Agricultural Advancements in India: The Role of Good Soil Practices Amidst Climate Adversity *

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June 15, 2023

Abstract

Amid climate shocks such as droughts and floods, smallholder farmers endure the most severe repercussions. Empowering these farmers with knowledge and skills in climate-resilient farming techniques becomes crucial in enabling them to overcome the challenges presented by climate-related adversity. In this paper, we study smallholder farmers in Maharashtra, India to assess the impact of Good Agricultural Practices (GAPs) on sugar cane yield and cultivation costs. We employ an instrumental variable approach and find that implementing more GAPs decreases a farmer's cultivation costs significantly and decreases their yields non-significantly.

Keywords: agriculture, good agricultural practices, instrumental variables, soil

1 Introduction

The advancement of agricultural technology is a double-edged sword. While countries that adopt modern farming techniques reduce poverty levels, they face long-term environmental degradation, contribute towards climate pollution, and leave behind farmers who are unable to adapt fast enough. Providing smallholder farmers with training in climate-smart agricultural practices is crucial for promoting sustainable agriculture, ensuring food security, and fostering equity. These practices help by maintaining high crop yields and reducing costs over the long term. This paper focuses on showing the direct effects of Good Agricutural Practices (GAPs) concerning soil management on yield and cultivation cost per acre for rural farmers in India.

Despite clear long-term benefits associated with GAPs, effectively motivating farmers to adopt them remains a challenge. Different approaches have been suggested to address this issue such as government subsidies and regulations to enforce and support adoption[24]. On the other hand, proponents of voluntary approaches suggest that by educating farmers about the benefits of GAPs, farmers will naturally be inclined to adopt practices purely by their desire to maximize their profits. Adoption should be understood as a multiple-stage process that is guided by social and

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cognitive processes in the early stages, which result in profit-maximizing behavior from farmers in the later stages[34]. Both perspectives offer potential solutions, and finding the right balance between subsidization and education is key to encouraging widespread adoption.

We present evidence showcasing the effect of adopting climate-smart soil practices on yield and cost per acre. We use an instrumental variable approach to estimate the causal effect of the adoption of GAPs on sugarcane yields and cultivation costs per acre. We use the distance from the nearest town center to instrument for GAP adoption. We find that implementing more GAPs leads to a non-statistically-significant decrease in sugarcane yield and a statistically significant decrease in cultivation cost.

Our data originates from a survey conducted by the Olam International group in partnership with the IFC. The purpose of the survey was to assess the impact of training programs aimed at enhancing farmers' climate resilience. This initiative comes at a particularly crucial time as agricultural regions in Maharashtra and Madhya Pradesh, India grapple with severe droughts[22;28;29]. The heavy reliance on monsoon rainfall, coupled with inadequate investment in irrigation infrastructure, leaves farmers highly susceptible to adverse conditions. Furthermore, unsustainable cultivation methods and excessive irrigation contribute to water waste and soil degradation. The situation is exacerbated by the unpredictable nature of monsoons, often leading to destructive flash floods that further deteriorate soil health[18]. Alongside these challenges, more than 10,000 Indian farmers took their own lives in 2020[21]. While the impacts droughts and floods affect all smallholder farmers, crops ,such as sugarcane which require substantial water resources, bear a disproportionate burden.

We aim to contribute to the growing body of literature by evaluating the effect of adopting GAPs. The aims of GAPs are to (1) increase productivity to produce more and better food and improve nutrition security, (2) enhance resilience to reduce farmer vulnerability to drought, pests, diseases, and other climate-related-risks, and (3) reduce emissions emissions for each calorie or kilo of food produced, avoid deforestation from agriculture, and to absorb carbon out of the atmosphere[6]. For example, climate change has adversely impacted wheat yields, even though there have been tremendous advances in crop breeding[8]. Ultimately, these short-sighted methods damage sustainability and food security. Smallholder farmers who invest in smart agricultural practices exhibit increased productivity, increased income, and contribute to more sustainable food systems[3].

Past literature has attempted to demonstrate how adopting GAPs benefit the developing world and provides a theoretical framework to understand its adoption. However, recent literature concentrates on the observed impacts of GAP and how effective its adoption is[7]. This can be challenging to evaluate as it relies on data collected in conditions that are often unreliable[14]. To make matters worse, our data was collected without randomized assignment, resulting selection bias. To assuage these issues, some researchers have resorted to using satellite data to supplement their research, while others have chosen to use econometric techniques to mitigate potential biases in survey designs[2;11;12;23]. Some have implemented both techniques, utilizing geographical data as instrumental variables to correct for endogeneity[13]. Ultimately, it is essential for the future of economics in agriculture to prioritize quality data to make effective policy objectives[10].

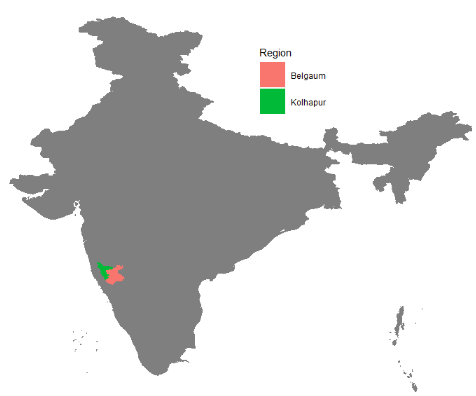
Beyond data quality, the adoption and retention of GAPs present an issue in itself as smallholder farmers often fail to adopt GAP practices that would seemingly benefit them. Addressing these barriers to adoption is often as important as understanding the effects of adopting GAPs. The most frequently cited explanations by researchers when discussing low adoption of GAPs or a product with positive net benefits are (1) a lack of money to invest in the new product and (2) a lack of information or awareness among users about the problem and possible solutions [5;24]. County-wide factors such as labor market failures can pose a significant challenge in implementing these practices, as they often require more workers [20]. Furthermore, there are other barriers that people living in poverty face in the context of behavioral change such as risk aversion, expected behavioral norms of others around them, and market participation [24;25]. When heavy subsidization is not possible but liquidity constraints are a key determinant of low demand, micro-loans may offer a promising option in the search for sustainable public health initiatives.

The paper is organized in the following manner. Section II provides a summary of the survey data collected by Olam, highlighting the initial problems encountered. Section III outlines the theoretical method adopted for our analysis. Section IV presents the results of the analysis. Finally, Section VI concludes the paper.

2 Data

We use data from a survey conducted by the Olam International Group, a worldwide agribusiness company with investments in the sugar industry in India in partnership with the IFC. The surveyors selected 1,136 farmers from villages nearby Rajgoli and Barwani, India to survey as a baseline in 2018. In 2022, the surveyors collected endline data on 727 individuals, some of whom were not surveyed previously. Between 2018 and 2022, a portion of these surveyed farmers received various trainings on sugarcane farming and other received other benefits through a partnership with Olam and the IFC.

Figure 1: Map of the Regions of Study



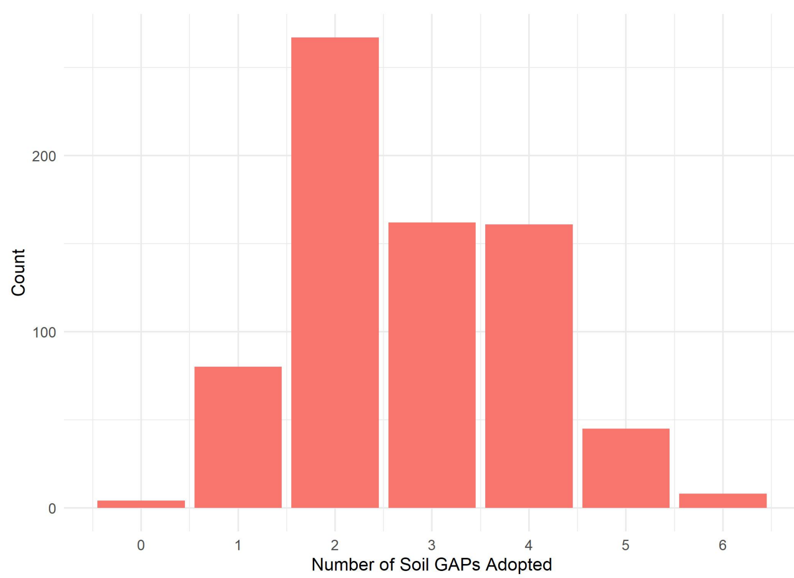
Note: The data to create this figure was obtained from The University of Texas at Austin GeoData.

The average farming household in our survey has a head-of-household who is a 60-year-old male, owns approximately 4 acres of land, and has a household size of 6 family members. 87% of the households in our survey expressed a desire to increase their sugarcane production. On average, these farmers adopted three soil GAPs, highlighting their engagement in sustainable farming techniques.

2.1 Data Preparation

Our dataset comprises 727 observations which were collected at the endline of the survey. We opt to conduct a cross-sectional analysis instead of a panel analysis because many farmers surveyed in the baseline were not followed up with during the endline. This decision allows us to maintain a larger sample size for our analysis, enabling more robust statistical inferences. The variables we include in our analysis are the number of GAPs a farmer adopted, their years of experience farming, the price they sell their sugarcane, their district, and their distance to the nearest town center.

Figure 2: Histogram of Number of GAPs Adopted



Note: This figure is a histogram of the number of soil GAPs each farmer in our study adopted. The maximum number of soil GAPs that it is possible to implement in our study is six.

Farmers most frequently adopted 2 soil GAPs, while those who adopted none or all of the GAPs we study are scarce.

To determine the distance from each farm to the nearest town or city, we utilize the freely available OpenStreetMaps mapping service. OpenStreetMaps provides information on towns and cities based

Table 1: Summary Statistics

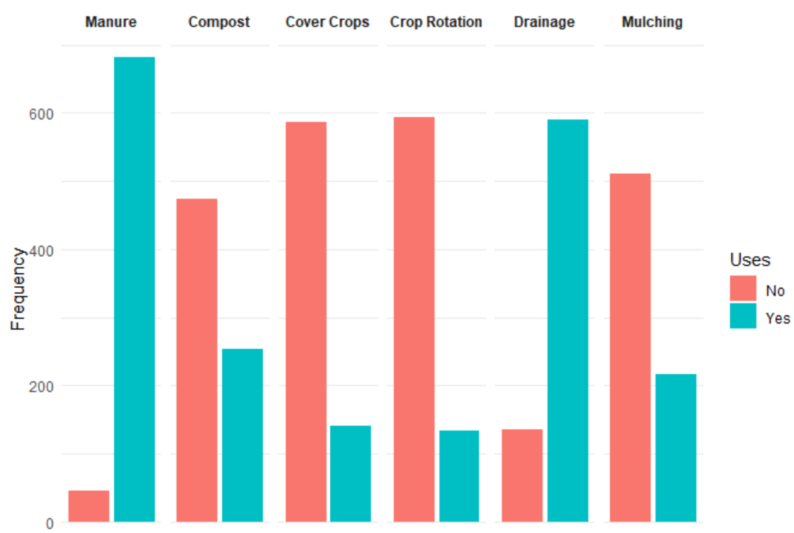
	Total
	(N=727)
Average Yield Per Acre (Tons)	
Mean (SD)	34.5 (10.3)
Median [Min, Max]	35.0 [10.0, 80.0]
Cultivation Cost (1000 Rupees)	
Mean (SD)	80.3 (73.4)
Median [Min, Max]	59.5 [5.73, 616]
Number of Soil Gaps	
Mean (SD)	2.77 (1.17)
Median [Min, Max]	3.00 [0, 6.00]
Sales Price per Ton (1000 Rupees)	
Mean (SD)	2.90 (0.0999)
Median [Min, Max]	2.93 [2.50, 3.20]
Missing	5 (0.7%)
Years of Sugarcane Cultivation Experience	
Below 5	28 (3.9%)
5 to 10	97 (13.3%)
Above 10	602 (82.8%)
Production Plans	
Increase Production	633 (87.1%)
Maintain Production	92 (12.7%)
Decrease Production	2 (0.3%)
District	
Belgaum	252 (34.7%)
Kolhapur	475 (65.3%)
Household Size	
Mean (SD)	5.61 (2.74)
Median [Min, Max]	5.00 [1.00, 15.0]
Age of Head of Household	
Mean (SD)	60.1 (10.6)
Median [Min, Max]	61.0 [30.0, 85.0]
Missing	601 (82.7%)
Total Land Owned (Acres)	
Mean (SD)	4.16 (4.42)
Median [Min, Max]	3.00 [0.00100, 40.0]

Note: This summary statistics table displays the means, standard deviations, and quartiles for the quantitative variables in our study. It displays frequencies for categorical variables in our study.

on the administrative council overseeing them.[1] By leveraging the coordinates of each town and city in proximity to the households, we are able to calculate the distance between each household and all towns and cities. Subsequently, we select the city with the shortest distance to determine the nearest city for each household. This approach enables us to identify the shortest distance from each farm to a city accurately.

We stratify soil GAP adoption into different groups in Figure 3. Manure application and drainage are the most widely adopted soil GAPs, while crop rotation and cover crops are scarce.

Figure 3: Bar Plot of GAP Adoption



Note: This figure is a barplot of GAP adoption broken down by GAP. Our sample size is 727 farmers.

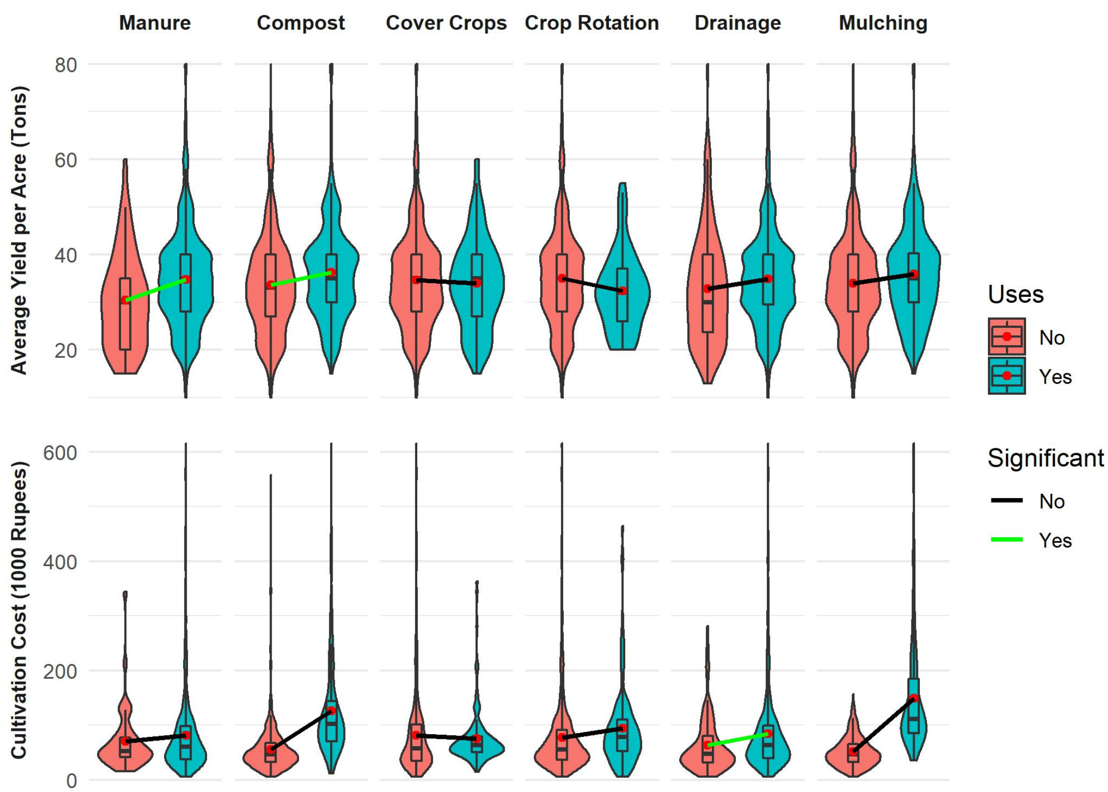
We include the soil GAPs that regard the utilization of manure, compost, cover crops, crop rotation, proper drainage practices, and mulching. These practices work to restore and maintain soil health. The application of manure and compost play a crucial role in replenishing vital nutrients and maintaining soil health. By adding manure and compost, the field receives a rich source of nutrients, ensuring the soil remains fertile and productive. Cover cropping is another beneficial practice where additional plant species are grown during the off-season or alongside cash crops, which help preserve soil structure and nutrients. They prevent erosion, capture excess nutrients, and contribute to the overall health of the soil. Unlike cover cropping, crop rotation involves the cultivation of different cash crops in a specific sequence, allowing for soil nutrient replenishment and reduction of pest and disease pressures. Mulching is a practice where the soil is covered with materials like straw or other organic substances. This protective layer minimizes water evaporation, mitigates erosion, and reduces nutrient loss. Mulching helps to maintain moisture levels in the soil, provides insulation, and creates a favorable environment for microbial activity. All of these practices contribute to

[1] For more information see the documentation: https://wiki.openstreetmap.org/wiki/India/Places

maintaining a healthy soil biome, which is vital for sustainable and long-term farming. However, many of the positive effects of these practices may take a few years after implementation until they are fully realized.

In Figure 4, we can see that adopting manure and compost GAPs are significantly correlated with higher yields. We can also see that adopting drainage GAPs is significantly correlated with higher costs.

Figure 4: Violin Plots of Outcomes by GAP Adoption



Note: This figure is a violin plot displaying the correlations between adopting GAPs and outcomes (yields or cultivation costs). Green lines represent a significant difference in mean outcomes.

2.2 Data Ethics

The adoption of GAPs is directly influenced by whether farmers receive training in these practices. Choosing proper smallholder farmers for training and administering climate-safe agriculture practices is difficult because of budget and resource constraints. By nature, this will create disparities between those who receive training, and those who do not. This specific study targeted farmers in the regions of Rajgoli and Barwani which exclude other regions. There are also underlying biases that affect the selection process of those who were surveyed and those not.

Selection for training is highly influenced by farmers who have a history of complying or demonstrating desirable characteristics. This bias excludes farmers who may not have the required characteristics that align with the training criteria or who have previously not adopted practices in the past. This could exclude groups of individuals (for example house headed women who are impoverished and illiterate) from receiving training over several generations. Underlying ethical factors such as inequity, political strife, and stratification of minority groups are inextricably linked with inferences made from data. It is crucial that we recognize and address appropriate data ethics concerning our research design as they will introduce unobserved biases otherwise.

For example, in many East Asian countries, as well as in India, the president (or its equivalent) heavily skews the selection process of the core officials and administrative agencies of the country which further perpetuates unethical political turnover [31]. Controlling the political turnover of public employees within a bureaucracy results in politically motivated replacement of important officials [4]. Corrupt actions by officials may dampen or confound the effects of GAPs that we find in the data.

Smallholder farmers lack influence and monetary resources to counteract corruption from rich farmers who collude with state officials, further impoverishing the rural poor [19]. Addressing institutional corruption becomes even more difficult because of nuances with the caste system and how it incentivizes corruption. Those who are able to purchase political influence within sugar cane societies tend to celebrate their capacity to engage in corrupt activities and boast of their abilities to deceive higher castes [19]. Corrupt and collusive institutions dampen causal effects of GAPs. For this reason, we pay particular attention to addressing both the biases that arise in the selection of the households (non random sampling) and to the treatment assignment (non random assignment of training) in our analysis below.

Climate-smart agricultural practices are crucial in addressing negative environmental impacts that arise from different implementations of agricultural methods. Multiple studies discuss the implications of global warming on a reduction in crop yield and the adverse climate effects of poor agricultural practices. Over the next 30 years, global temperatures are projected to increase by 0.2 Celsius and smallholder farmers need more capacity and stability to cope with these changes [3]. Furthermore, agriculture and its associated activities are the primary sources of rising green house gases (GHG) in the atmosphere [30]. These changes have an even bigger effect on smallholder farmers who generally reside in developing or under-developed areas. The farmers in these areas are largely dependent on agriculture for subsistence and lack proper infrastructure to adapt to climate change, as opposed to more developed regions. Instead, climate-friendly practices such as agroforestry, organic farming, rainwater harvesting, irrigation planning, and manure management should be implemented to promote climate-smart practices [30].

3 Methods

Given the non-randomized uptake of GAP adoption by the farmers in our survey, it is challenging to determine the impact of their adoption crop yield and cost. This is a problem because of the possibility of selection bias in our survey, which hinders our ability to establish causal inference in our estimates. Selection bias could arise from the fact that farmers with certain characteristics are more likely to adopt GAPs. To address this issue, we implement an instrumental variable approach that controls for selection bias by exploiting the random variation in GAP adoption introduced by our instrument to estimate the causal effect of the treatment variable on the outcome variables of interest. We use geospatial data from OpenStreetMaps to find the shortest distance from each farmer's household to the closest towns and use it as an instrument.

3.1 Yield

We begin with measuring the effects of adopting good agricultural practices in soil management on average crop yield. Our regression framework for measuring the effects of adopting GAPs on yield is outlined below, where equation 1 is our first stage framework and equation 2 is our second stage.

First Stage:

$$\begin{aligned} GAPs_i = &\tau_0 + \tau_1 TownDistance_i + \tau_2 Experience_i + \\ &\tau_3 SalesPrice_i + \tau_4 District_i + \upsilon_i \end{aligned} \tag{1}$$

Second Stage:

$$\begin{aligned} AverageYieldperAcre_i = &\beta_0 + \beta_1 GAPs_i + \beta_2 Experience_i + \\ &\beta_3 SalesPrice_i + \beta_4 District_i + \epsilon_i \end{aligned} \tag{2}$$

$AverageYieldperAcre_i$ is our outcome of interest and represents the average sugarcane yield per acre of farmer i. $GAPs_i$ is our dependent variable of interest and represents the number of GAPs farmer i has adopted. $TownDistance_i$ represents the distance of a farmer's house to the nearest town center, $Experience_i$ is an indicator for whether or not a farmer has been farming for over ten years, $SalesPrice_i$ represents the price at which a farmer sells a ton of sugarcane, and $District_i$ is an indicator for whether or not a farmer lives in Kolhapur. Each τ_j and β_j represents the effect of its corresponding variable for the first and second stages respectively. υ_i and ϵ_i are error terms for the first and second stages respectively.

3.2 Costs

We calculate costs by performing a summation on different reported costs for smallholder farmers, which is expressed by the variable $CultivationCostperAcre_i$. Our regression framework for measuring the effects of adopting GAPs on cultivation cost is outlined below, where equation **??** is our first stage framework and equation 4 is our second stage.

First Stage:

$$\begin{aligned} GAPs_i =& \tau_0 + \tau_1 TownDistance_i + \tau_2 Experience_i + \\ & \tau_3 SalesPrice_i + \tau_4 District_i + \upsilon_i \end{aligned} \tag{3}$$

Second Stage:

$$\begin{aligned} CultivationCostperAcre_i =& \beta_0 + \beta_1 GAPs_i + \beta_2 Experience_i + \\ & \beta_3 SalesPrice_i + \beta_4 District_i + \epsilon_i \end{aligned} \tag{4}$$

$CultivationCostperAcre_i$ is our outcome of interest and represents the average cultivation cost per acre of sugarcane farmland for farmer i. All other variables and coefficients have the same interpretations as in Section 3.1.

3.3 Instrumental Variable Approach

A variable is considered endogenous when its value is influenced by other known and unknown variables inside the equation. Addressing endogeneity is important because failing to do so will result in biased estimates. The potential sources of this bias include omitted variable bias, measurement error, and selection bias. However, our primary concern lies with selection bias due to the non-randomized nature of GAP adoption in our sample. The potential presence of selection bias complicates our ability to accurately determine whether the observed effects from GAP adoption are truly due to adoption or whether they are influenced by other unobservable factors that affect the uptake of GAPs. To mitigate this issue in our research, we employ an instrumental variable approach. However, this will only work if we select good instruments.

The exclusion restriction is key in establishing causal relationships among observed variables and outcome variables. It states that valid instruments should be unrelated to the error term in the regression equation. In other words, the instruments should not be affected by the same factors that influence the outcome variable directly. This assumption ensures that the instrumental variables only affect the endogenous explanatory variables and do not have any direct effect on the outcome variable. Instruments must fit the following assumptions: (1) relevance: the IV causes a change in the treatment received; (2) effective random assignment: the IV is independent of unmeasured confounding conditional on covariates as if it was randomly assigned conditional on covariates; and (3) exclusion restriction: the IV does not have a direct effect on outcomes. That is, it only affects outcomes through the treatment[?] .

3.4 Distance to Town Centers as an Instrument

We use the distance to the closest town center from each farmer's household as an instrument for GAP adoption. We expect that farmers who reside further from a town center require more farming assistance and have higher propensities to adopt GAPs. Our first stage results and weak instruments test statistic also support this expectation. Therefore, distance to a town center is a relevant instrument. Distance to a town center should also have no direct effect on average crop yield and cultivation cost or any of the variables that effect those outcomes. Since a farmer's decision on where to live with respect to a town center should be made randomly, distance to the closest town center is an exogenous variable. Therefore, our instrument also satisfies the exclusion restriction. This establishes the distance to the closest town center as a sound instrument.

3.5 Methods in Literature

The lack of randomization in the implementation of agricultural training by Olam poses a challenge in accurately identifying the effectiveness of different types of agricultural trainings. The difficulty lies within the quality of survey data and identifying variables to help isolate causal effects. For example, we simply could not run difference-in-difference models because our baseline and endline data were wildly inconsistent.

We turn to instrumental variable approaches as an alternative method for identifying training effects while accounting for endogeneity. Instrumental variables serve as statistical tools employed to tackle the issues of endogeneity and omitted variable bias when estimating causal inference. They entail the utilization of external variables, referred to as instruments, which exhibit correlation with the independent variable under investigation while bearing no direct association with the outcome variable[16]. By meeting the criteria of relevance and exogeneity, instrumental variables facilitate the estimation of the causal impact of the independent variable on the outcome variable, effectively simulating the characteristics of a randomized controlled experiment.

Selecting appropriate instruments to address endogeneity in farmer training programs is a complex task that requires careful consideration. The chosen instruments should exhibit a correlation with the treatment or adoption of the training while remaining uncorrelated with the outcome variable. Leveraging GPS data, particularly farm location, can be an effective approach to enhance the validity of the analysis by incorporating publicly available information alongside survey data. Farm location often plays a significant role in the selection process for training participation, while exerting minimal direct influence on farm outcomes[13].

For instance, previous studies have used river gradients and distance from dams as instruments to identify the degree to which large construction projects, such as dams, affect agricultural productivity, poverty, and health[15]. Additionally, distance from a town, marketplace, or office have been used instrument to address endogeneity in various contexts[13]. Moreover, latitude and longitude themselves can be utilized as instruments, providing additional options for instrument selection in addressing endogeneity concerns[17].

4 Results

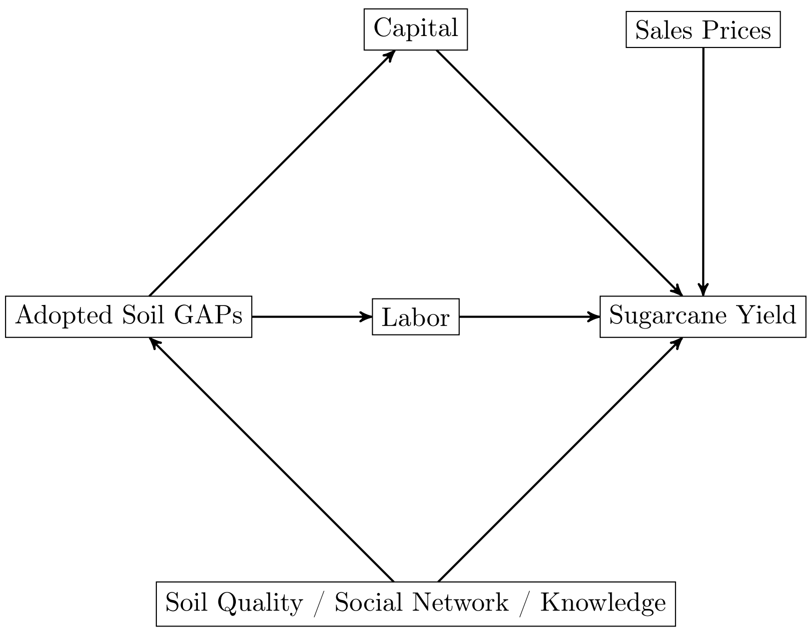
We adopt an instrumental variable framework to estimate the effect of good soil agricultural practices on sugarcane yields and cultivation costs. We find that implementing more of GAPs has no significant effect on yields but leads to a significant reduction in cultivation costs.

We perform robustness checks with an instrumental variable approach on GAP individually. GAPs show a heterogeneous effect on yield and cost. However, many of the GAPs report a low test statistic for the weak instrument test.

4.1 GAPs have no significant effect on yields

The mechanism by which GAPs affect yields can be seen in the directed acyclic graph (DAG) in Figure 5. This DAG represents a typical production function that is commonly studied in economic research, where the adoption of GAPs affects crop yield through both the farmer's labor and capital.

Figure 5: DAG of the Effect of Soil GAPs on Sugarcane Yield



To model this function, we estimate equation 2 from the previous section and report the results in Table 2. Columns 1 and 2 display the results for a naive ordinary least squares (OLS) model of average sugarcane yield per acre on the number of gaps a farmer has adopted. Based on column 2, each additional GAP a farmer adopts is associated with a 0.591 ton increase in average sugarcane yield per acre. This result is significant at the 10% level.

However, there are unobserved variables affecting both GAP adoption and yields that cannot be controlled for in our OLS model. This makes the results from our naive model dubious. For example, soil quality affects sugarcane output, and a farmer who wants to improve their soil would be more likely to adopt more soil GAPs. Another factor affecting both GAP adoption and yield is a farmer's social network. A strong social network provides a farmer with tools and resources that help increase sugarcane output, along with improving a farmer's knowledge and awareness of soil GAPs and how to implement them. Because soil quality and social-network-belonging were not measured in our data, they confound our results and necessitate an alternative estimation method to OLS. We, therefore, use an instrumental variable approach to estimate the effect of GAP adoption on sugarcane yield using only the exogenous variation in GAP adoption.

We use the distance of a farmer's household to the nearest town center as an instrument for GAP adoption. This is a valid instrument because satisfies exclusion restriction and relevance as shown in 3.4. The weak instruments test returns a test statistic of 8.7 which is close to the commonly accepted heuristic of 10.3 or above[33]. This provides further evidence that distance to the nearest town center is a valid instrument.

The results from our instrumental variable estimation are reported in columns 3 and 4 in Table 2. We can see that for each additional GAP a farmer adopts, their average sugarcane yield per acre decreases by 7.6 tons. This result is not statistically significantly different from zero at the 5% level. However, it is economically significant and an unexpected result. To put this into context, our results imply that a farmer with the average yield per acre in our sample (34.5 tons) would see their output drop by about 22 percentage points for each new GAP they implemented.

Table 2: Yield

	Dependent variable:			
	Average Yield Per Acre (Tons)			
	OLS		*Instrumental Variable*	
	(1)	(2)	(3)	(4)
Number of Soil GAPs	0.786**	0.591*	−4.784*	−7.596*
	(0.333)	(0.332)	(2.819)	(4.085)
Experienced Grower		0.573		2.782
		(0.988)		(1.761)
Sales Price		0.018***		0.028***
		(0.004)		(0.008)
Kolhapur		−1.468*		−0.761
		(0.874)		(1.212)
Constant	32.339***	−19.231*	47.794***	−28.361*
	(1.042)	(11.097)	(7.834)	(16.394)
Observations	727	722	727	722
R2	0.008	0.035	-0.394	-0.813
Adjusted R2	0.007	0.03	-0.396	-0.823
Residual Std. Error	10.275 (df = 725)	10.16 (df = 717)	12.179 (df = 725)	13.928 (df = 717)
F Statistic	5.573 ** (df = 1 ; 725)	7.157 *** (df = 4 ; 717)		
Chi Squared Statistic			2.881 * (df = 1 ; 725)	15.619 *** (df = 4 ; 717)
Weak Instruments			13.805 ***	8.691 ***
Wu-Hausman			5.626 **	7.712 ***
Note:				*p<0.1; **p<0.05; ***p<0.01

This result might differ in sign from our OLS estimate because unobserved farmer knowledge and social connections could be upward biasing our OLS estimate. These variables have a positive effect on both GAP adoption and sugarcane yield. Therefore, the positive effect of GAP adoption in our OLS estimate could be affected by farmers who implement more GAPs and have better knowledge and social networks which increase their yield and not the practice itself. Implementing an instrumental variable approach removes the effect of farmers-specific confounders that are correlated with adoption, and allows us to estimate the effect of GAP adoption on yield without these confounders.

Still, it might seem counter-intuitive that implementing more GAPs decreases yields. This could be caused by heterogeneous effects among different GAPs, which are not captured by our aggregate GAP variable. For example, two farmers could each have adopted three GAPs, but these could be a different combination of three GAPs. Since certain GAPs could affect yields in different directions and by different magnitudes, these two farmers would have different effects for the same number of GAPs implemented. This will be explored further in Section 4.3.

Our finding is not statistically different from zero because implementing more GAPs may not actually have an effect on yield. This could be the case if GAPs simply replace previous agricultural practices with climate-smart practices without improving the efficiency of practices. This supports GAP implementation because it makes yield more resilient and likely decreases the impact of adverse events such as droughts.[27] Furthermore, our results may not be statistically significant because soil GAPs take a few years until they become effective.[9;26] Since our data is comprised of farmers participating in an Olam-IFC partnership that focuses on improving climate-resilient practices, many of these farmers could have recently implemented GAPs. If that is the case, there would be no effect of soil GAPs on yield to pick up on.

We believe that our result for the effect of soil GAPs on sugarcane yields can be generalized to other farmers who grow sugarcane in similar climates to the farmers in our study. We would be cautious to generalize further because crop and climate likely have a great impact on yield.

4.2 GAPs decrease cultivation costs

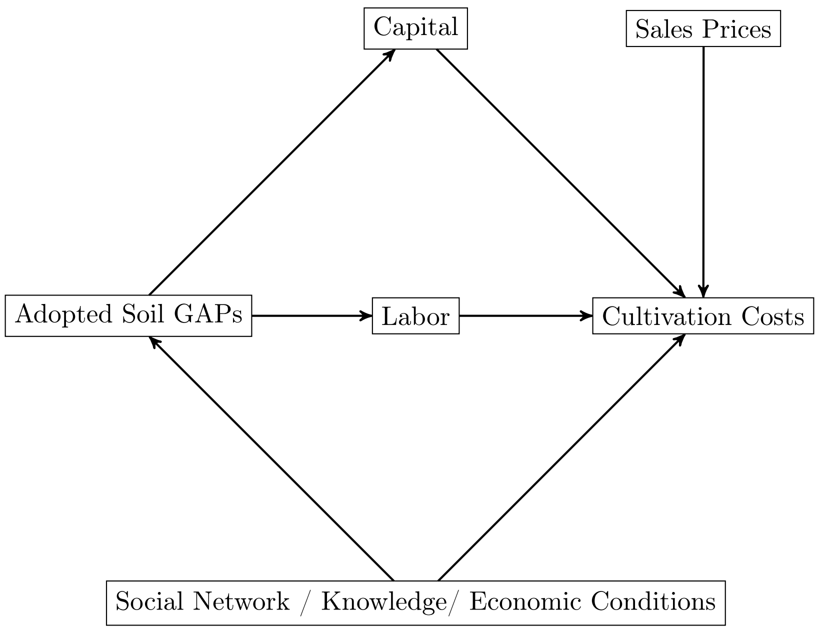
This section is laid out similarly to Section 4.1 and will, therefore, be briefer. Here, we are estimating the effect of GAP adoption on sugarcane cultivation costs. The mechanism through which GAPs affect cultivation costs can be seen in the production function DAG in figure 6.

To model this function, we estimate Equation 4 and report the results in Table 3. Columns one and two report the results from an OLS regression. From column two, for each additional GAP a farmer adopts, their sugarcane cultivation costs decrease by 2,557 rupees. This result is statistically significant at the 1% level but should not be interpreted as causal.

Consistent with our previous estimation, there are multiple variables that could confound soil GAP adoption and cultivation costs such as a farmer's social network, their knowledge, and economic conditions. To break these confounding relationships, we, again, implement instrumental variable estimation using a farmer's distance to the nearest town center as an instrument for GAP adoption. The justification for this instrument is the same as in Section 4.1 because we are using the same first-stage equation.

Columns three and four in Table 3 report the results for our instrumental variable regression. We can see that for each additional GAP a farmer adopts, their cultivation costs decrease by 11.5 thousand rupees. This result is statistically significant at the 1% level as well as economically significant. To put this into context, a farmer with the average cultivation cost in our sample

Figure 6: DAG of the Effect of Soil GAPs on Cultivation Costs



(80.3 thousand rupees) would see their cultivation costs decrease by 14 percentage points for each additional GAP they implement.

GAPs likely reduce costs by improving farmers' efficiency in utilizing inputs and reducing farm waste. For example, Cover Crops can prevent nutrient leaching in the soil thus reducing fertilizer input.[1] Additionally, Composting reduces organic waste on farms.[32] In combination, it makes sense that farmers who implement more GAPs have lower cultivation costs. As before, the effect of GAPs on cultivation costs may be heterogeneous. This will be addressed further in Section 4.3.

We believe that our result for the effect of soil GAPs on cultivation costs is generalizable to other farmers who grow sugarcane and experience similar economic conditions to what the farmers in our study experienced. We are cautious to generalize further, as crop and economic conditions likely have a great impact on costs.

Table 3: Cost

	Dependent variable:			
	Cost Per Acre (1000 Rupees)			
	OLS		*Instrumental Variable*	
	(1)	(2)	(3)	(4)
Number of Soil GAPs	-2.507^{***}	-2.557^{***}	-8.209^{***}	-11.507^{***}
	(0.324)	(0.327)	(2.878)	(4.330)
Experienced Grower		-0.240		2.175
		(1.081)		(1.867)
Sales Price		0.009^{**}		0.020^{**}
		(0.004)		(0.008)
Kolhapur		0.041		0.813
		(0.834)		(1.285)
Constant	42.938^{***}	17.687	58.757^{***}	7.707
	(1.032)	(12.398)	(7.999)	(17.378)
Observations	727	722	727	722
R2	0.073	0.078	-0.305	-0.835
Adjusted R2	0.072	0.073	-0.307	-0.845
Residual Std. Error	10.482 (df = 725)	10.466 (df = 717)	12.436 (df = 725)	14.764 (df = 717)
F Statistic	60.018 *** (df = 1 ; 725)	15.834 *** (df = 4 ; 717)		
Chi Squared Statistic			8.134 *** (df = 1 ; 725)	8.386 * (df = 4 ; 717)
Weak Instruments			13.805 ***	8.691 ***
Wu-Hausman			5.665 **	8.697 ***
Note:				*p<0.1; **p<0.05; ***p<0.01

4.3 Robustness Checks

In this section, we supplement our findings by exploring the effects of individual GAPs on yields and cultivation costs. Tables 4 and 5 report the results from our robustness checks for yields and cultivation costs, respectively. Columns one through six in both tables display the results of an instrumental variable estimation of the following equations:

$$\begin{aligned} AverageYieldperAcre_i =& \beta_0 + \beta_1 GAPofInterest_i + \beta_2 Experience_i + \\ & \beta_4 SalesPrice_i + \beta_5 District_i + \Omega_i \end{aligned} \tag{5}$$

$$\begin{aligned} CultivationCostperAcre_i =& \beta_0 + \beta_1 GAPofInterest_i + \beta_2 Experience_i + \\ & \beta_4 SalesPrice_i + \beta_5 District_i + \omega_i \end{aligned} \tag{6}$$

which are each estimated six times, with $GAPofInterest_i$ changing to represent each of the six GAPs we are interested in. We use distance to the nearest town center as an instrument for each GAP for similar reasons as before.

Column seven of each table displays the results of an OLS estimation of the following equations:

$$\begin{aligned} AverageYieldperAcre_i = & \beta_0 + \beta_1 CoverCrop_i + \beta_2 Drainage + \beta_3 Manure_i + \\ & \beta_4 Composting_i + \beta_5 CropRotation_i + \beta_6 Mulching_i + \\ & \beta_7 Experience_i + \beta_8 SalesPrice_i + \beta_9 District_i + \Omega_i \end{aligned} \tag{7}$$

$$\begin{aligned} CultivationCostperAcre_i = & \beta_0 + \beta_1 CoverCrop_i + \beta_2 Drainage + \beta_3 Manure_i + \\ & \beta_4 Composting_i + \beta_5 CropRotation_i + \beta_6 Mulching_i + \\ & \beta_7 Experience_i + \beta_8 SalesPrice_i + \beta_9 District_i + \omega_i \end{aligned} \tag{8}$$

As expected, GAPs have heterogeneous effects on yield and cultivation costs. It is important to note that our instrument does not seem valid for the composting and mulching GAPs due to the low test statistics reported for their respective weak instruments tests. Because of this, the results from columns 4 and 6 in Tables 4 and 5 should not be interpreted as causal effects. However, we do not believe that these weak tests invalidate our use of the instrument in our main analysis.

Using cover crops decreases yield significantly at the 5% level. Using manure and crop rotation decreases yield significantly at the 10% level. Only drainage increases yield significantly at the 5% level. These results support our main finding that implementing these GAPs decreases yield on average.

We cannot address the potential for interaction effects between different GAPs with our estimation method. Since instrumental variable models must be just or over identified, and we only have one valid instrument, we cannot estimate a regression equation that includes all possible GAPs, let alone their interactions.

Table 4

	Dependent variable:						
	Average Yield Per Acre (Tons)						Average Yield Per Acre (Tons)
	Instrumental Variable						*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cover Crop	-12.391^{**}						-0.888
	(5.324)						(0.918)
Drainage		19.473^{**}					1.056
		(9.252)					(1.055)
Manure			-41.154^{*}				4.843^{***}
			(23.858)				(1.584)
Composting				-72.166			2.427^{***}
				(103.162)			(0.938)
Crop Rotation					-24.892^{*}		-3.337^{***}
					(12.740)		(0.828)
Mulching						-41.718	0.167
						(35.755)	(0.971)
Experienced Grower	0.958	-0.501	1.625	5.357	-0.059	6.337	0.293
	(1.102)	(1.348)	(1.568)	(7.552)	(1.369)	(5.279)	(0.962)
Sales Price	0.021^{***}	0.010	0.016^{***}	0.039	0.022^{***}	0.029^{**}	0.019^{***}
	(0.005)	(0.006)	(0.006)	(0.033)	(0.006)	(0.012)	(0.004)
Kolhapur	-1.012	-2.441^{**}	-1.153	-2.992	-1.543	-0.517	-1.442^{*}
	(0.943)	(1.134)	(1.259)	(3.817)	(1.105)	(2.002)	(0.859)
Constant	-24.591^{*}	-8.025	25.639	-56.439	-24.846	-41.887	-24.288^{**}
	(12.745)	(15.013)	(31.382)	(66.950)	(15.202)	(31.391)	(10.938)
Observations	722	722	722	722	722	722	722
R2	-0.158	-0.415	-1.107	-11.811	-0.642	-3.605	0.073
Adjusted R2	-0.164	-0.423	-1.119	-11.883	-0.651	-3.631	0.061
Residual Std. Error	11.129 (df = 717)	12.306 (df = 717)	15.015 (df = 717)	37.024 (df = 717)	13.256 (df = 717)	22.198 (df = 717)	9.995 (df = 712)
F Statistic							7.052 *** (df = 9 ; 712)
Chi Squared Statistic	24.463 *** (df = 4 ; 717)	20.009 *** (df = 4 ; 717)	13.441 *** (df = 4 ; 717)	2.21 (df = 4 ; 717)	17.243 *** (df = 4 ; 717)	6.149 (df = 4 ; 717)	
Weak Instruments	28.877 ***	12.091 ***	6.806 ***	0.566	7.285 ***	1.863	
Wu-Hausman	5.704 **	5.658 **	8.251 ***	7.07 ***	5.232 **	7.093 ***	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5

	Dependent variable:						
	Cost Per Acre (1000 Rupees)						Cost Per Acre (1000 Rupees)
	Instrumental Variable						*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cover Crop	−18.771***						−4.029***
	(6.013)						(0.879)
Drainage		29.499**					0.047
		(12.002)					(0.946)
Manure			−62.343**				−2.451
			(28.569)				(1.929)
Composting				−109.321			−1.066
				(141.719)			(0.982)
Crop Rotation					−37.708**		1.432
					(17.485)		(0.878)
Mulching						−63.197	−7.501***
						(44.119)	(1.017)
Experienced Grower	−0.589	−2.799	0.421	6.075	−2.130	7.560	0.315
	(1.244)	(1.749)	(1.878)	(10.374)	(1.879)	(6.513)	(1.057)
Sales Price	0.009*	−0.008	0.002	0.037	0.011	0.021	0.008*
	(0.005)	(0.008)	(0.007)	(0.045)	(0.008)	(0.015)	(0.004)
Kolhapur	0.433	−1.732	0.219	−2.567	−0.371	1.182	0.110
	(1.064)	(1.471)	(1.508)	(5.244)	(1.517)	(2.470)	(0.808)
Constant	13.418	38.513**	89.509**	−34.827	13.032	−12.783	17.541
	(14.393)	(19.474)	(37.580)	(91.972)	(20.863)	(38.734)	(12.360)
Observations	722	722	722	722	722	722	722
R2	-0.33	-1.145	-1.721	-20.778	-1.786	-5.316	0.13
Adjusted R2	-0.337	-1.157	-1.737	-20.9	-1.802	-5.351	0.119
Residual Std. Error	12.569 (df = 717)	15.963 (df = 717)	17.98 (df = 717)	50.862 (df = 717)	18.193 (df = 717)	27.39 (df = 717)	10.2 (df = 712)
F Statistic							12.279 *** (df = 9 ; 712)
Chi Squared Statistic	11.571 ** (df = 4 ; 717)	7.174 (df = 4 ; 717)	5.654 (df = 4 ; 717)	0.707 (df = 4 ; 717)	5.523 (df = 4 ; 717)	2.436 (df = 4 ; 717)	
Weak Instruments	28.877 ***	12.091 ***	6.806 ***	0.566	7.285 ***	1.863	
Wu-Hausman	10.157 ***	14.212 ***	12.058 ***	12.654 ***	13.306 ***	11.396 ***	
Note:							*p<0.1; **p<0.05; ***p<0.01

4.4 Welfare Analysis

This section provides a simple calculation to explore the welfare effect of implementing GAPs. The average sales price per ton of sugarcane for a farmer in our sample is 2,900 Rupees. Combining that number with our previous results, we find that each additional GAP a farmer implements will cost them 10,521 Rupees per acre based on the following equation:

$$11,507 \;\; Rupees/Acre + (-7.596 \;\; tons/Acre \times 2,900 \;\; Rupees/ton) = -10,521 \;\; Rupees/Acre \quad (9)$$

This implies that farmers should be given a subsidy to encourage them to implement more GAPs. While that would almost certainly work, the subsidy, if necessary, would probably not have to be as much as 10,521 Rupees per acre. This number fails to capture some of the long-term and unmeasured benefits of GAPs such as more resilient crops and more efficient labor hours. Still, some GAPs might have a high initial cost to implement that many of the farmers in our study could not afford. In cases like this, some type of subsidy would be warranted.

5 Conclusion

In the face of rising climate adversity in India, smallholder farmers in the developing world are confronted with a crucial decision: whether to adhere to traditional farming techniques or to embrace more sustainable, resilient practices. To improve climate resilience among smallholder farmers, households must prioritize the adoption of Good Agricultural Practices (GAPs). These practices are designed to minimize environmental impact, conserve water resources, preserve soil quality, and ultimately enable farmers to safeguard the sustainability of their farming operations for future generations. However, the effects of GAPs are difficult to measure because of poor data quality with complex surveys, recall bias, and a lag effect associated with adoption. We utilize an instrumental variable approach that incorporates the proximity to towns as an instrument for GAP adoption to estimate the effect of adopting GAPs on cultivation cost per acre and sugarcane yield.

Through our study, we identify a non-significant decrease in yield by 7.6 tons per acre for each additional GAP a farmer implements. Moreover, we find a significant decrease in cultivation cost per acre of 11,500 Rupees for each additional GAP a farmer implements. Using the average cost per ton of sugarcane in our sample, each additional GAP a farmer adopts decreases their welfare by 10,500 Rupees per acre.

Moving forward, research must concentrate on assessing the effectiveness of other GAPs in bolstering farm efficiency. Households naturally choose to adopt practices when doing so maximizes the profits of their farms. To encourage the adoption of GAPs among farmers, it is crucial for organizations to conduct training to emphasize the cost reduction associated with these practices. However, it is important to acknowledge that farmers may encounter initial reductions in yields, necessitating consideration of short-term subsidies and the development of a comprehensive long-term implementation strategy.

6 Attribution

Jesse took on the bulk of creating document outlines and slideshow presentation formatting. He created LaTex formats, wrote introduction slides, instrumental variable methods, and imported graphics as well as formatted tables in the slide show. In the main latex document, he was the primary editor and continuously maintained proper document formatting and checked for grammar and passive voice, along with assisting in data cleaning and estimation methods. Jon created the notebook for both the causal group and machine learning group for accessing AWS in R for seamlessly accessing data. He laid the groundwork for the GitHub repository along with writing the README. He also used OpenStreetMaps to calculate the distance to the nearest town. Jon contributed to the paper by writing parts of the intro, data section, methods, and all of the conclusion. He provided a thorough explanation of specific GAP practices and provided information about valid instruments in both a slideshow format and our main document. Joe contributed substantially to the data cleaning and was the main lead on conducting the analysis. He also created all of the tables and figures used in the final paper. Joe wrote a majority of the results section, and some of the data, methods, and conclusion sections. He also edited most of the other sections and made corrections where necessary. Joe created and presented the results section of the slideshow and onward.

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