecological zone they live in, table S5); and when we cluster the robust standard errors at the EA level (figure S1 and table S6). Due to data limitations, we were unable to control for crop prices and yields.

The magnitude of the revenue differential between irrigators and non-irrigators is particularly pronounced at a village irrigation prevalence level of 50%. Panel A in figure 3 shows that the revenue differential between irrigators and non-irrigators is, on average, 240% larger ($p = 0.001$, table S7) for farmers who report living in villages where approximately half of the residents are irrigating (compared to farmers who report living in villages with less than 10% prevalence). The revenue differential between irrigators and non-irrigators is not statistically different for farmers living in villages with less than half (25%–33%), more than half (66%–75%) or near universal (>90%) irrigation penetration (panel A in figures 3, S2, and tables S7–S11).

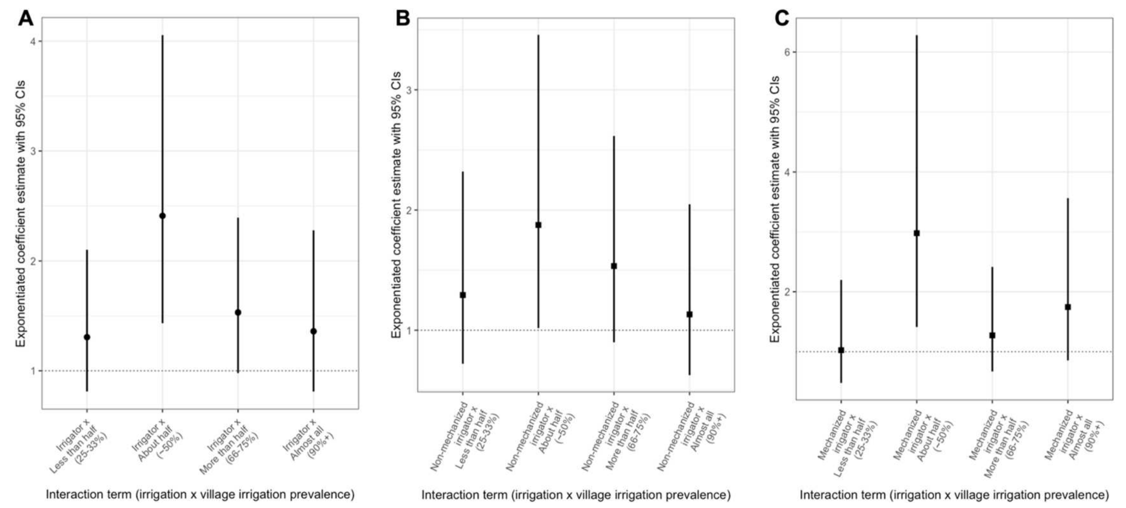

Figure 3. Exponentiated interaction effect coefficients with village irrigation prevalence modeled as a 5-level ordinal variable (very little, less than half, about half, more than half, almost all). In panel A (n = 985), irrigation is modeled as a binary variable (irrigator, non-irrigator). In panels B and C (n = 981), irrigation is modeled as a 3-level categorical variable (non-mechanized irrigator, mechanized irrigator, non-irrigator). All models have the same outcome (log-transformed annual crop revenue) and set of covariates.

The moderating effect of village irrigation prevalence is stronger for mechanized *versus* non-mechanized irrigation technology users. On average, farmers using mechanized irrigation technologies earn 250% more when they live in villages with high *versus* low irrigation prevalence (panel B, figure 1). Among farmers using non-mechanized irrigation technologies, the differential is 120% (panel B, figure 1). We test this hypothesis more formally by modelling irrigation as a 3-level categorical variable (mechanized irrigator, non-mechanized irrigator, and non-irrigator) and find that the interaction term between 'irrigation' and 'high village irrigation prevalence' is indeed larger for mechanized irrigators (beta = 2.1 implying an 8X revenue differential, p = 0.002) compared to non-mechanized irrigators (beta = 1.4 implying a 4X revenue differential, p = 0.04, panel B in figure 2 and table S12). This association is robust when we control for agricultural, household, and contextual covariates (e.g., total area cultivated, education and sex of household head, engagement in non-farm livelihoods, reported distances to primary markets and paved roads); when we model village irrigation prevalence as a 5-level ordinal variable (panels B and C in figure 3 and table S13); and when we cluster the robust standard errors at the EA level (tables S14 and S15).

The farming practices of high-prevalence irrigators differ significantly from those of low-prevalence irrigators along several dimensions. This is best illustrated in figure 4, which compares agricultural behaviors between high-prevalence and low-prevalence irrigators. The odds that high-prevalence irrigators report selling their dry season crops are 3.5 times higher than those for low-prevalence irrigators (adjusted p-value = 0.005, panel D in figure 4). High-prevalence irrigators are also more likely to report selling to intermediary traders at their farms or local markets (rather than traders at city markets and households at local and city markets; aOR = 4.2, adjusted p-value = 0.003, panels B and D in figure 4). The two groups differ in their timing of crop planting as well. The odds of high-prevalence irrigators planting at least one of their highest earning crops in the dry season (typically October to February) are 3.9 times higher as compared to low-prevalence irrigators (adjusted p-value = 0.003, panels C and D in figure 4). In addition, high-prevalence irrigators are more likely to grow a greater diversity of dry season crops. The number of crops planted increases by a factor of 1.8 (aRR, adjusted p-value < 0.001, panel D in figure 4) when comparing high-prevalence irrigators to low-prevalence irrigators. These associations are robust when we stratify our results by mechanized *versus* non-mechanized irrigation technologies (figure S3).

We observe no significant differences between high- and low-prevalence irrigators with respect to their use of pesticides, chemical and manure fertilizers, seeds purchased from formal sellers, hired labor, or agricultural machinery (panel A in figure 4).

Discussion

The extent to which farmers generate financial returns from small-scale irrigation is strongly associated with the prevalence of irrigation around them. On average, the revenue differential between irrigators and non-irrigators is 160% larger for farmers who report living in villages with high *versus* low village irrigation

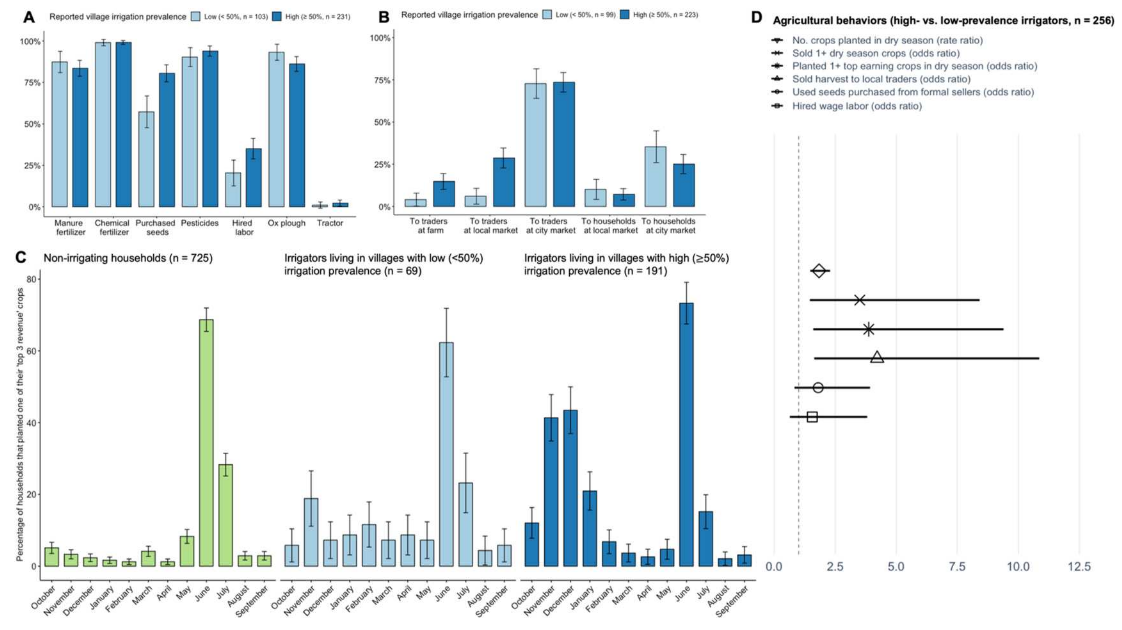

Figure 4. Comparing agricultural behaviors between irrigators that live in villages with high *versus* low reported irrigation prevalence. In panel A, the percentage of households that used each type of input is displayed (n = 334). In panel B, the percentage of households that relied on each point of sale is displayed (n = 322). In panel C, the percentage of households that planted their top 3 revenue crops in each month are displayed (n = 985). In panel D, rate ratios and odds ratios adjusted for robust standard errors and household, agricultural, and contextual covariates are displayed (n = 256). The dotted line marks a value of 1. All error bars represent 95% CIs.

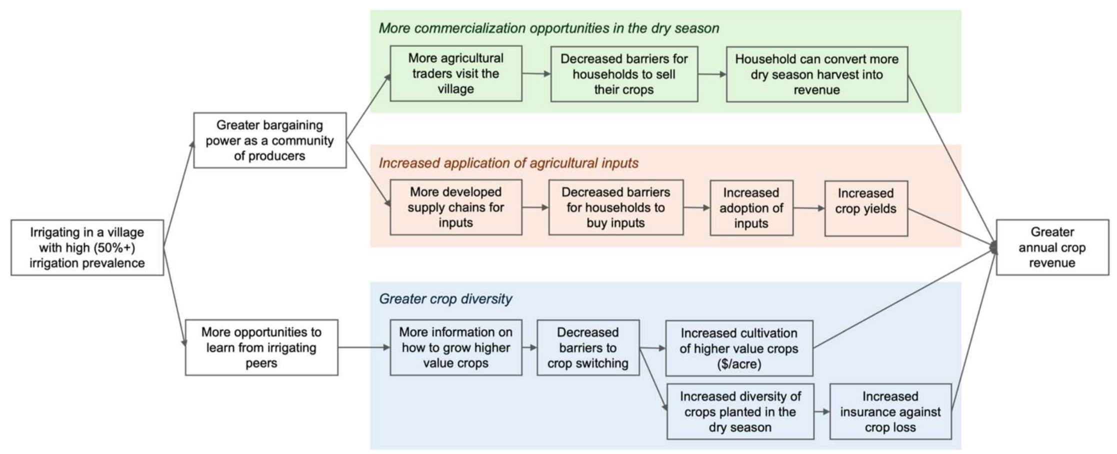

Figure 5. Simplified representation of hypothesized causal mechanisms between irrigating in a village with high irrigation prevalence and greater annual crop revenue.

prevalence (p = 0.002, figure 2). These incremental revenues can be consequential for the households in our sample, 74% of whom earn most of their income from cultivating crops.

We hypothesize that the revenue discrepancies between high- and low-prevalence irrigators might be explained by three mechanisms: (1) greater crop diversity, (2) increased application of agricultural inputs, and (3) more commercialization opportunities (figure 5) [27]. First, the ability to observe and learn from irrigating farmers nearby can facilitate better informed choices about crop cultivation strategies [28–30]. This learning can subsequently decrease barriers to crop switching, facilitate cultivation of higher-value crops, and increase the diversity of crops planted in the dry season (which can be an important risk mitigation strategy for small-holder farmers) [31–33]. In our sample of farmers, high-prevalence irrigators are indeed more likely to grow a higher diversity of dry season crops compared to low-prevalence irrigators (figure 4, panel D).

Second, in a village with widespread irrigation, farmers can pool their demand for inputs in ways that motivate the development of local supply chains [34, 35]. Increased access to local suppliers can decrease the transportation barriers associated with procuring inputs, increase the use of fertilizers and other complementary inputs that enhance irrigation efforts, and increase overall crop yields. In our sample, however, high- and low-prevalence irrigators do not differ significantly with respect to their use of pesticides, chemical and manure fertilizers, seeds purchased from formal sellers, hired labor, or agricultural machinery (figure 4, panels A and D).

Third, high-prevalence irrigators may have more opportunities to commercialize their crops during the dry season. In rural Ethiopia intermediary traders play an important role in connecting remote, rural farmers to market opportunities [36]. Intuitively, we expect intermediary traders to preferentially visit communities where they can meet their quotas with a relatively small number of transactions. High irrigation prevalence villages can thus be appealing; they generate larger quantities of harvest and a greater diversity of crops for traders to purchase in the dry season. Visits from agricultural traders can remove significant barriers for irrigators looking to sell their harvest because it eliminates the need to arrange for transportation to city markets [37–39]. Even irrigators who have the means to transport their harvest to more distant markets may find it advantageous to sell to local traders due to the reduced risks and costs [40]. For example, transporting perishable crops to the city market only to be met with minimal demand may lead to a worse financial outcome than selling the harvest locally for a lower price. Irrigating in a village with high irrigation prevalence can thus reduce some of the most important constraints to converting irrigation efforts into meaningful financial returns [41].

In comparing the agricultural practices of high- and low-prevalence irrigators, we indeed find evidence for enhanced commercialization opportunities. All irrigators in our sample report cultivating crops in the dry season, but high-prevalence irrigators are significantly more likely to sell their harvested crops ($aOR = 3.5$, $p = 0.005$, panel D in figure 4) and use local traders to do so ($aOR = 4.2$, $p = 0.003$, panels B and D in figure 4). Equally important, high-prevalence irrigators appear to benefit from a second earning season that low-prevalence irrigators do not. High-prevalence irrigators are significantly more likely to plant at least one of their highest earning crops in the dry season ($aOR = 3.9$, p-value < 0.001, panels C and D in figure 4). By contrast, low-prevalence irrigators primarily plant their top revenue crops in the rainy season.

A second earning season provides more than just an opportunity to enhance farmers' agricultural revenues. It can also make households more resilient to agricultural shocks that might otherwise trigger a descent into poverty or chronic food insecurity [42]. Unusually low crop yields in the rainy season—whether induced by climate variability or other factors—may not be catastrophic for farmers in Ethiopia if they have another opportunity to cultivate and sell crops in the dry season. The benefits of a second earning season can also extend to wage labourers and agricultural traders. Given that the agricultural sector employs 85% of the labor force in Ethiopia, a second growing season can activate sections of the economy that would otherwise go dormant in the dry season.

If our hypothesis about the commercialization mechanism is correct, it would be productive for decision-makers to consider strategies to increase market opportunities for irrigators who are geographically isolated from other irrigating farmers. Establishing farmer cooperatives to aggregate individual harvest contributions is one strategy that could strengthen irrigators' bargaining power with traders [43, 44]. Other strategies could involve improving output market information (e.g., by using information and communications technologies to decrease information asymmetry), creating new connections between market participants (e.g., by using online or mobile trading platforms to facilitate harvest sales), and providing storage infrastructure to give farmers more choice about when to sell [45].

It could also be worthwhile for practitioners to concentrate project resources in areas with low baseline levels of irrigation. In these settings, it would be productive to engage a large number of households at the outset to quickly reach a level of adoption where farmers start to benefit from economies of scale. This implementation approach can greatly amplify the value that an irrigation project delivers to recipient households (as well as to existing irrigators). To be clear, the practice of making irrigation distribution decisions based on contextual features is not new. For example, proximity to a water source is an eligibility criterion for Uganda's Micro-scale Irrigation Program, a collaboration between The World Bank and Uganda's Ministry of Agriculture. However, our findings emphasize the importance of prioritizing contextual features beyond natural resource availability, including the share of other farmers irrigating in the village.

Whereas the findings presented in this paper are consistent across various robustness checks, one key limitation is worth mentioning. Based on landholding data collected during the pilot phase of this study, and in an effort to prevent respondent fatigue, we collected information from each farmer about the three largest plots they cultivate. We acknowledge the possibility for variation in our results if we had the opportunity to detail information on every plot. At the same time, because households in our sample cultivate an average of 3.8 plots, we are confident that the lion's share of relevant information was captured and included in our analysis.

The cross-sectional nature of this study precluded our conducting an in-depth investigation of the mechanisms driving observed differences in crop revenue, but these mechanisms are worth exploring further (particularly with panel data that facilitate comparisons over time). It would also be instructive to understand whether the moderating effect of village irrigation prevalence is indeed characterized by a dose–response relationship.

We observed a pronounced moderating effect in villages with 50% irrigation prevalence, but our sample size may not have been large enough to characterize the effect at other prevalence levels. Elucidating whether threshold values exist (e.g., do moderating effects only emerge once a minimum prevalence threshold is reached due to network effects? Do moderating effects start to attenuate when prevalence exceeds an upper threshold due to market saturation?) as well as the factors that drive these dynamics (e.g., do price competition or natural resource constraints emerge once a village is saturated with irrigators?) can better inform project design and implementation decisions [46–48]. We also see value in understanding why the revenue gains associated with high-prevalence irrigators largely accrue to those who use mechanized irrigation technologies. For example, mechanized technologies can reduce manual labor requirements compared to non-mechanized methods. These labor savings can allow irrigators to spend more time and money on inputs (fertilizers, pesticides) that are necessary for optimal crop yields. Mechanized technologies might also make it more feasible for irrigators to cultivate higher-value crops that require more precise and reliable application of water. In general, the resources (time, labor, credit, and capital) and institutional arrangements (the degree of water source and infrastructure sharing, the cooperative water management structures) associated with mechanized *versus* non-mechanized methods are meaningfully different. Clarifying how these differences (among others) impact the moderating effect of village irrigation prevalence can better inform decisions about when each irrigation type should be promoted. Finally, we did not find evidence to support that input usage was statistically different between high- and low-prevalence irrigators. Future research could explore whether this observation is a consequence of capital constraints or limited local supply chains.

Governments and their development partners in sub-Saharan Africa have committed billions of dollars to develop irrigation projects. These investments have the potential to transform rural livelihoods, but they do not benefit everyone equally. The amount of revenue that smallholder farmers earn from irrigation is strongly associated with the share of households irrigating around them. High-prevalence irrigators earn more agricultural revenue and have more commercialization opportunities in the dry season. If these two observations are indeed related, then supporting low-prevalence irrigators with policies that improve market access could greatly amplify their ability to generate financial returns and build resilience against a changing climate. Such investments can have outsized returns for the farmers who are directly involved as well as for the wider economy.

Methods

Village selection

This observational study took place in three woredas in the Amhara region of Ethiopia: Dera, Farta, and North Mecha. Agriculture plays an important role in the Amhara region; according to the Amhara Agricultural Research institute, 90% of the local labor force is engaged in agriculture. However, agricultural productivity in this region is constrained by low input use, poor soil fertility, and limited investment in agricultural machinery. The Amhara region is home to four major river basins (Abbay, Tekeze, Awash, and the Danakil Depression) and 24% of the land suitable for small-scale irrigation in Ethiopia, yet irrigation adoption remains low (6%) [49, 50].

We used a stratified random sampling approach to select twenty-four study villages from each woreda ($n = 72$ in total). We started with the full list of enumeration areas (EA) drawn by the Central Statistical Agency (CSA) for the 2019 population and housing census in Ethiopia. Each EA was assigned an urban or rural classification by the CSA. The number of urban and rural EAs included in the final study sample was based on the proportion of urban and rural EAs that constituted each woreda. We made one exception for Farta, where we randomly selected a second urban EA to facilitate the calculation of standard errors. The probability of selection of each EA was proportional to the number of households as recorded in the 2019 census. In our study area, each EA corresponded to a separate village. EAs were only replaced (with randomly pre-selected substitutes) when the data collection teams encountered logistical constraints (e.g., heavy rains) that prevented them from safely conducting the household surveys. Only one rural EA was replaced (by another rural EA) in each woreda.

Sample frame development

To generate an initial sample frame, we surveyed all households in each selected EA. We defined a household, consistent with Ethiopia's population and housing census, as a group of individuals who live together, pool their money and resources, and share at least one meal each day. We interviewed one respondent from each household, preferentially the head of household or spouse where possible. Respondents were eligible if they provided informed consent and reported being (i) a household member, (ii) 18 years or older, and (iii) able to answer questions about the household's water supply services. In this first survey round, we collected information about each household's demographics, ownership of assets, and irrigation use. We surveyed a total of 8,630 households (n = 2,938 in Dera, n = 2,758 in Farta, and n = 2,934 in North Mecha) between June and July 2022.

Household selection

We employed two-stage proportional stratified random sampling to select 1,800 households for the final study sample (n = 600 from each woreda). Household selection was stratified by wealth quintile and reported irrigation use. We classified households as irrigating if they reported planting at least one crop during the last dry season using any non-rainfall water source (e.g., river, pond, borehole). Within each EA, we classified households into wealth quintiles using the Demographic and Health Surveys (DHS) Program's wealth index. The DHS wealth index is a composite measure based on a household's reported ownership of assets (e.g., appliances, furniture, land, livestock) and access to services (e.g., water, sanitation, energy) [51]. We computed each household's wealth index score following the DHS Program procedures, using the urban- and rural-specific wealth index constructions derived from the 2019 Ethiopia Mini Demographic and Health Survey [51].

Data collection

Between August and September 2022, we interviewed households selected in the final study sample to collect information about their crop cultivation practices, agricultural water management strategies, and annual crop revenue. We made three attempts to interview the head of the household or their spouse before interviewing another adult member of the selected household. If an eligible respondent was not identified after three visits, we replaced the household with a pre-selected substitute in the same wealth and geographic stratum. Of the 1,800 households selected, 46 households (2.5%) were replaced (44 households did not have eligible respondents after three attempts, 1 household refused to participate, and 1 household's dwelling could not be located).

All surveys were conducted in Amharic by trained enumerators recruited by the Ethiopian Public Health Association. All enumerators completed at least two weeks of training and participated in at least one full day of instrument piloting before the start of each data collection effort. All data were collected on tablet computers using DigitalOcean (New York, USA). We reviewed the collected data regularly (daily, where possible) to identify data inconsistencies, unanticipated survey responses, and opportunities for re-training. Changes to the raw data were only made for confirmed data entry errors. Confirmation of these errors and their corrected values were obtained by reviewing enumerators' field notebooks and following up with enumerators and household respondents where necessary.

Data analysis

Interviewed households were included in subsequent analyses if they (i) resided in a rural EA, (ii) reported cultivating at least one crop in the last 12 months, and (iii) lived in an EA where at least one household reported to irrigate during the previous dry season. We applied the last criterion to reduce the impact of potential confounders (i.e., EAs with no irrigators are likely systematically different from EAs with at least one irrigator). A total of 985 households were included in the analysis after applying these criteria (figure S4). Data were analyzed using R version 4.2.2 (Vienna, Austria) in RStudio (Boston, Massachusetts).

A household's village was chosen as the spatial unit of interest for three reasons. First, the stratified random sampling approach was applied at the village level. Second, we wanted to control for other village-level characteristics that could moderate the relationship between irrigation and annual crop revenue (e.g., reported travel time to the primary market, reported travel time to the nearest paved road, and reported travel time to the primary market). Third, the small-scale irrigation methods used by households in our sample were largely contained within their own village.

The primary study outcome was a household's annual crop revenue. We asked respondents to report up to three crops that earned their household the most amount of money in the last 12 months. For each crop, we asked respondents to report the total revenue earned from harvest sales between June 2021 and May 2022. An estimate of the household's annual crop revenue was calculated by taking the sum of these self-reported earnings. The final variable was log-transformed because the underlying data were right-skewed.

The explanatory variable of interest is dry season irrigation use. We asked respondents to report information about each parcel of land their household cultivated in the last 12 months. If a household cultivated more than 3 parcels of land, we asked respondents to report information on the three largest parcels by area. For each parcel of land, we asked respondents to report all the water sources that they used during the last dry season. Households were considered to be irrigating if they reported using any non-rainfall water source (e.g., lakes, rivers, boreholes, public taps) on any of their (3 largest) cultivated parcels in the dry season.

We used multivariate log-linear regression to model the relationship between small-scale irrigation and log-transformed annual crop revenue. Linear regression assumptions were tested using residuals-fitted plots, normal Q-Q plots, and Breusch-Pagan tests in R. All linear regression assumptions were reasonably met, except for the assumption of homoscedasticity. To adjust for heteroscedasticity, we calculated Eicker–Huber–White robust standard errors for all regression coefficients. We checked for multicollinearity by evaluating variable inflation factors, all of which were consistently below 3.

All models included controls for household characteristics (sex of head of household, household size, whether the head of household attended any formal schooling, ownership of mobile phones, and whether the household engaged in any non-farm activities); agricultural practices (size of cultivated land and whether the household hired wage labor); and other geographic and spatial features (woreda, reported travel time to the primary market, reported travel time to the nearest paved road, and reported travel time to the primary market). We conducted additional robustness checks by controlling for each household's Food and Agriculture Organization's global agro-ecological zone classification and their probability of living below the international poverty line based on the Poverty Probability Index [52, 53].

To test the extent to which village irrigation prevalence moderates the relationship between irrigation and annual crop revenue, we incorporated an interaction term between irrigation and reported village irrigation prevalence. We first operationalized reported village irrigation prevalence as a binary variable. In the survey, we asked respondents: '*As far as you know, what share of farmers in your village PLANTED during the DRY season last year between June 2021 and May 2022? Would you say it was…*' We then prompted respondents to select one of five responses: 'Very few (<10%),' 'Less than half (25%–33%),' 'About half (~50%),' 'More than half (66%–75%),' or 'Almost all (90%+).' Households that reported 'Very few' or 'Less than half' were classified as living in villages with 'low' irrigation prevalence while households that reported 'About half', 'More than half,' or 'Almost all' were classified as living in villages with 'high' irrigation prevalence. To test the robustness of our results, we also operationalized reported village irrigation prevalence as a 5-level categorical variable (i.e., in its original form).

To compare agricultural behaviors between irrigators that reported living in villages with high *versus* low irrigation prevalence, we used Poisson regression to test for differences in count variables (e.g., the reported number of crops planted and sold in the last 12 months) and binary logistic regression to test for dichotomous variables (e.g., whether the household used a particular agricultural input). We tested Poisson regression results for overdispersion and found no evidence that true dispersion is greater than one, suggesting that Poisson model assumptions were met.

Ethical approvals

All study participants provided informed consent. The Stanford University Institutional Review Board (protocol 57868) and Ethiopian Public Health Association (protocol EPHA/OG/736/22) approved the study.

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Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/All data needed to replicate these results are available at Open Science Framework (https://osf.io/2f47u/, DOI: https://doi.org/10.17605/OSF.IO/2F47U). The code needed to replicate these results are available at GitHub (https://github.com/cjpu/amplifying_irrigation_impact).

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