Yield effects of rust-resistant wheat varieties in Ethiopia

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Abstract

Breeding crops for disease resistance is a sustainable approach to reduce yield losses. While significant research on the adoption and impacts of improved crop varieties exists, most studies have analyzed yield effects in general, without distinguishing between different varietal traits and characteristics. Here, panel data from wheat farmers in Ethiopia are used to compare improved varieties that are resistant to stripe rust (caused by *Puccinia striiformis f. sp. tritici*) with improved susceptible and traditional susceptible varieties. Production function estimates suggest that improved resistant varieties raise effective yields by 8% in comparison to local susceptible varieties. The yield difference between improved resistant and improved susceptible varieties is positive but small, because rust levels were not very high in the years under study. However, under drought and other abiotic stresses, improved varieties – with and without resistance to stripe rust – perform notably worse than local varieties. The worse performance under abiotic stress may also explain why many farmers recently switched back to growing traditional varieties. Sustainable adoption needs a combination of various traits in the same varieties, including high yield potential, grain quality, disease resistance, and tolerance to drought and other production stresses.

1. Introduction

Plant pests and diseases cause considerable crop losses in worldwide agriculture (Oerke 2006; Strange and Scott 2005; Savary et al. 2012; Savary et al. 2017). In many regions, crop losses caused by insects, fungi, bacteria, viruses, and other pathogens are estimated at 15-20% on average; during acute epidemics actual losses can be much higher (Oerke 2006; FAO 2014). Plant genetic improvement through breeding can help to reduce such losses without having to increase the use of chemical pesticides (Dixon et al. 2006; Savary et al. 2006, 2012; Stuthman et al. 2007; Velu and Singh 2013). Reducing crop losses and thus sustainably increasing effective yield is key for meeting future food demand (Hertel 2015; Kassie et al. 2015; Savary et al. 2017).

However, breeding plants for resistance is a complex and enduring process. Evolving pest and pathogen populations can overcome existing plant genetic resistance so that there is continuous need to identify and develop new resistance mechanisms. Furthermore, pest and disease resistance traits have to be introduced to locally adapted and preferred varieties. Otherwise, advantages through lower crop losses from pests and diseases could be canceled out by disadvantages resulting from the use of germplasm not well adapted to soil and climatic conditions or quality preferences in a particular context (Krishna et al. 2016; Qaim et al. 2006; Smale et al. 1998). Lack of local adaptation may in turn affect the willingness of farmers to adopt new pest- and disease-resistant varieties.

While such linkages are well understood in theory, they have rarely been examined in empirical research with data from farmers' fields. Many studies on the adoption of improved crop varieties have evaluated yield effects in general, yet without differentiating between different crop traits and varietal characteristics (Di Falco et al. 2007; Matuschke et al. 2007; Mazid et al. 2015; Teklewold et al. 2013; Walker and Alwang 2015). We contribute to this literature by unpacking yield differentials of three varietal traits: disease resistance, yield potential, and adaptation to local abiotic stresses. Specifically, using data from a panel survey of wheat farmers in Ethiopia we compare yields of improved resistant varieties with and without disease resistance and yields of traditional varieties. The results could help to better understand whether crop improvement programs have succeeded in developing and disseminating varieties that are well adapted to biotic and abiotic stresses of local relevance.

Wheat is one of the most important food security crops in the world, accounting for a sizeable share of the global calories and protein consumed (Shiferaw et al. 2013). The importance of wheat in Africa is also increasing. Wheat is affected by various diseases, the most important of which are rusts caused by fungal pathogens. There are different types of wheat rust with multiple races (Hodson 2011; Chen et al. 2014; Morgounov et al. 2012; Velu and Singh 2013). The most common rusts are stem rust (*Puccinia graminis f. sp. tritici*), leaf rust (*Puccinia triticina*), and stripe rust (or yellow rust) (*Puccinia striiformis f. sp. tritici*). The Ug99 pathotype of stem rust was recently detected in East Africa (Chaves et al. 2013). While Ug99 has caused considerable damage in Kenya, in Ethiopia significant yield losses through Ug99 were not reported until very recently (Olivera et al. 2015). Over the last 10 years, stripe rust was much more damaging in Ethiopia (ICARDA 2013; Olivera et al. 2015; Yami et al. 2012). Hence, our analysis focuses on stripe rust. In what follows, we use the term “stripe rust-resistant” or “rust-resistant” varieties for wheat cultivars that show high or at least moderate levels of resistance to stripe rust. Such rust-resistant varieties have been promoted by Ethiopia’s extension service since 2010 (Olivera et al. 2015; Yami et al. 2012). According to our data, stripe rust-resistant varieties are now grown on about half of the total wheat area in Ethiopia. We are not aware of previous research that has evaluated the yield performance of these resistant varieties in farmers’ fields.

The data used in this study were collected in Ethiopia in two rounds, namely in 2009/10 and 2013/14. We develop and estimate field-level production functions, including farmers’ varietal choices as explanatory variables while controlling for other inputs and for farm, farmer, and regional characteristics. We also include interaction terms between varietal traits and various production stresses, in order to gain a better understanding of the performance of improved and traditional varieties under local conditions. The panel structure of the data, with variation in the adoption of different types of varieties over time, help to reduce issues of selection bias that are commonplace in studies with observational data (Krishna et al. 2016). The next section introduces the data and the econometric strategy in more detail. Then, results are presented and discussed before the last section concludes.

2. Materials and methods

2.1 Data

We use data from a panel survey of smallholder farmers in Ethiopia that were collected in two rounds by the International Maize and Wheat Improvement Center (CIMMYT) and the Ethiopian Institute of Agricultural Research (EIAR). The purpose of this survey was to document wheat variety adoption dynamics in Ethiopia (Tolemariam et al. 2016). The two survey rounds cover the 2009/10 and 2013/14 agricultural seasons. In the sampling frame, 148 major wheat-growing districts of Ethiopia were purposively selected. Within these districts, farmers' associations (communities) were randomly selected. Within each selected farmers' association, 15 to 18 households were randomly selected, leading to 2096 households in the sample. Most of these households were interviewed in both survey rounds. The sample is representative of farmers in major wheat-growing areas of Ethiopia.

The structured questionnaire for the survey was developed by CIMMYT scientists in Ethiopia together with EIAR colleagues and field officers. The questionnaire was pre-tested in a pilot survey before it was finalized. The actual survey data were collected through face-to-face interviews with farmers conducted by well-trained enumerators in local languages. A wide range of farm and farmer characteristics and variables describing the broader socioeconomic context were elicited. In both survey rounds, detailed data for all fields cultivated by sample farmers were also collected.

The pooled data include over 20000 fields, out of which 6001 were grown with wheat. For the wheat fields, farmers were asked to report the types and quantities of inputs used and the output harvested during the particular season. Farmers were also asked to specify the wheat variety used in each field. For the analysis, we differentiate between traditional and improved varieties. Traditional varieties are mostly of the durum type, whereas improved varieties are bread wheat. All traditional varieties are susceptible to stripe rust (Gebre-Mariam et al. 1991). For the improved varieties, we further differentiate between varieties that are either resistant or susceptible to stripe rust. Farmers reported 34 different improved varieties. The resistance classification is based on the available literature and additional discussions with experts from EIAR, as shown in Table A1 in the Appendix. Overall, we consider and compare three types of varieties, namely (i) traditional varieties susceptible to stripe rust, (ii) improved varieties susceptible to stripe rust, and (iii) improved varieties resistant to stripe rust.

Farmers were also asked whether or not they had experienced particular production stresses for each field during the particular season. These were closed-ended questions, meaning that a set of biotic (pests and diseases) and abiotic (e.g., drought) stress factors were specified in the questionnaire. As yield losses due to particular stress factors are difficult to estimate for farmers, the response options for each stress were simply "yes" or "no". The list of stress factors included was developed after a thorough review of the major wheat production problems in the country. Pre-testing of the questionnaire helped to use classifications that farmers could easily distinguish. Closed-ended questions are easier to use than open-ended questions in the statistical analysis. However, in addition to the pre-defined stress factors, other stresses mentioned by farmers were recorded and coded during data processing.

Unfortunately, out of the 6001 total wheat field observations, we are only able to use 4751 for the statistical analysis. A sizeable number of field observations (1132) had to be dropped because the official name of the wheat variety grown was not known and could not be found out, even after further investigation. Without knowing the official name, we could not reliably verify whether the variety is resistant or susceptible to stripe rust. Dropping these observations may mean that the sample is not fully representative of wheat farming in Ethiopia anymore. In addition, we dropped 106 extreme yield observations: recent research showed that observations below the 1st or above the 99th percentile of the yield distribution may affect the results in unexpected ways (Abdul-Salam and Phimister 2017; Aguilar et al. 2015). Finally, we had to drop 12 observations with missing data for some of the other variables of interest.

2.2 Econometric strategy

Large bodies of literature exist on the estimation of yield losses resulting from crop diseases. One literature strand focuses on the estimation of actual yield losses using field experiments, regression approaches, simulation models, and other tools (Cooke et al. 2006; James 1974; Savary et al. 2006, 2012). Another literature strand analyzes potential yield losses and losses avoided by breeding disease-resistant varieties (Lantican et al. 2016; Marasas et al. 2003, 2004; Mather et al. 2003; Smale et al. 1998). Some of the latter studies also go beyond reporting percentage yield losses (or losses avoided) and calculate benefit-cost ratios, which is useful for research priority setting (Pardey et al. 2006). However, whenever yield losses (or avoided losses leading to effective yield gains) are estimated from data collected in farmers' fields, outside of controlled experimental settings, it is important to account for possible confounding factors, such as differences in input use, soil quality, farmers' management ability etc.

In this study, we analyze yield losses that farmers can avoid by using wheat varieties that are resistant to stripe rust. In particular, we analyze the yield of improved rust-resistant wheat varieties in comparison to the yield of improved susceptible and traditional susceptible varieties after controlling for input use, field characteristics, and other contextual variables. We estimate a production function of the following type:

$$Y_{ijt} = \alpha + \beta_1 IR_{ijt} + \beta_2 IS_{ijt} + \delta \boldsymbol{S}_{ijt} + \gamma \boldsymbol{X}_{ijt} + \rho \boldsymbol{F}_{ijt} + \vartheta \boldsymbol{H}_{jt} + \pi \boldsymbol{D}_j + \tau T_t + \varepsilon_{ijt} \qquad (1)$$

where Y_{ijt} is wheat yield on field i of farm household j in year t, and IR_{ijt} and IS_{ijt} are two dummy variables representing the use of improved resistant and improved susceptible varieties, respectively (referring to stripe rust). The coefficients β_1 and β_2 compare yield levels of these two improved types of varieties with those of traditional susceptible varieties. Since improved varieties are generally higher yielding than traditional varieties, we expect positive and significant coefficients for β_1 and β_2.

When researchers breed for rust resistance, the objective is to develop new varieties with yield levels at least as high as those of susceptible varieties (Gebre-Mariam et al. 1991). We expect positive yield effects of rust-resistant varieties in years with high rust infection (because of lower crop damage with resistant varieties), whereas the difference may be small or non-existent in years with low rust infection. We have the advantage of being able to compare yields of improved wheat varieties with and without the rust resistance traits. If β_1 is greater than β_2, the resistance traits help to reduce crop losses and increase effective yields. The difference between β_1 and β_2 is an indication of the yield loss that would have occurred had the resistant varieties not been developed and adopted (Marasas et al. 2003).

The other variables in equation (1) control for possible confounding factors. $\boldsymbol{S}_{ijt}$ is a vector of dummy variables representing the incidence of different production stresses (e.g., diseases, drought, and other abiotic stresses), $\boldsymbol{X}_{ijt}$ is a vector of other production inputs, such as labor, fertilizer, and pesticides, and $\boldsymbol{F}_{ijt}$ is a vector of field-level controls, such as field size, soil quality, and slope of the land. $\boldsymbol{H}_{jt}$ is a vector of household-level characteristics, such as farmers' age and education, and $\boldsymbol{D}_j$ is a vector of district dummy variables to control for differences in unobserved regional factors (e.g., infrastructure, rainfall, agroecological potential). T_t is a time dummy variable that takes a value of one for the second survey round 2013/14, with 2009/10 as the reference. $\varepsilon_{ijt} = u_j + e_{ijt}$, where u_j is the unobserved heterogeneity for farm household j, and e_{ijt} is the random error term. As many farm household have more than one wheat field, we need to account for the possibility that the error term is heteroskedastic. This could lead to incorrect standard errors of the coefficient estimates. To avoid bias, we use a procedure to estimate standard errors that are cluster-corrected at the farm household level (Greene 2012).

2.3 Functional form

The technical relationship between inputs and outputs in a production function tends to be non-linear; higher input use usually leads to higher yield, but with decreasing marginal effects. The most commonly used functional forms in production function analysis are the Cobb-Douglas and the translog, both of which use logarithms of the input and output variables (Coelli et al. 2005). The translog function is more flexible, as it does not impose restrictions on the substitutability between different inputs. Which of the two functions is more appropriate in a particular context can be tested. In our case, the statistical test rejects the null hypothesis that the more restrictive Cobb-Douglas function fits the data well (test results are shown below), so we use the translog specification to estimate the production function in equation (1).

One problem with log-transforming inputs and output is that several farmers used zero quantities of certain inputs. As the logarithm of zero is not defined, these observations would be lost if not dealt with specifically. We use the method proposed by Battese (1997) to handle zero input quantities: after taking logs, undefined values are replaced by zero, and additional dummy variables are added to indicate zero quantities of particular inputs. Battese (1997) showed that this method leads to consistent production function estimates.

2.4 Testing for local adaptation of improved varieties

In equation (1), we only included dummy variables for the improved varieties with and without stripe rust resistance to look at simple yield effects. To gain a better understanding of whether improved varieties are well adapted to different types of local production stresses, we estimate another set of production function models with interaction terms as follows:

$$Y_{ijt} = \alpha + \beta_1 IR_{ijt} + \beta_2 IS_{ijt} + \varphi\left(IR_{ijt} \times \boldsymbol{S}_{ijt}\right) + \omega\left(IS_{ijt} \times \boldsymbol{S}_{ijt}\right) + \cdots + \varepsilon_{ijt} \quad (2)$$

Other control variables are included as in equation (1), but not shown in equation (2) for brevity. To illustrate the interpretation of the coefficients of the interactions between production stresses ($\boldsymbol{S}_{ijt}$) and the improved varieties (IR_{ijt} and IS_{ijt}), we use the incidence of drought as an example. In equation (2), β_1 alone indicates the yield effect of rust-resistant varieties in situations with no drought, whereas φ shows whether rust-resistant varieties perform better or worse than local varieties under drought conditions. A negative coefficient φ would indicate that rust-resistant varieties perform worse under drought. This could happen when the rust-resistance traits were not integrated into germplasm that is well adapted to drought situations. Such lack of local adaptation would discourage the adoption of rust-resistant varieties in drought-prone locations. In addition to drought, $\boldsymbol{S}_{ijt}$ can also represent other production stresses.

2.5 Accounting for possible selection bias

The models in equations (1) and (2) involve panel data and can be estimated with either random effects (RE) or fixed effects (FE) estimators (Greene 2012). The RE estimator is more efficient but can lead to bias when there is unobserved heterogeneity that is jointly correlated with any of the explanatory variables and the outcome variable. For instance, farmers who adopt certain types of varieties may systematically differ from non-adopters (Alemu and Bishaw 2015; Barrett et al. 2004; Mather et al. 2003). Such systematic and unobserved heterogeneity between adopters and non-adopters would be a typical case of selection bias. The FE estimator builds on differencing within households over time so that time-invariant unobserved heterogeneity is canceled out. This is a neat way of reducing selection bias. However, for robust estimation the FE estimator requires sufficient variation over time for all variables of interest. If the variation over time is small, an alternative to the standard FE estimator can be used, as proposed by Mundlak (1978). We employ the random effects model with the Mundlak FE version, rewriting equation (1) as follows:

$$Y_{ijt} = \alpha + \beta_1 IR_{ijt} + \beta_2 IS_{ijt} + \delta \boldsymbol{S}_{ijt} + \gamma \boldsymbol{X}_{ijt} + \rho\, \boldsymbol{F}_{ijt} + \vartheta \boldsymbol{H}_{jt} + \pi \boldsymbol{D}_j + \tau T_t + \theta \overline{\boldsymbol{M}}_{ijt} + \varepsilon_{ijt} \quad (3)$$

where $\overline{\boldsymbol{M}}_{ijt}$ is a vector of cluster means of all time-varying observations. Mundlak's FE estimator controls for unobserved heterogeneity that may correlate with the explanatory variables in equation (3) (Di Falco and Veronesi 2014; Mundlak 1978). If the estimated parameters θ are jointly zero, unobserved heterogeneity does not cause bias, so that the RE estimator can be used. Testing for the significance of θ is an alternative to the Hausman test (Greene 2012; Rabe-Hesketh and Skrondal 2012).

3 Results and discussion

3.1 Descriptive statistics

Table 1 shows a list of variables used in the analysis with explanations and units of measurement. Table 2 characterizes the role that wheat production plays in sample farm households. The total average cultivated area per farm household is around 2 ha, out of which one-third is cultivated with wheat. Wheat accounts for over 40% of the total value of production (approximately 8500 Birr or 446 US$ in both survey years).

Insert Table 1 here

Insert Table 2 here

Wheat is affected by various production stresses, with significant temporal and spatial variation. According to farmers' own statements, 8% of the wheat fields were affected by drought in 2009/10 as shown in Table 3. In 2013/14, the share of drought-affected fields was only 1%. Other abiotic stresses, such as waterlogging, frost, or hailstorms affected around 9-10% of the fields in both seasons. Wheat diseases, including stripe rust and other disease problems, were reported in 13% and 20% of the fields in 2009/10 and 2013/14, respectively. While wheat rust problems have increased in Ethiopia in recent years, both survey rounds refer to seasons with moderate rust infection levels.

Insert Table 3 here

Figure 1 shows the adoption of different types of wheat varieties over the two survey rounds (Figure A1 in the Appendix differentiates by agroecology). The use of traditional varieties is limited. In 2009/10, only 7% of all wheat fields were grown with traditional varieties. Strikingly, however, this share had increased to 20% in 2013/14. This increase in the use of traditional varieties suggests that not all farmers were satisfied with the performance of improved varieties in previous years, possibly due to the role of biotic and abiotic stress factors. Among the improved varieties, in 2009/10 most were susceptible to stripe rust. By 2013/14, the share of improved varieties with resistance to stripe rust had increased to 51%. The increased adoption of rust-resistant varieties reflects intensified promotion efforts by various organizations in Ethiopia as a response to recent rust epidemics in East Africa (Olivera et al. 2015; Tolemariam et al. 2016; Yami et al. 2012).

Insert Figure 1 here

Insert Figure 2 here

Figure 2 shows aggregate mean wheat yields obtained by farmers, differentiating by type of variety grown. Traditional varieties consistently have the lowest average yields, whereas improved rust-resistant varieties have the highest average yields. Yields in our survey are lower than the national average of 2200 kg reported by CSA (2015). Differences may possibly be due to different methods used in yield estimations. While our data are based on farmers' statements, CSA (2015) uses actual crop cuts. It is possible that farmers underestimate yields, or that the crop cut method overestimates the actual harvest obtained by farmers. Discrepancies between yield data obtained with different methods were also reported in other studies (Sapkota et al. 2016). Regardless of the method used, average wheat yields obtained by farmers are much lower than those on experimental stations in Ethiopia (Figure 2). One reason is that experimental stations are often located in areas with good soil quality and water availability. Furthermore, due to various constraints farmers often use lower than recommended quantities of fertilizer and other inputs (Bellon 2006; Getnet et al. 2016; Gollin et al. 2005).

Figure 3 depicts density functions of wheat yield by type of variety. Improved susceptible varieties dominate the distribution of traditional varieties, while improved resistant varieties dominate both other distributions. This pattern is observed consistently for both survey rounds. In line with the literature, the yields are not normally distributed but positively skewed to the left, suggesting that more than half of the farmers have below average yields (Ramirez et al. 2003).

Insert Figure 3 here

Table 4 reports the intensity of input use. For fertilizers and herbicides, different types of products are used (e.g., DAP, urea fertilizer), so we express them in monetary terms. Farmers reported that they had used fertilizer in more than 80% of their wheat fields. However, the intensity of fertilizer use shows significant variation. Table 4 also shows that wheat is grown in a very labor-intensive way in Ethiopia, with an average of 89 labor days and 24 oxen days per ha and season.

Insert Table 4 here

Figure 4 shows input use by type of wheat variety. On average, improved varieties are grown on somewhat larger fields than traditional varieties. Also the intensity of input use seems to differ across varietal types. Farmers with improved wheat varieties tend to spend more on fertilizers and herbicides. On the other hand, farmers with improved rust-resistant varieties use less manure and less labor. The differences in input use underline the importance of controlling for possible confounding factors when analyzing yield effects of different types of wheat varieties.

Insert Figure 4 here

3.2 Econometric results

Before looking at the production function estimates, we discuss the statistical tests that we carried out for functional form and possible selection bias. The test results shown in Table 5 refer to the models explained above in equations (1) and (3). The first test relates to functional form. Our null hypothesis is that the coefficients of the input interaction terms in the translog production function are jointly insignificant. In that case, the Cobb-Douglas functional form would be appropriate. However, the test rejects this null hypothesis, so we conclude that the more flexible translog functional form with input interaction terms is appropriate to use. The second test relates to the role of unobserved heterogeneity among farmers, which could lead to selection bias. The null hypothesis is that the θ coefficients for the Mundlak fixed effects are jointly zero. This null hypothesis cannot be rejected. We conclude that the normal RE estimator can be used to obtain unbiased results.

Insert Table 5 here

The translog production function estimates are shown in Table 6. For brevity, the coefficients of the input interaction terms and district dummy variables are not shown in Table 6. These additional coefficients are shown in Table A2 in the Appendix. The coefficients of the district dummies in Table A2 suggest that there are significant regional differences in yield, even after controlling for inputs and other field and farmer characteristics. These differences may be due to agroecological factors. In all models in Table 6, the inputs are mean centered, so the coefficients can be interpreted directly as elasticities at sample means. The elasticity is the percentage change in yield for a 1% change in a particular input.

In model (1) of Table 6, we only include inputs and other control variables. We control for neither the variety dummies nor dummies for production stresses. As can be seen, all input coefficients have the expected positive signs, and most of them are statistically significant. These estimates suggest that wheat farmers can obtain higher yields by further increasing their input intensity. The highest input elasticity is observed for chemical fertilizer: a 1% increase in the use of fertilizer increases yield by 0.3% on average.

The results of model (1) further suggest that higher yields are obtained on smaller fields, which may be related to a higher share of family labor on small farms. Due to different incentives, family labor is often more productive than hired labor. A negative correlation between farm/field size and yield has also been shown in other studies (Barrett et al. 2010; Carletto et al. 2013; Kilic et al. 2017; Sen 1966). Fields managed by households with better-educated household heads have higher yields. On the other hand, the sex of the household head does not seem to influence yield after controlling for field characteristics and input use. In terms of land characteristics, lower yields are obtained on land with steep slopes than on flat land. Less favorable land is also associated with lower wheat yields, as one would expect.

In Model (2) of Table 6, we include a dummy variable for the incidence of wheat diseases as an additional control variable. As mentioned, the most relevant disease is stripe rust, but other diseases are also included. The coefficient for this variable suggests that stripe rust and other diseases have caused yield damage of 19%. Note that this is not the average loss for the entire sample, but only refers to those fields where farmers reported disease incidence during the respective years. For comparison, during the 2010 stripe rust outbreak in Syria, yield declines of 20-70% were reported, depending on infection levels in a particular region (ICARDA 2011). Also in Ethiopia, yield losses through stripe rust of more than 20% were reported for particular years (Alemu et al. 2015; Denbel et al. 2013; Hailu and Fininsa 2007; Tadesse et al. 2010). Against this background, the 19% loss derived from our data on fields with disease incidence are relatively low. But it should be mentioned that overall stripe rust levels were not particularly high in the two years covered by the survey.

In model (3) of Table 6, we include the two dummy variables for improved varieties with and without resistance to stripe rust. The estimates suggest that improved resistant varieties outperform traditional varieties that are susceptible to stripe rust. Compared to traditional varieties, growing improved resistant varieties increases yield by 8% on average. It can be expected that yield gains of resistant varieties will still be higher in locations with high rust infection levels. One way to analyze this further would be to interact the variable for resistant varieties with rust infection levels. Unfortunately, this is not possible with our farmer-reported disease incidence variable, because this variable is endogenous: when farmers have adopted rust-resistant varieties they naturally observe lower disease problems in their own fields.

Model (3) further suggests that the yield gain of improved susceptible varieties is 6%. The difference between improved resistant and improved susceptible varieties is 2%. The 2% extra yield gain is the percentage that would have been lost if resistant varieties had not been adopted. That this difference is small (and statistically not significant) should not surprise given that there was no major rust epidemic in the two seasons covered by the survey. It seems that breeders were successful in terms of avoiding a yield penalty when introducing the rust resistance traits into improved germplasm. Such a penalty could potentially occur if rust resistance was negatively correlated with other plant traits that influence yield.

In model (4) of Table 6, we additionally introduce an interaction term between rust-resistant varieties and the year dummy variable. The positive and significant coefficient of this interaction term suggests that the yield gains of rust-resistant varieties were higher in 2013/14 than in 2009/10. This difference between years suggests that there is temporal variation in disease infection levels. In seasons with severe rust infection, the benefits of resistant varieties are likely much larger.

In model (5), we include two dummy variables for different types of abiotic stresses, one for drought and the other for shocks such as waterlogging, frost, and hailstorms combined. Both variables have large negative coefficients, suggesting that abiotic stresses can reduce wheat yield significantly; each type of shock reduces yield by more than 30%. Hence, the attractiveness and performance of improved and disease-resistant varieties will also depend on their adaptation to common abiotic stresses. This is further analyzed in the following.

Insert Table 6 here

In Table 7, we present results of models with interaction terms between the types of varieties and different production stresses (see equation 2). In each model, we also control directly for the same stress factors so we can interpret the coefficients of the interaction terms as the yield performance of improved varieties in comparison to local varieties in situations of abiotic stress.

Insert Table 7 here

In model (6) of Table 7, we focus on drought situations. In model (7), we look at other abiotic stresses, whereas in model (8), we combine all stresses together in one dummy variable. All interaction terms have a negative sign, but some of the coefficients are statistically insignificant. The statistical insignificance of the coefficients is due to the small number of farmers reporting production stresses and a certain degree of collinearity that is common when including variables directly and as interaction terms. Nevertheless, some of the negative interaction term coefficients are quite large in magnitude, suggesting that improved varieties – with and without stripe rust resistance – perform notably worse under abiotic stress than traditional varieties. At the same time, especially in model (8), the coefficients of the variety dummies themselves increase in comparison to results in Table 6, where these interaction terms were not included.

These results suggest that the improved wheat varieties commonly grown in Ethiopia are yield increasing under favorable production conditions, but not perfectly adapted to drought and other relevant abiotic stresses. The inferior performance of improved varieties under abiotic stress and the growing frequency of weather extremes through climate change may also explain why many farmers recently switched back to growing traditional varieties, as observed in the second round of the survey (see Figure 1). The dis-adoption of improved varieties is associated with lower average productivity, as traditional varieties perform worse than improved varieties when there are no extreme production stresses. Combining high yield potential with disease resistance, as successfully done for improved rust-resistant varieties, is one important step towards developing better-adapted high-yielding varieties. Further adding higher tolerance to drought and other abiotic stresses remains an important future challenge for wheat breeding programs.

4. Conclusion

In developing country agriculture, sizeable crop losses due to a wide range of pests and diseases occur. Breeding crops for pest and disease resistance is a sustainable way to reduce such losses without having to increase the use of chemical pesticides. However, in order to make resistant varieties attractive for farmers and really increase effective yields, pest and disease resistance traits have to be combined with other important crop traits such as high yield potential and tolerance to drought and other abiotic stresses. Previous research on the impact of improved crop varieties has mostly looked at yield effects in general, without differentiating between different varietal traits and characteristics. In this study, we have used panel data from wheat farmers in Ethiopia to analyze yield effects of varieties that are resistant to stripe rust. In particular, we have compared yields of improved rust-resistant wheat varieties with yields of improved susceptible and traditional susceptible varieties.

Production function estimates suggest that the adoption of improved rust-resistant varieties has raised yields by 8% in comparison to traditional susceptible varieties. Improved susceptible varieties have 6% higher average yields than traditional varieties, after controlling for other factors. The yield difference between improved resistant and improved susceptible varieties is relatively small, which is largely because the survey data were collected in seasons with only moderate stripe rust infection levels. While wheat rust problems have increased recently in Ethiopia and other countries of East Africa, the survey does not cover seasons with severe stripe rust outbreaks. Rust-resistant varieties perform equally well or better than other improved varieties in years with low or moderate rust infection. The above average performance of the rust-resistant improved varieties, relative to the improved susceptible varieties, indicates that breeders were able to combine rust-resistance traits with high yield potential successfully. In years with higher rust infection, resistant varieties will likely outperform improved susceptible varieties.

We have also analyzed the performance of improved wheat varieties in fields where abiotic production stresses (e.g., drought, waterlogging) affect yield by using interaction terms. Under abiotic production stresses, improved varieties – with and without stripe rust resistance – perform notably worse than traditional varieties. In other words, the improved wheat varieties commonly grown in Ethiopia are not perfectly adapted to drought and other unfavorable weather conditions. This – together with the fact that the frequency of weather extremes is rising with climate change – may explain why many farmers in Ethiopia recently switched back to growing traditional varieties. In order to foster sustainable adoption, traits of high yield potential, disease resistance, grain quality, and tolerance to drought and other abiotic stresses need to be combined in the same varieties. This is a challenge for breeders not only because some of these traits may be negatively correlated in available genetic pools, but also because pathogens evolve so that searching for new plant resistance mechanisms remains a continuous task. Modern biotechnology, including new tools for genome editing, may help to overcome some of the complexities involved.

Our results may contribute to further tailoring breeding programs to the needs of smallholder farmers. Yet, more conceptual and empirical research is needed to better understand the linkages between different types of varietal traits, evolving environmental, climatic, and socioeconomic conditions, farmers' technology adoption behavior, and impacts of technologies on agricultural productivity.

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Conflict of interest

The authors declare that they have no conflict of interest.

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Table 1. Description and measurement of variables used in the analysis

Variables	Description and measurement
Dependent variable	
Yield	Quantity of wheat output per hectare (kg/ha)
Types of wheat varieties	
TS (traditional susceptible)	1 if traditional varieties susceptible to stripe rust were used; 0 otherwise
IS (improved susceptible)	1 if improved varieties susceptible to stripe rust were used; 0 otherwise
IR (improved resistant)	1 if improved varieties resistant to stripe rust were used, 0 otherwise
Input use	
Fertilizer	Expenses on fertilizer (Birr/ha), log transformed
Herbicide	Expenses on herbicide (Birr/ha), log transformed
Oxen days	Oxen days per hectare, log transformed
Labor	Labor days per hectare, log transformed
Manure	Quantity of manure(kg/ha), log transformed
Pesticide	1 if fungicides or insecticides were used, 0 otherwise
Field level biotic and abiotic shocks	
Drought	1 if there was an incidence of drought; 0 otherwise
Other abiotic	1 if there was an incidence of waterlogging, frost, or hailstorm; 0 otherwise
Diseases	1 if there was an incidence of wheat diseases; 0 otherwise
Any stress	1 if there was an incidence of any production stress; 0 otherwise
Other field level characteristics	
Field size	Size of field (ha)
Good soil	1 if the soil is of good quality, according to farmer; 0 otherwise
Medium soil	1 if the soil is of medium quality, according to farmer; 0 otherwise
Poor soil	1 if the soil is of poor quality, according to farmer; 0 otherwise
Flat slope	1 if the field was flat sloped; 0 otherwise
Medium slope	1 if the field was medium sloped; 0 otherwise
Steep slope	1 if the field was steep sloped; 0 otherwise
Farmer characteristics	
Age	Age of the farmer (household head) in years
Male	1 if the farmer (household head) is male; 0 if female
Education	Years of schooling of the farmer (household head)
Survey round	
Year	1 if the observation if from the 2013/14 survey round; 0 if 2009/10

Table 2. Importance of wheat for sample households

Variables	2009/10		2013/14	
	Mean	SD	Mean	SD
Total crop area cultivated by the household (ha)	2.11	1.77	2.45	2.02
Total wheat area cultivated by the household (ha)	0.74	0.88	0.70	0.71
Share of wheat area to total area cultivated (%)	36	21	31	19
Share of wheat to total value of crop production (%)	44	26	43	26
Value of total crop production (Birr) [a]	15649	18235	14633	21114
Value of wheat production (Birr) [a]	8638	13616	8312	13506
Number of household observations	2069		1921	

[a] The official exchange rate was 1 US$ = 19.05 Birr in 2013. Monetary values are expressed in real terms for easier comparison across survey rounds.

Table 3. Field level incidence of various abiotic and biotic stresses

Type of stress	Number of fields	Both rounds	2009/10	2013/14
Drought	4751	0.04	0.08	0.01
Other abiotic [a]	4751	0.09	0.09	0.10
Diseases	4751	0.17	0.13	0.20

[a] Other abiotic stresses include waterlogging, frost, and hailstorm.

Table 4. Intensity of input use

Inputs	Both rounds		2009/10		2013/14	
	Mean	SD	Mean	SD	Mean	SD
Fertilizer use (% of fields)	84		80		88	
Fertilizer (expenses)	847	685	762	687	914	676
Herbicide use (% of fields)	60		62		59	
Herbicide (expenses)	39	57	33	43	42	66
Oxen days	24	12	24	13	25	11
Labor	89	68	91	69	88	66
Manure use (% of fields)	17		18		17	
Manure	284	900	308	976	265	837
Pesticide use (% of fields)	4		3		4	
Number of fields	4751		2096		2655	

Notes: Expenses are expressed in Birr/ha. The official exchange rate was 1 US$ = 19.05 Birr in 2013. Monetary values are expressed in real terms for easier comparison across survey rounds. For other details of variable definitions, see Table 1.

Table 5. Model diagnostics

Null hypothesis	Chi squared test statistic	Degrees of freedom	Chi squared critical value	p-value
Cobb-Douglas function fits the data	71.75	15	24.996	0.000
Mundlak's fixed effects are jointly zero	14.7	11	19.675	0.197

Table 6. Determinants of wheat yield (different model specifications)

	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
IR (improved resistant) [a]					0.080***	0.027	0.019	0.037	0.070***	0.027
IS (improved susceptible) [a]					0.059**	0.028	0.044	0.028	0.046*	0.027
IR x year							0.081**	0.036		
Drought									-0.328***	0.061
Other abiotic									-0.332***	0.042
Diseases			-0.188***	0.029						
Fertilizer	0.229***	0.020	0.226***	0.020	0.226***	0.020	0.224***	0.020	0.227***	0.019
Herbicide	0.074***	0.020	0.079***	0.019	0.075***	0.020	0.072***	0.020	0.077***	0.019
Oxen days	0.047	0.044	0.036	0.044	0.049	0.044	0.049	0.044	0.043	0.044
Labor	0.094***	0.036	0.104***	0.036	0.095***	0.036	0.096***	0.036	0.090**	0.035
Manure	0.057**	0.024	0.054**	0.024	0.056**	0.024	0.058**	0.024	0.053**	0.023
Pesticide	0.093	0.075	0.116	0.071	0.092	0.074	0.099	0.073	0.078	0.074
Field size	-0.127***	0.039	-0.127***	0.039	-0.128***	0.039	-0.126***	0.040	-0.117***	0.036
Medium soil [b]	-0.039*	0.022	-0.036*	0.022	-0.038*	0.022	-0.037*	0.022	-0.026	0.021
Poor soil [b]	-0.082**	0.035	-0.076**	0.035	-0.083**	0.035	-0.082**	0.034	-0.071**	0.033
Medium slope [c]	-0.035	0.023	-0.022	0.023	-0.035	0.023	-0.034	0.023	-0.038*	0.022
Steep slope [c]	-0.108**	0.046	-0.093**	0.045	-0.106**	0.046	-0.110**	0.045	-0.120***	0.046
Age	-0.003***	0.001	-0.003***	0.001	-0.003***	0.001	-0.003***	0.001	-0.003***	0.001
Male	0.026	0.040	0.022	0.040	0.027	0.040	0.028	0.040	0.026	0.039
Education	0.015***	0.003	0.014***	0.003	0.015***	0.003	0.015***	0.003	0.014***	0.003
Year	-0.008	0.020	0.005	0.020	-0.006	0.020	-0.037	0.025	-0.025	0.020
Constant	-0.529***	0.203	-0.471**	0.203	-0.590***	0.203	-0.559***	0.203	-0.568***	0.200
Number of fields	4,751		4,751		4,751		4,751		4,751	

Notes: The dependent variable in all models is the logarithm of wheat yield (kg/ha). Coefficient estimates are shown with cluster-corrected standard errors in parentheses. For variable definitions, see Table 1. Dummies to correct for zero input use, input interaction terms, and district dummies are included in all models but not shown here for brevity (see Table A2 in the Appendix). [a] The base catergory are traditional varieties. [b] The base category is good soil. [c] The base category is flat slope. *** p<0.01; ** p<0.05; * p<0.1

Table 7. Role of interactions between types of varieties and production stress in explaining wheat yield

	Model (6)		Model (7)		Model (8)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
IR (improved resistant)	0.076***	0.027	0.076***	0.028	0.104***	0.029
IS (improved susceptible)	0.055**	0.028	0.054*	0.029	0.091***	0.031
Drought	-0.124	0.148	-0.329***	0.061		
Abiotic stress	-0.332***	0.041	-0.292***	0.075		
Any stress					-0.217***	0.051
Interaction terms						
IR x drought	-0.195	0.155				
IS x drought	-0.246*	0.145				
IR x abiotic stress			-0.039	0.084		
IS x abiotic stress			-0.055	0.078		
IR x any stress					-0.122**	0.055
IS x any stress					-0.084	0.053
Constant	-0.574***	0.201	-0.575***	0.201	-0.528***	0.200
Number of fields	4,751		4,751		4,751	

Notes: The dependent variable in all models is the logarithm of wheat yield (kg/ha). Coefficient estimates are shown with cluster-corrected standard errors in parentheses. Only the main variables of interest are shown. Other included variables are the same as those in model (1) of Table 6. *** p<0.01; ** p<0.05; * p<0.1

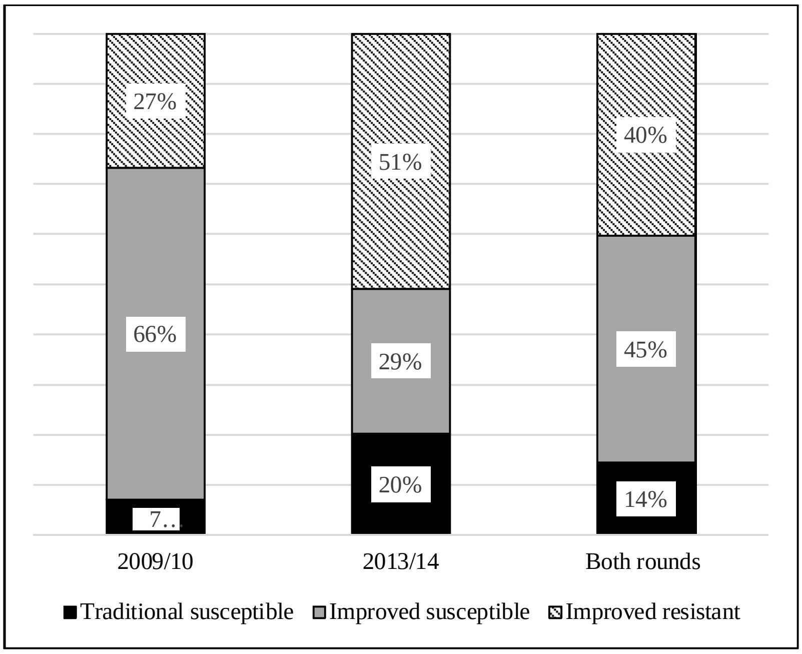


Figure 1: Percentage of wheat fields by type of variety

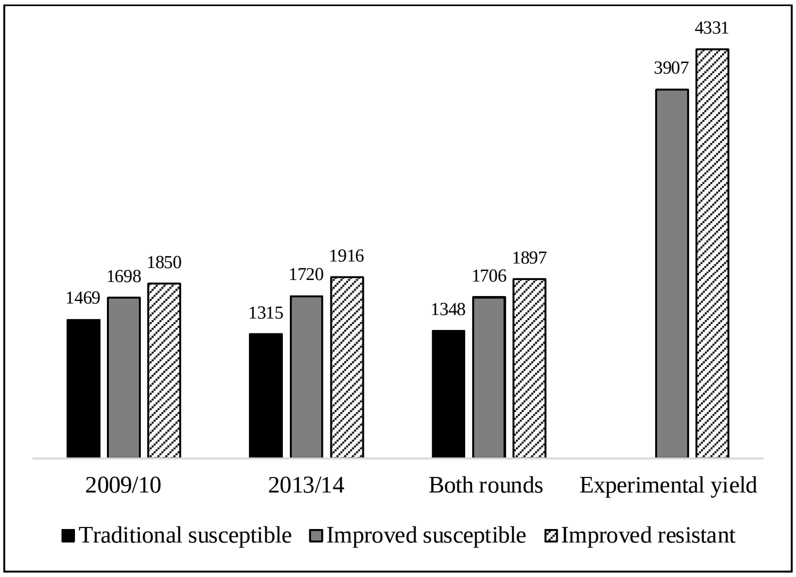
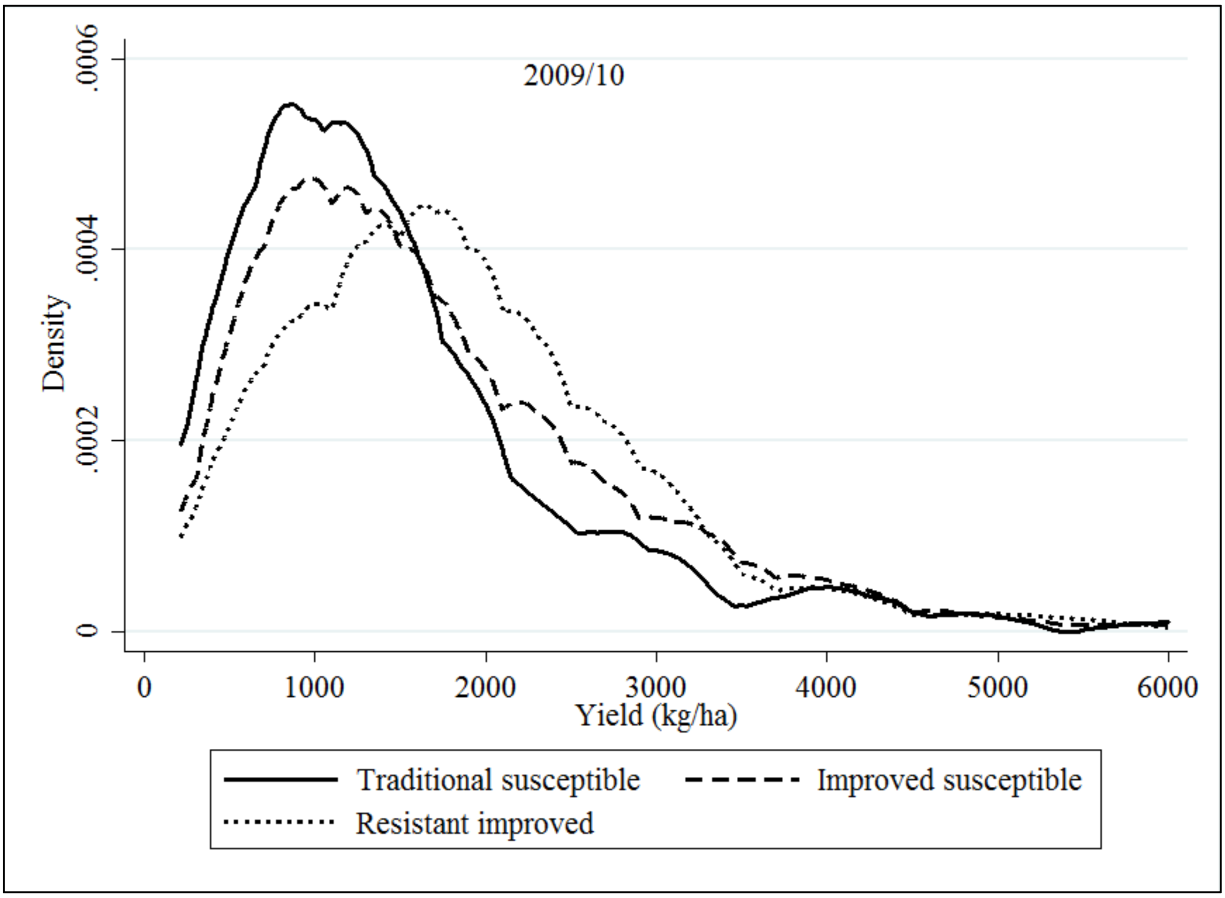


Figure 2. Mean wheat yields on sample fields and experimental stations (kg/ha)

Note: Experimental yields are average values obtained from various sources listed in Table A1 in the Appendix.


2009/10
Density
0
.0002
.0004
.0006
0
1000
2000
3000
4000
5000
6000
Yield (kg/ha)
Traditional susceptible
Improved susceptible
Resistant improved

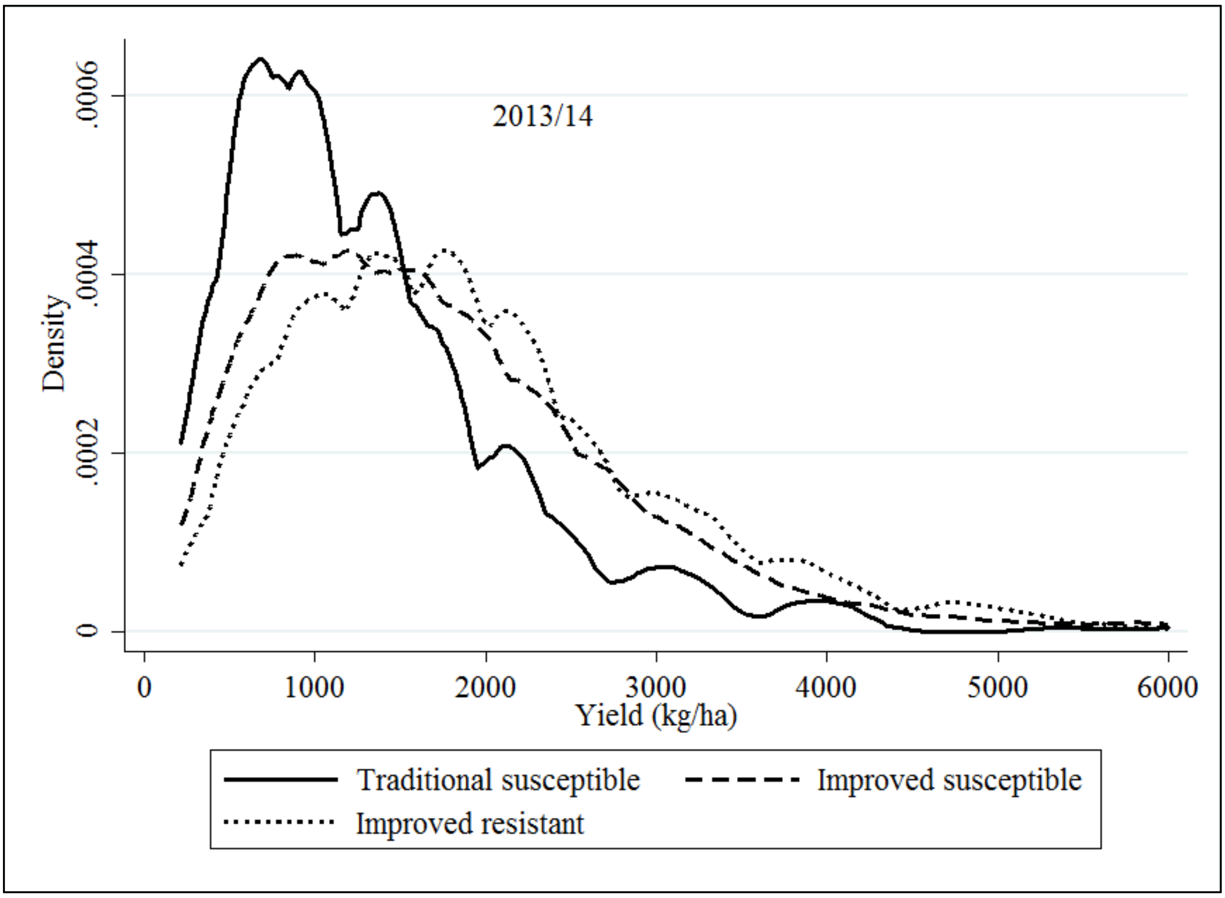


Figure 3. Distribution of wheat yield by type of variety

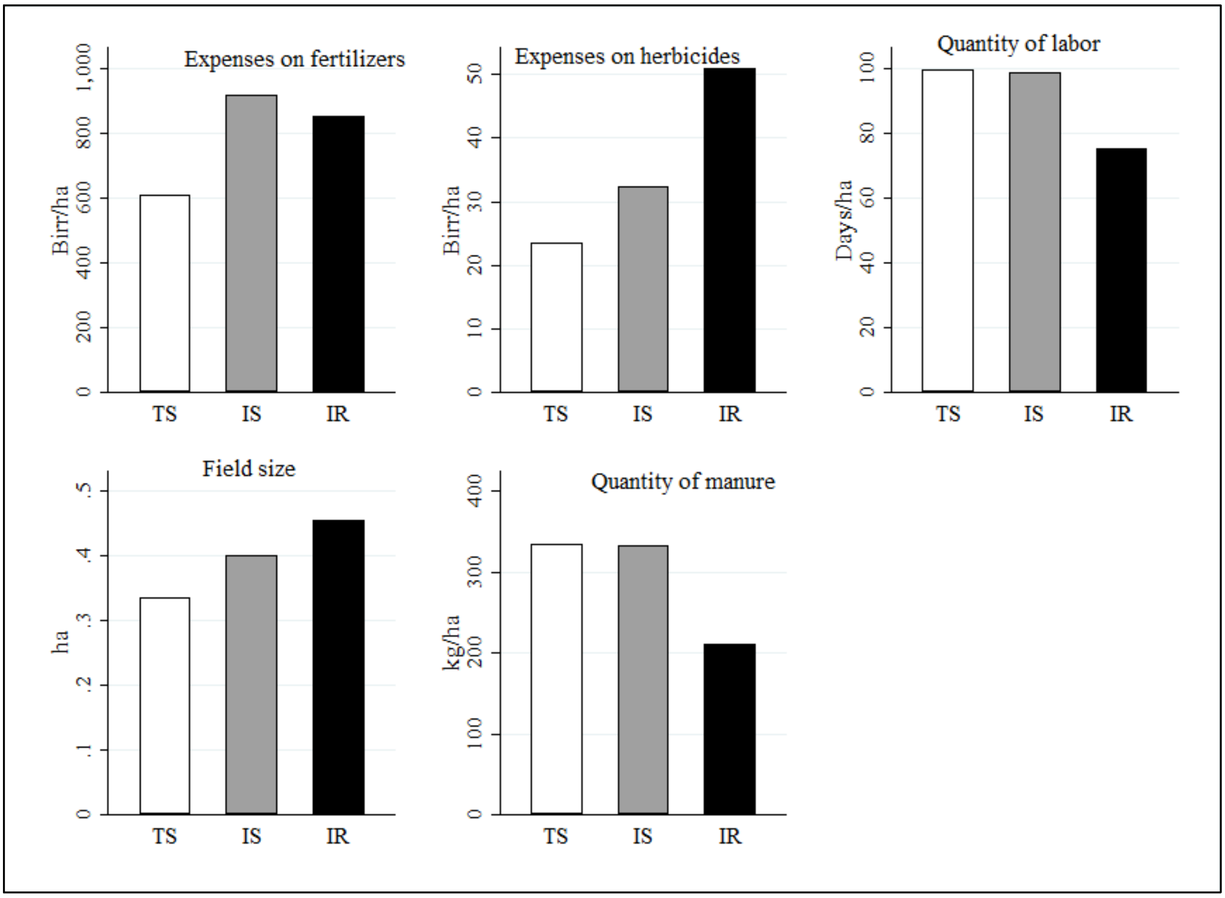


Figure 4. Field characteristics and input use by type of wheat variety

Note: TS, traditional susceptible; IS, improved susceptible; IR, improved resistant (stripe rust resistant).

Appendix

Table A1. List of improved wheat varieties and levels of stripe rust resistance

Variety name	Level of stripe rust resistance	Frequency of fields (%)	Year released	Sources of information for stripe rust resistance
Kubsa	Susceptible	32.18	1994	Alemu et al. (2015)
Digelu	Resistant	19.09	2005	Alemu et al. (2015)
Galema	Susceptible	8.66	1995	Yami et al. (2012)
Dashen	Susceptible	8.34	1984	Bishaw et al. (2014)
Pavon	Resistant	4.58	1982	Yami et al. (2012)
Tusie	Resistant	4.38	1997	Yami et al. (2012)
Dakeba (Picaflor)	Resistant	4.06	2010	http://wheatatlas.org/ug99
Mada-Walabu	Resistant	3.91	2000	Alemu et al. (2015)
Dande'a (Danphe)	Resistant	3.76	2010	http://wheatatlas.org/ug99
ET-13	Resistant	3.59	1981	Yami et al. (2012)
Enkoye	Susceptible	1.94	1974	Bishaw et al. (2014)
Simba	Resistant	1.25	2000	Communication with experts from EIAR
Wabe	Susceptible	1.06	1994	Hailu and Fininsa (2017)
Hawii	Resistant	1.06	2000	Yami et al. (2012)
Sof-Oumer	Resistant	0.39	2000	Alemu et al. (2015)
Dure	Resistant	0.39	2001	Alemu et al. (2015)
Millennium	Susceptible	0.37	2007	Alemu et al. (2015)
Kulilit/Kulkulit	Resistant	0.25	2009	Zerihun et al. (2012)
Shina	Susceptible	0.25	1999	Communication with experts from EIAR
Menzie	Resistant	0.07	2007	Zerihun et al. (2012)
K6295-4A	Resistant	0.07	1980	Yami et al. (2012)
Sirbo	Resistant	0.05	2001	Tadesse et al. (2010)
Wetera	Susceptible	0.05	2000	Communication with experts from EIAR
Doddota	Susceptible	0.05	2001	Communication with experts from EIAR
Bobitcho	Resistant	0.05	2002	Communication with experts from EIAR
Bollo	Susceptible	0.02	2009	Zerihun et al. (2012)
KGB-01	Resistant	0.02	1980	Yami et al. (2012)
Obsa	Resistant	0.02	2006	Communication with experts from EIAR
Magala	Susceptible	0.02	1997	Communication with experts from EIAR
Tay	Resistant	0.02	2005	Communication with experts from EIAR
Gasay	Resistant	0.02	2007	Communication with experts from EIAR

Table A2. Input interaction terms and district dummies from wheat yield model

	Coeff.	SE		Coeff.	SE
0.5 x fertilizer squared	0.070***	0.024	Hitosa (yes=1)	0.685***	0.101
0.5 x herbicide squared	0.048***	0.018	Limuna Bilbilo (yes=1)	0.584***	0.102
0.5 x oxen days squared	-0.017	0.054	Munesa (yes=1)	0.606***	0.101
0.5 x labor squared	0.159***	0.029	Seru (yes=1)	0.044	0.119
0.5 x Manure squared	0.022	0.017	Shirka (yes=1)	0.383***	0.100
Fertilizer x herbicide	-0.002	0.002	Sude (yes=1)	0.185	0.114
Fertilizer x oxen days	-0.008	0.007	Gasera (yes=1)	0.594***	0.121
Fertilizer x labor	-0.009	0.006	Goba (yes=1)	0.180	0.140
Fertilizer x manure	0.000	0.001	Adami Tulu Jido Komb (yes=1)	0.308***	0.114
Herbicide x oxen days	-0.008	0.012	Adea (yes=1)	0.391***	0.091
Herbicide x labor	0.002	0.008	Dugda (yes=1)	0.195*	0.113
Herbicide x manure	-0.002	0.002	Lomme (yes=1)	0.438***	0.137
Oxen days x labor	-0.010	0.027	Mulo (yes=1)	0.029	0.112
Oxen days x manure	0.004	0.007	Qercha (yes=1)	-0.252*	0.131
Labor x manure	-0.005	0.006	Uraga (yes=1)	-0.275**	0.138
Fertilizer is zero (yes=1)	-0.087	0.506	Dedo (yes=1)	-0.045	0.112
Herbicide is zero (yes=1)	0.056	0.148	Kuyu (yes=1)	-0.263**	0.115
Oxen days is zero (yes=1)	0.289	0.234	Wuchale (yes=1)	-0.138	0.114
Manure is zero (yes=1)	-0.001	0.372	Wonchi (yes=1)	-0.084	0.116
Awabel (yes=1)	0.217**	0.108	Adaba (yes=1)	0.240**	0.106
Enarj Enawga (yes=1)	0.075	0.138	Arsi Negele (yes=1)	0.452***	0.098
Enemay (yes=1)	0.242*	0.131	Dodola (yes=1)	0.517***	0.101
Goncha Siso Enese (yes=1)	0.173*	0.094	Gedeb Asasa (yes=1)	0.704***	0.109
Huletej Enese (yes=1)	0.068	0.105	Shashemene (yes=1)	0.381***	0.108
Angolelana Tera (yes=1)	0.219*	0.112	Adea Berga (yes=1)	0.160*	0.096
Basona Werana (yes=1)	0.231**	0.101	Gende Beret (yes=1)	0.108	0.114
Menz Gera Meder (yes=1)	-0.025	0.109	Meskan (yes=1)	0.008	0.126
Menz Mama Meder (yes=1)	0.032	0.133	Sodo (yes=1)	0.248**	0.112
Bugna (yes=1)	0.388***	0.125	Soro (yes=1)	0.031	0.107
Meket (yes=1)	0.066	0.117	Kedida Gamela (yes=1)	-0.374***	0.129
Kay Gayint (yes=1)	-0.052	0.144	Hula (yes=1)	-0.157	0.154
Misrak Este (yes=1)	-0.225*	0.129	Halaba S/district (yes=1)	0.124	0.202
Debresina (yes=1)	-0.291***	0.095	Yem special (yes=1)	-0.244**	0.113
Delanta (yes=1)	0.083	0.120	Degua Temben (yes=1)	0.146	0.171
Sayint (yes=1)	-0.083	0.101	Werei Leke (yes=1)	0.179	0.113
Were Ilu (yes=1)	0.158	0.103	Saese Tsaeda Emba (yes=1)	0.085	0.107
Wogidi (yes=1)	-0.267**	0.114	Enderta (yes=1)	0.172	0.176
Bure (yes=1)	0.256*	0.131	Ofla (yes=1)	0.513***	0.111
Sekela (yes=1)	-0.078	0.109	Dabat (yes=1)	0.025	0.113
Arsi-Robe (yes=1)	0.021	0.106			

Notes: These estimates belong to model (5) in Table 6 with the logarithm of wheat yield (kg/ha) as the dependent variable. Coefficient estimates are shown with cluster-corrected standard errors in parentheses. The base category for the district dummies is Ankasha Guagusa. *** p<0.01; ** p<0.05; * p<0.

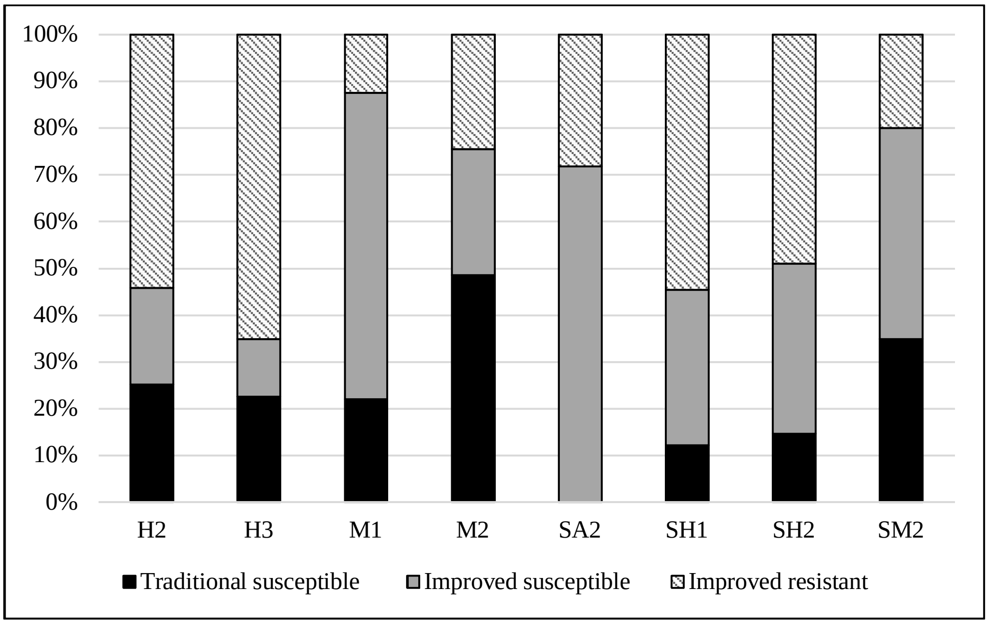


Figure A1. Field level adoption of varieties by agroecology (both survey rounds).

Notes: H2, tepid to cool humid mid-highlands (n=888); H3, cold to very cold humid sub-Afro-Alpine (n=107); M1, hot to warm moist lowlands (n=143); M2, tepid to cool moist mid-highlands (n=1350); SA2, tepid to cool semi-arid mid highlands (n=62); SH1, hot to warm sub-humid lowlands (n=2019); SH2, tepid to cool sub-humid mid highlands (n=668); SM2, tepid to cool sub-moist mid highlands (n=1314).