Call Me Maybe: Impact assessment of the cell phone based Early Warning System for Wheat Rust

By Simon Taye

Grinnell College

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*Wheat is one of the primary crops grown in Ethiopia. Amongst the main challenges for smallholder wheat farmers is wheat rust – a devastating disease that has been responsible for massive losses. To combat the disease the Early Warning System alerts farmers in high-risk areas and provides information on how to combat the disease through a hotline and SMS texts. I examine whether the EWS had an impact on wheat productivity using a triple difference-in-difference approach that examines if cellphone-owning wheat farmers had increased yields after the implementation of the program. My findings indicate that the program had no impact on productivity suggesting that cellphone-based programs alone cannot overcome the various structural issues faced by smallholder farmers*.

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1. **Introduction**

72 percent of Ethiopians are employed in the agricultural sector, about 95% of which are smallholder farmers (FAO, 2018). Despite being a significant part of the national economy, smallholder farmers face a variety of challenges that constrain their productivity. The Agricultural Transformation Agency (ATA) of Ethiopia was established in 2010 to address this issue. One of the means through which the ATA plans to increase smallholder productivity is through the increased use of ICT. In 2017, the ATA in collaboration with various institutes and governmental agencies launched a program to combat Wheat Rust. Wheat Rust is a major issue for wheat production with reported loss of crops due to past epidemics ranged from 50-100% in affected fields.[[1]](#footnote-1) The ATA’s Early Warning System (EWS) tracks the spread of the disease and forecasts possible areas of infection. EWS then sends out alerts to farmers in affected areas and provides information on how to best deal with it. The goal of this paper is to assess the impact the program had on smallholder farmer productivity.

Access to phones and increasing use of technology is not a fix all solution for productivity constraints. However, cell phones have become cheap and accessible even in developing countries, particularly in Sub-Saharan Africa. They have already reduced the barrier to banking, payments, and financial services. And more directly related to the small holder farmers, phones can reduce market inefficiencies by lowering the search cost for information through cheap access to knowledge that would otherwise require travel. They also allow people to actively look for information they want instead of passively consuming data from other sources such as the radio or newspaper. Thus, effective programs that make use of cellphones to help smallholder farmers could potentially have a significant impact. (Aker and Mbiti, 2011).

Aker (2010) shows that access to mobile phone reduced the grain price dispersion in Niger by about 10-16%. The effect was stronger for markets that were more distant or connected by unpaved roads, hinting at the fact that search costs are indeed a barrier. However, market and climate information provided by the Reuters Market Light to one hundred randomly chosen villages in Maharashtra, India did not lead to increased prices received by farmers, improved cultivation practices or reduced crop damage due to weather shocks (Fafchamps and Marcell, 2012). A more comprehensive review of literature on ICT impact on agricultural development finds that the results are mixed. Effects are often heterogeneous by crop and not always replicable (Nakasone et al., 2014). Mottaleb et al. (2021) reviews the EWS and finds that those who received the ATA’s warnings used more fungicide to counter the spread and were more aware of the disease; however, their yield was lower. Due to the use of non-random survey data restricted to only two regions of Ethiopia (Oromia and Amhara) the study cannot make causal claims and its findings do not generalize.

My goal is to fill in this gap through a more robust assessment of the program that makes use of the Ethiopian Socioeconomic Survey. The survey was collected by the Ethiopian Government’s Central Statistics Agency in collaboration with the World Bank. It is a nationally representative panel that includes comprehensive information on agricultural activities, cell ownership and various socioeconomic indicators. The data was collected during 2013, 2015 and 2018 allowing us to see the impact of the program by comparing yield before and after its implementation as well as check assumptions of the methodology.

I make use of a triple difference-in-difference approach to determine the causal impact of the program, with the outcome variable of interest being yield per area. Access to the EWS alerts is dependent on owning a cell phone. However, owning mobile phones is correlated to higher income and access to various other resources making endogeneity a concern. In our difference-in-difference model, we define the treatment group as wheat farmers who owned cell phones in 2018. This accounts for any productivity boost that owning a cell provides, yearly changes in productivity or diseases and issues that would impact output as well as the difference in wheat yield relative to other crops. To my knowledge, there is no mobile-phone based program implemented between 2015 and 2018 that raises concern of omitted variable bias. Furthermore, we are able to verify the parallel trends assumption required by this methodology.

I find that the ATA’s program had no impact on productivity with a statistically insignificant coefficient centered around zero. The result holds across various regions of Ethiopia and is robust to the inclusion of Woreda (the equivalent of districts) level fixed effects as well as controls for education and annual consumption. To account for spillover effects, I calculate the proportion of households that own cell phones in each Kebele (village). Using the cell density does not change the result of our analysis suggesting that the null result of our original model is not just due to spillover effects.

The rest of the paper is organized as follows: Section II discusses Wheat Rust as well as the ATA’s program. Section III discusses the data used and the empirical methodology. Section IV discusses results, and robustness checks while Section V presents the conclusions.

1. **Background**

Wheat is one of the main crops grown in Ethiopia and is amongst the nations primary source of calories – about 13% – behind only sorghum and maize. One of the main challenges of wheat production in Ethiopia is wheat rust: a fungal disease responsible for massive crop losses. In 2010, a devastating wheat rust epidemic affected about 600,000 ha of wheat – about one third of Ethiopia’s wheat area. Economic loss due to the epidemic was about US$250 million and despite US$3 million spent nationally on fungicide, wheat production losses were still estimated to be about 15-20%. [[2]](#footnote-2) Since 2010, wheat rust continues to be a major problem. Figure A, sourced from Meyer et al. (2021) shows the losses due to wheat rust from 2010 – 2019.

Farmers have three primary ways of coping with wheat rust: switching to other crops, using less productive but more resistant wheat varieties, or applying fungicide once rust has been diagnosed on their fields. There is no evidence of farmers switching away from wheat, as discussed later in the results section. Given that wheat rust is unlikely to be new to smallholder farmers in Ethiopia and the fact that the EWS alerts only give only a short-term notice, means that switching wheat varieties is a viable response to the wheat rust advisories.

While the sustainable long-term solution is the use of resistant strains, fungicide provides a costly but short-term solution to reducing damage due to the disease. Fungicide use is still very low in Ethiopia, relative to advanced economies such as the UK (Singh et al., 2016). Figure B sourced from Singh et al.. (2016) shows relative difference of fungicide use between the two countries. The EWS program was implemented with the goal of increasing awareness to increase use of fungicide in the short run and to promote use of disease resistant strains of wheat in the long term. [[3]](#footnote-3)

The EWS was implemented through the collaboration of six organizations, namely the Ethiopian Institute of Agricultural Research, the Ethiopian Ministry of Agriculture and Livestock Resources (MoALR), Ethiopian Agricultural Transformation Agency (ATA), the International Maize and Wheat Improvement Center (CIMMYT), the UK Met Office and the University of Cambridge. Piloted in a 2015 study, the EWS is built upon a 7-day forecast of wheat rust spore dispersion. Based on surveys and reports of existing wheat rust infection, the EWS sends out wheat rust advisories such as the MoALR, Federal and Regional Government agencies, FAO and more. Starting in 2017, wheat rust advisories were sent out directly to agricultural extension agents and smallholder farmers through the ATA’s 8028 Hotline – an interactive hotline as well as SMS-based source of agricultural information. [[4]](#footnote-4)

Mottaleb et al. (2021) finds that farmers in Oromia who received alerts from the EWS in 2015 all used fungicide compared to only 38% of farmers who did not receive it. In 2020 all farmers used fungicide, regardless of whether they received EWS alerts or not. However, the study finds that yields went down for those who received the alert. The authors do not provide an explanation for this result.

Between August – November 2017, 8 wheat advisories were distributed by the EWS with about 11 more being distributed throughout 2018. About 125,000 small holder farmers and 10,000 extension agents received these advisories through ATA’s 8028 hotline providing them with a three-week window to apply fungicide on their fields. However, the extent to which farmers responded to these messages or the impact it had on yield is not known. While there is a lack of data on fungicide use, I aim to see if the EWS advisories caused an increase in productivity.

1. **Data and Methodology**

To determine the causal impact of the EWS, I make use of the Ethiopian Socioeconomic Survey (ESS). The survey is a collaborative project between the Central Statistics Agency of Ethiopia and the World Bank Living Standards Measurement Study. The first wave of the ESS, known as the Ethiopian Rural Socioeconomic Survey (ERSS), was collected during 2011 and did not include urban areas. However, additional households were included in the subsequent waves of the survey, in addition to those found in the ERSS so that the serves as a nationally representative panel. The 2013 and 2015 ESS consisted of 5,262 households. The 2018 ESS which consists of an entirely new panel sampled about 6770 households from a planned 7,527.

The missing households not included in the 2018 ESS was due to local conflict and displacements. The majority of these were from the Benishangul Gumuz region. For a few households, partial data is available (e.g., agricultural data but not demographics or vice versa). All observations with the variables of interest have been included in this study. While the missing households do raise some concern about selection bias, the most populous regions - Oromia, Amhara, Tigray and SNNP - where most agricultural activity takes place were not significantly affected.

Another concern is that the 2013/2015 ESS are not regionally representative for the less populous regions. That is, they are nationally representative as well as representative of the four most populous regions mentioned earlier but not for the remaining regions. About 4,954 households were interviewed in the 2015 ESS, down from 5,262 households in 2013.[[5]](#footnote-5) No information is provided about the missing households, so it is impossible to determine whether the 2015 panel is still nationally representative.

Keeping these concerns in mind, the data itself is rich and contains detailed information on agricultural activities as well as various other information about the households in the survey. I make use of the harvest data, which details the harvested quantity, measured in kilograms, as well as the field size they were grown in, measured in square meters. Some households grew multiple crops in the same field and gave the proportion of the field used for each crop. These proportions were not all exact – less than ¼ of the field and more ¾ of the field alongside ¼, half, and ¾ were the possible values – so I compute the yield per area for each crop using both the upper and lower bound of the field area that could have been used. Using either value for the yield does not affect my findings.

The methodology I use depends on the kind of crop grown and cellphone ownership in addition to household education levels and consumption which are used as controls. All of these variables are available directly in the ESS. Using cellphone ownership at the individual level, I calculate the cell density at the kebele level (kebeles are the smallest administrative units in Ethiopia) as the proportion of households that own a cellphone in each kebele. Cell density is intended to capture spillover effects of owning a cellphone as neighbors living in the same village are likely to share information with each other. Below are some summary statistics of the variables of interest.

Table 1. Summary Statistics for Wheat Growing Households

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Mean | Median | SE | Obs |
| Crop Area - Upper Bound (Sq Meters) | 3014.2 | 1820.7 | (4788.3) | 2313 |
| Yield per Area - Upper Bound (Kg / Sq Meters) | 0.174 | 0.110 | (0.494) | 2245 |
| Highest grade completed in HH | 5.436 | 6 | (3.283) | 2313 |
| Total annual consumption | 28427.0 | 21354.3 | (25182.1) | 2246 |
| Oldest Female Member in HH | 42.12 | 40 | (15.12) | 2313 |
| Oldest Male Member in HH | 43.09 | 42 | (18.86) | 2313 |
| Male Member of age 18-39 in HH | 0.629 | 1 | (0.483) | 2313 |
| Female Member of age 18-39 in HH | 0.738 | 1 | (0.440) | 2313 |

Table 2. Summary Statistics for Non-Wheat Growing Households

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Mean | Median | SE | Obs |
| Crop Area - Upper Bound (Sq Meters) | 5449.2 | 2250.6 | (39482.8) | 15101 |
| Yield per Area - Upper Bound (Kg / Sq Meters) | 1.782 | 0.110 | (96.84) | 14778 |
| Highest grade completed in HH | 5.006 | 5 | (3.419) | 15101 |
| Total annual consumption | 28407.1 | 20882.7 | (28945.9) | 14584 |
| Oldest Female Member in HH | 40.58 | 38 | (15.21) | 15098 |
| Oldest Male Member in HH | 41.12 | 40 | (18.86) | 15098 |
| Male Member of age 18-39 in HH | 0.638 | 1 | (0.481) | 15101 |
| Female Member of age 18-39 in HH | 0.736 | 1 | (0.441) | 15101 |

Note the near 10-fold larger mean productivity of non-wheat crops as well as the much larger standard error and small median. Those results are mostly driven by a single enumeration area which consists of about sixty households. Table 3 presents summary statistics with that enumeration area dropped, bringing the numbers much closer to what we expect, and Table 4 presents summary statistics for the dropped area. No explanation is provided for the much higher yields of that area so most of the analysis in this paper excludes it. The estimated coefficients with those households included are still statistically insignificant, however the actual values are different given that all the households dropped do not grow wheat. Regression results with those households included can be found in the appendix.

Table 3. Summary Statistics for Non-Wheat Growing Households (Outliers Excluded)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Mean | Median | SE | Obs |
| Crop Area - Upper Bound (Sq Meters) | 5454.4 | 2256.1 | (39506.1) | 15083 |
| Yield per Area - Upper Bound (Kg / Sq Meters) | 0.635 | 0.109 | (13.55) | 14760 |
| Highest grade completed in HH | 5.006 | 5 | (3.419) | 15083 |
| Total annual consumption | 28400.8 | 20879.1 | (28958.0) | 14566 |
| Oldest Female Member in HH | 40.58 | 38 | (15.21) | 15080 |
| Oldest Male Member in HH | 41.12 | 40 | (18.85) | 15080 |
| Male Member of age 18-39 in HH | 0.637 | 1 | (0.481) | 15083 |
| Female Member of age 18-39 in HH | 0.737 | 1 | (0.440) | 15083 |

Table 4: Summary Statistics for Outlier Households

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  | Mean | SE | Obs |
| Crop Area - Upper Bound (Sq Meters) | 1140.1 | (980.2) | 18 |
| Crop Area - Lower Bound (Sq Meters) | 1140.1 | (980.2) | 18 |
| Yield per Area - Upper Bound (Kg / Sq Meters) | 942.1 | (2656.2) | 18 |
| Yield per Area - Lower Bound (Kg / Sq Meters) | 942.1 | (2656.2) | 18 |
| Highest grade completed in HH | 5.056 | (3.190) | 18 |
| Total annual consumption | 33481.5 | (16101.4) | 18 |
| HH has individual with a cellphone | 0.611 | (0.502) | 18 |
| Wheat | 0 | (0) | 18 |

To estimate the causal impact of the ATA’s Early Warning System, I use a triple difference in difference approach. I do so to get around the endogeneity problem that would arise if I ran a simple OLS regression using cell phone ownership as the independent variable. Since access to treatment is dependent on owning a cell phone, a simple model like the one below may seem viable.

However, owning a cell phone is correlated with higher consumption and education. Any increase we estimate will suffer from omitted variable bias.

Table 5: Summary Statistics for Households that own a Cell Phone

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Mean | Median | SE | Obs |
| Yield per Area - Upper Bound (Kg / Sq Meters) | 2.184 | 0.114 | (133.9) | 7178 |
| Highest grade completed in HH | 6.612 | 7 | (3.203) | 7413 |
| Total annual consumption | 34237.9 | 27103.5 | (28032.1) | 7159 |
| Total annual consumption divided by HH size | 6738.2 | 4959.6 | (6747.9) | 7159 |

Table 6: Summary Statistics for Households that do not own a Cell Phone

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Mean | Median | SE | Obs |
| Yield per Area - Upper Bound (Kg / Sq Meters) | 1.122 | 0.108 | (31.88) | 9842 |
| Highest grade completed in HH | 3.915 | 4 | (3.078) | 9998 |
| Total annual consumption | 24084.2 | 17168.9 | (28006.4) | 9668 |
| Total annual consumption divided by HH size | 5350.8 | 3733.0 | (6118.0) | 9668 |

Using wheat as our independent variable instead would cause similar concerns. The inherent productivity of wheat differs from other crops since it responds differently to climate conditions, soil quality and so on relative to other crops. It is also possible we would capture the effect of wheat rust itself. Interacting either wheat or cell ownership with the year of observation would account for the concerns mentioned above. However, yearly variation in productivity unrelated to the EWS program would still be a concern.

A graph of a number of crops

Description automatically generatedA chart of a wheat crop

Description automatically generated with medium confidence

Figure 1. Productivity of Wheat and Non-Wheat Crops by Year

To account for these concerns, I use a triple difference in difference approach, interacting year, cell ownership and an indicator variable for whether a household variable is growing wheat or not. This approach accounts for the omitted variables and the selection bias concerns discussed above. Thus, the final estimated model is:

With the coefficient of interest being which indicates the estimated increase in wheat yield for cellphone owning in 2018, after the implementation of the ATA’s program. I also include models with Woreda level fixed effects as well as controls for education and annual per capita consumption of a household for robustness. However, it is important to note that the estimate of this model is likely biased towards to 0 since it assumes that owning a cellphone implies that a household will use it to access the information provided by the ATA. Namely, we are measuring the access to treatment effect instead of the impact of the actual treatment. Spillover effects are also a concern since a household with a cellphone that gets information from the ATA is likely to share it with their neighbors. As a robustness test, an alternate specification with cell phone ownership density at the Kebele level is provided as a robustness check. Note that a continuous difference in difference requires a stronger set of assumptions and is not tested in this paper.

My model makes two main assumptions: First, that there were no cellphone-based programs that were implemented between 2015 and 2018 that would only impact wheat yield. To my knowledge, there were not any such programs. The second one is the parallel trends assumption. I test this assumption using the 2013 and 2015 ESS data and find that the coefficient on the interaction term of interest is not statistically significant. Thus, the parallel trends assumption holds. Figure 2 shows productivity of wheat and non-wheat crops by cellphone ownership and how it changes from 2013 to 2015. Table 7 presents the results of the regression used to test the parallel trends assumption.

A graph of a number of crops

Description automatically generatedA graph of wheat and no cell

Description automatically generated

Figure 2: Productivity of Crops by Year and Cellphone Ownership

Table 7: Test Parallel Trends Assumption: Effects on Yield per Area

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Yield per Area - Upper Bound (Kg / Sq Meters) | Yield per Area - Lower Bound (Kg / Sq Meters) | Yield per Area - Upper Bound (Kg / Sq Meters) | Yield per Area - Lower Bound (Kg / Sq Meters) |
| Wheat | -0.229\*\*\* | -0.281\*\* | -0.223\*\* | -0.285\*\* |
|  | (0.0556) | (0.0867) | (0.0602) | (0.0840) |
|  |  |  |  |  |
| Year == 2015 | 0.306 | 0.171 | 0.343 | 0.198 |
|  | (0.204) | (0.122) | (0.219) | (0.131) |
|  |  |  |  |  |
| HH has individual with a cellphone | 0.127 | 0.0325 | 0.169 | 0.0392 |
|  | (0.152) | (0.163) | (0.164) | (0.161) |
|  |  |  |  |  |
| Year \* Wheat | -0.233 | -0.101 | -0.284 | -0.145 |
|  | (0.213) | (0.131) | (0.218) | (0.136) |
|  |  |  |  |  |
| Year \* Cell | -0.434 | -0.274 | -0.468 | -0.301 |
|  | (0.238) | (0.178) | (0.247) | (0.185) |
|  |  |  |  |  |
| Cell \* Wheat | -0.0401 | 0.0516 | -0.0570 | 0.0412 |
|  | (0.150) | (0.156) | (0.155) | (0.161) |
|  |  |  |  |  |
| Cell \* Year \* Wheat | 0.304 | 0.148 | 0.367 | 0.204 |
|  | (0.234) | (0.168) | (0.237) | (0.172) |
|  |  |  |  |  |
| Highest grade completed in HH |  |  | -0.00217 | 0.00768 |
|  |  |  | (0.0193) | (0.0108) |
|  |  |  |  |  |
| Total annual per capita consumption |  |  | -0.0000196 | -0.0000146 |
|  |  |  | (0.0000133) | (0.0000119) |
|  |  |  |  |  |
| Constant | 0.369\*\*\* | 0.423\*\*\* | 0.450\*\* | 0.451\*\* |
|  | (0.0553) | (0.0897) | (0.127) | (0.148) |
| Observations | 12962 | 12980 | 12382 | 12400 |
| Adjusted *R*2 | 0.000 | -0.000 | 0.000 | -0.000 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

1. **Results and Robustness**

The results of the main regression, with and without controls are presented in Table 8. The coefficient of the interaction of three variables that determine our treatment – cell ownership, post (i.e., year is 2018) and wheat – is statistically insignificant. The coefficients are negative and close in magnitude to the mean yield per area for wheat presented in Table 1. The standards errors are also similar in magnitude to the coefficient. These two facts suggest that our results are not being driven by outliers nor are they being driven by heterogenous results on subgroups of our households.

Table 8: Effects on Yield per Area

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Yield per Area - Upper Bound (Kg / Sq Meters) | Yield per Area - Lower Bound (Kg / Sq Meters) | Yield per Area - Lower Bound (Kg / Sq Meters) | Yield per Area - Upper Bound (Kg / Sq Meters) |
| Wheat | -0.462\* | -0.381\* | -0.430\* | -0.514\* |
|  | (0.208) | (0.182) | (0.187) | (0.210) |
|  |  |  |  |  |
| Year == 2018 | -0.334 | -0.264 | -0.297 | -0.364 |
|  | (0.202) | (0.177) | (0.178) | (0.199) |
|  |  |  |  |  |
| HH has individual with a cellphone | -0.306 | -0.241 | -0.262 | -0.326 |
|  | (0.222) | (0.201) | (0.176) | (0.187) |
|  |  |  |  |  |
| Year \* Wheat | 0.299 | 0.230 | 0.279 | 0.351 |
|  | (0.205) | (0.178) | (0.181) | (0.204) |
|  |  |  |  |  |
| Year \* Cell | 0.281 | 0.218 | 0.239 | 0.306 |
|  | (0.222) | (0.202) | (0.204) | (0.222) |
|  |  |  |  |  |
| Cell \* Wheat | 0.264 | 0.200 | 0.239 | 0.308 |
|  | (0.211) | (0.190) | (0.196) | (0.215) |
|  |  |  |  |  |
| Cell \* Year \* Wheat | **-0.233** | **-0.171** | **-0.211** | **-0.276** |
|  | **(0.217)** | **(0.195)** | **(0.199)** | **(0.216)** |
|  |  |  |  |  |
| Highest grade completed in HH |  |  | -0.000479 | -0.00247 |
|  |  |  | (0.0175) | (0.0211) |
|  |  |  |  |  |
| Total annual per capita consumption |  |  | 0.000000652 | -0.000000303 |
|  |  |  | (0.00000187) | (0.00000235) |
|  |  |  |  |  |
| Constant | 0.675\*\* | 0.594\*\* | 0.622\* | 0.719\* |
|  | (0.207) | (0.182) | (0.249) | (0.292) |
| Observations | 10544 | 10557 | 10212 | 10199 |
| Adjusted *R*2 | 0.000 | -0.000 | -0.000 | -0.000 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

Table 9 and 10 show the results of our model applied to the different regions. Note that we have one statistically significant result in Harari. However, Harari is not a major agricultural region and thus we only have ten households in our sample from Harar that grow wheat. Thus, it is likely our result is due to noise. Similar to the previous results, the coefficients are close to the mean yield with standard errors not much larger in magnitude.

Table 9: Effects on Yield per Area by Region – Group 1

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Tigray | Afar | Amhara | Oromiya |
| Wheat | -0.180 | 0 | -0.183\*\* | -0.255 |
|  | (0.0880) | (.) | (0.0527) | (0.202) |
|  |  |  |  |  |
| Year == 2018 | -0.0409 | -0.333 | -0.0503 | -0.0843 |
|  | (0.123) | (0.151) | (0.0606) | (0.209) |
|  |  |  |  |  |
| HH has individual with a cellphone | -0.150 | 0.970 | -0.0922 | 0.0944 |
|  | (0.0949) | (1.083) | (0.0599) | (0.237) |
|  |  |  |  |  |
| Cell \* Year \* Wheat | -0.769 | 0 | -0.0361 | 0.151 |
|  | (0.406) | (.) | (0.0651) | (0.270) |
| Observations | 1944 | 105 | 3971 | 3625 |
| Adjusted *R*2 | 0.017 | 0.001 | -0.000 | -0.001 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

Table 10: Effects on Yield per Area by Region – Group 2

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Benishangul Gumuz | SNNP | Gambella | Harari |
| Wheat | -2.624 | -0.620\* | 0 | -0.516\*\* |
|  | (1.966) | (0.234) | (.) | (0.0269) |
|  |  |  |  |  |
| Year == 2018 | -2.287 | -0.377 | -10.20 | -0.400\* |
|  | (2.032) | (0.263) | (6.549) | (0.0554) |
|  |  |  |  |  |
| HH has individual with a cellphone | -2.877 | -0.286 | -4.634 | -0.0437 |
|  | (3.149) | (0.193) | (4.665) | (0.0135) |
|  |  |  |  |  |
| Cell \* Year \* Wheat | 0 | -0.279 | 0 | 0.0500 |
|  | (.) | (0.265) | (.) | (0.0144) |
| Observations | 793 | 4179 | 405 | 696 |
| Adjusted *R*2 | -0.006 | -0.001 | -0.001 | 0.012 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

Another concern is spillover bias. While farmers may need a phone to access information from the EWS alert directly, there is nothing stopping them from getting that information from their neighbor who has a cellphone. To account for this possibility, I estimated a similar model as described previously but with cell density substitute for cell phone ownership. I calculate cell density by determining the proportion of households that own a cellphone at the kebele level. The results presented in Table 11 are similar to the previous model. It is important to note that a continuous difference in difference model has stronger assumptions not tested in this paper. It is included here simply as a robustness test, and we should be careful when interpreting the results.

Table 11: Effects on Yield per Area

|  |  |  |
| --- | --- | --- |
|  | (1) | (2) |
|  | Yield per Area - Upper Bound (Kg / Sq Meters) | Yield per Area - Lower Bound (Kg / Sq Meters) |
| Wheat | -0.245 | -0.174 |
|  | (0.243) | (0.228) |
|  |  |  |
| Year == 2018 | -0.106 | -0.0524 |
|  | (0.226) | (0.212) |
|  |  |  |
| Proportion of HH that have cell in the same Kebele | 0.319 | 0.348 |
|  | (0.611) | (0.546) |
|  |  |  |
| Year \* Wheat | 0.122 | 0.0617 |
|  | (0.234) | (0.219) |
|  |  |  |
| Year \* Cell Density | -0.222 | -0.262 |
|  | (0.538) | (0.482) |
|  |  |  |
| Cell Density \* Wheat | -0.256 | -0.301 |
|  | (0.567) | (0.516) |
|  |  |  |
| Cell Density \* Year \* Wheat | 0.188 | 0.234 |
|  | (0.529) | (0.478) |
|  |  |  |
| Highest grade completed in HH | -0.0154 | -0.0119 |
|  | (0.0271) | (0.0223) |
|  |  |  |
| Total annual per capita consumption | -0.00000183 | -0.000000741 |
|  | (0.00000305) | (0.00000233) |
|  |  |  |
| Constant | 0.494 | 0.405 |
|  | (0.248) | (0.238) |
| Observations | 10199 | 10212 |
| Adjusted *R*2 | -0.000 | -0.000 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

Other factors that could be driving results is farmers switching away from wheat due to the warnings or prevalence of Wheat Rust. However, nothing in the data suggests this is happening as we can see from Figure 3.

A graph of a farmer's harvest

Description automatically generatedA graph of growing crops

Description automatically generated

Figure 3. Proportion of Wheat Farmers by Year and Region

1. **Conclusions**

Given the damaging nature of Wheat Rust, it is a little disappointing that our results suggest that the ATA’s program to combat it had no impact. However, there are various possible explanations. First, cellphone ownership may not be a good indicator for access to the information provided by the ATA. Households who own cellphones may not be aware they can access the information, or it is possible they have already received it from other sources, such as the agricultural extension agents.

Second, it is possible that a lack of information was never a barrier to countering Wheat Rust. For example, it is possible that farmers could not access or afford the fungicide needed. Or farmers in at risk areas could have already switched to disease resistant varieties. In this scenario, the ATA’s program may still provide value by helping farmers be efficient in their use of fungicide. That is, only those that really need will use it since they can rely on the Early Warning System, thus reducing costs for those who are not in danger. At the same time, those who are exposed to the disease can minimize crop loss because of the program. A major limitation of this paper is the lack of qualitative information and data on fungicide use which would help us interpret our results better and investigate further.

An area of future research could be to fill this gap by determining better indicators of access to the Wheat Rust warnings. Similarly, data on households that received the program as well as more information on its implementation would be valuable in assessing the program. As it is, however, the results of this paper alongside the various literature that analyzes similar programs suggests that cellphones may still have potential as tool of agricultural productivity improvement and general development aid; but this is conditional on them being applied to right problem. The kinds of problems phones can be used to address and how they can be used to address them still needs to be further studied.

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1. **Appendix**

A graph of different colored lines

Description automatically generated

Figure A: Losses due to Wheat Rust (2010-2019)

A graph of a number of individuals

Description automatically generated with medium confidence

Figure B: Fungicide Use in Ethiopia (1995 – 2010)

A diagram of a wheat survey system

Description automatically generated

Figure C: EWS Infrastructure

**Results with Outliers Included**

Below are the results of regressions with outlier houses included.

Table A: Effects on Yield per Area – Outliers Included

|  |  |  |
| --- | --- | --- |
|  | (1) | (2) |
|  | Yield per Area - Lower Bound (Kg / Sq Meters) | Yield per Area - Upper Bound (Kg / Sq Meters) |
| Wheat | -0.256 | -0.340 |
|  | (0.291) | (0.308) |
|  |  |  |
| Year == 2018 | 5.913 | 5.848 |
|  | (6.333) | (6.340) |
|  |  |  |
| HH has individual with a cellphone | 0.435 | 0.370 |
|  | (0.795) | (0.803) |
|  |  |  |
| Year \* Wheat | -4.622 | -4.551 |
|  | (4.997) | (5.001) |
|  |  |  |
| Year \* Cell | 12.76 | 12.84 |
|  | (12.87) | (12.87) |
|  |  |  |
| Cell \* Wheat | 0.203 | 0.268 |
|  | (0.252) | (0.272) |
|  |  |  |
| Cell \* Year \* Wheat | -12.66 | -12.73 |
|  | (12.79) | (12.79) |
|  |  |  |
| Highest grade completed in HH | -0.132 | -0.134 |
|  | (0.158) | (0.158) |
|  |  |  |
| Total annual per capita consumption | -0.000254 | -0.000256 |
|  | (0.000264) | (0.000264) |
|  |  |  |
| Constant | 2.126 | 2.225 |
|  | (1.609) | (1.614) |
| Observations | 10230 | 10217 |
| Adjusted *R*2 | 0.000 | 0.000 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

Table B: Cell-Share effect on Yield per Area – Outliers Included

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | Yield per Area - Upper Bound (Kg / Sq Meters) | Yield per Area - Lower Bound (Kg / Sq Meters) | Yield per Area - Upper Bound (Kg / Sq Meters) | Yield per Area - Lower Bound (Kg / Sq Meters) |
| Wheat | -0.257 | -0.188 | -0.227 | -0.170 |
|  | (0.228) | (0.217) | (0.289) | (0.269) |
|  |  |  |  |  |
| Year == 2018 | 0.108 | 0.169 | 1.955 | 2.007 |
|  | (1.981) | (2.003) | (3.191) | (3.201) |
|  |  |  |  |  |
| Proportion of HH that have cell in the same Kebele | 0.273 | 0.311 | 0.835 | 0.865 |
|  | (0.542) | (0.496) | (0.816) | (0.773) |
|  |  |  |  |  |
| Year \* Wheat | -0.0741 | -0.136 | -0.329 | -0.378 |
|  | (1.959) | (1.981) | (1.932) | (1.947) |
|  |  |  |  |  |
| Year \* Cell Density | 23.91 | 23.85 | 22.75 | 22.70 |
|  | (24.02) | (24.03) | (22.82) | (22.83) |
|  |  |  |  |  |
| Cell Density \* Wheat | -0.184 | -0.224 | -0.114 | -0.121 |
|  | (0.539) | (0.492) | (0.614) | (0.570) |
|  |  |  |  |  |
| Cell Density \* Year \* Wheat | -24.00 | -23.95 | -23.46 | -23.45 |
|  | (23.99) | (23.99) | (23.57) | (23.61) |
|  |  |  |  |  |
| Highest grade completed in HH |  |  | 0.0349 | 0.0380 |
|  |  |  | (0.0845) | (0.0825) |
|  |  |  |  |  |
| Total annual per capita consumption |  |  | -0.000233 | -0.000232 |
|  |  |  | (0.000237) | (0.000236) |
|  |  |  |  |  |
| Constant | 0.408 | 0.340 | 1.057 | 0.968 |
|  | (0.230) | (0.218) | (0.696) | (0.699) |
| Observations | 10562 | 10575 | 10217 | 10230 |
| Adjusted *R*2 | 0.000 | 0.000 | 0.000 | 0.000 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

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2. Jaleta and others. [↑](#footnote-ref-2)
3. Clare Allen-Sader and others, ‘An Early Warning System to Predict and Mitigate Wheat Rust Diseases in Ethiopia’, *Environmental Research Letters*, 14.11 (2019), 115004 <https://doi.org/10.1088/1748-9326/ab4034>. [↑](#footnote-ref-3)
4. Allen-Sader and others. [↑](#footnote-ref-4)
5. The information document for the 2015 ESS contains a discrepancy in the number of households in the panel. The document states about 4981 households were interviewed and 478 were not, bringing the total to 5,459. This is inconsistent with the rest of the document which states that the panel size is 5,262 consistent with the 2013 ESS. [↑](#footnote-ref-5)