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Agricultural Technology Diffusion in a Post-Conflict Setting: Evidence from an Experimental Study in Eastern Turkey

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Summary

This paper considers the impact of an agricultural extension program, The Özyeğin Rural Development Program, implemented in eastern Turkey, on rates of agricultural technology adoption. Using a uniquely designed experimental panel survey collected in treatment and control villages before and after program implementation, the paper analyses the heterogeneous impact of this agricultural extension program, on the adoption rates of different groups in the villages. The main results in the paper are consistent with the predictions of the model presented, whereby in the early stages of adoption, the existence of the agricultural extension program increases the adoption rates in the villages significantly for all households: treatment is associated with an increase in the rate of adoption of inoculation of fruit trees by 26.2-31.4 percentage points depending on the empirical specification. The paper also finds evidence for the ``inclusiveness'' of the NGOs efforts by looking at the heterogeneous impact of the program of adoption rates of the "excluded" groups using various economic and political exclusion criteria. the paper also considers the role of social networks in access to information and rates of adoption of new technologies and finds that even in the presence of inclusive policies that reach out to economically or politically vulnerable sub-sections in the villages, those who do not have many social interactions with the rest of the village community may remain excluded from the benefits of the program.

Keywords: Agricultural Technology Diffusion, Rural Development, Social Networks and Learning, Turkey.

JEL Classification Numbers: Q16, D74, D83, D78, O12

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1 Introduction

Adoption of newly introduced agricultural technologies by rural communities has strong implications for increasing economic welfare and reducing poverty in these settings and has therefore been a topic of interest among development economists. One of the earliest works looking at patterns of agricultural technology diffusion was by Zvi Griliches, who observed in his empirical assessment of the diffusion of hybrid corn in the United States that there is a general "S-shaped pattern" of diffusion of new technologies, *"where the rate of adoption is slow at first, accelerating until it reaches its peak at approximately the mid-point of development and then slowing again as the development approaches its final level"* [Griliches, 1960]. He identified three parameters that determine the shape of a diffusion curve: the date of beginning (origin), relative speed of adoption (slope) and final level (ceiling) and states that the observed patterns of adoption timing can be largely explained by the profitability of innovation to the individual farmer.

Following Griliches' seminal empirical work, Feder and Slade [1984] have presented a theoretical decision model for adoption of new technologies, whereby the speed at which farmers of different characteristics reach the level of 'saturation' (the ceiling) at different points in time and adoption patterns are differentiated mainly by land size and assets. All farmers make a decision to adopt the technology if they think it will enhance their profits or utility, even if there is a level of uncertainty associated with the returns of the technology. Farmers with more convenient access to information and better endowments (and thus lower risk aversion) are more likely to acquire higher levels of knowledge and adopt technologies sooner. Therefore, in this model farmers with more assets or with more human capital are expected to adopt a technology earlier than others. Over time, most farmers adopt the new technology, and the differences in adoption levels disappear as the level of use converges to the ceiling.

Several other papers have also considered the role of social networks in the diffusion of agricultural technologies. Foster and Rosenzweig [1995] discuss the impact of farmers own experience and their neighbors experience with high yielding seed varieties on adoption and profitability of new crops. Using a nationally representative panel survey of households in Rural India through the Green Revolution, they find evidence of learning spill-overs: farmers with experienced neighbors are significantly more profitable than those with inexperienced neighbors and the former are likely to devote more of their land to the new technologies. Bandiera and Rasul [2006] consider farmer's decisions to adopt a new crop, sunflower, in Mozambique and show an inverse U shaped relationship between the number of adopters in the network and the probability of each farmer's adoption. In other words, they find that social effects are positive when there are few adopters in the network, though become negative when there are many.

Some authors have modelled the role of social links, exclusion and networks in technology diffusion. Isham et al. [2002] extends the theoretical model of technology adoption by Feder and Slade [1984] by including characteristics of local social structures as an input into the household's adoption decision. He introduces into the model the quantity of public information in the village that is affected by the village-wide "cumulative proportion of adopters", as well as "social capital" at the village level. The following predictions come out of his formal model: the farmers that adopt more rapidly are those that (i) have more assets and obtain more private information, (ii) have neighbours that adopt and thus have more cumulative information around them, (iii) live in villages with higher levels of social capital and thus have better access to information, and/or (iv) live in villages where agricultural extension services exist. He then takes this developed model to a data set collected in rural Tanzania and shows that the probability of adoption -in this case, of improved fertilizer- is positively correlated, as predicted by the model, with the size of land under cultivation (assets), cumulative adoption patterns in the village, ethnically based social affiliations and the availability of extension services.

This paper contributes to an expanding literature on technology adoption, social networks and exclusion by looking at the impact of an agricultural extension program implemented in a post-conflict setting in Turkey. By making use of a uniquely designed panel survey implemented in project and treatment villages before and after the program, the paper looks at the heterogeneous impact of the agricultural extension program on groups that are "laggards" or have been politically/economically or socially excluded from main stream information and agricultural technology. It looks at the changes in levels of utilization for some agricultural technologies and compares levels and rates of adoption across groups, focusing primarily on a "politically" excluded "non-Turkish speaking" minority group. It turns out that the socially excluded and ethnically/economically excluded are not necessarily the same, and while the extension program may benefit those who are "politically excluded" (have low human capital, asset capital and are excluded in terms of language) – the program may be *less* effective in reaching out to those who are "socially excluded" in their community.

The main research questions answered in the paper are the following: (i) What patterns are observed in the adoption of new agricultural technologies by community characteristics – do the excluded have higher or lower levels of adoption given the extension program? (ii) Does the kind of exclusion - "political" vs. "social"- matter in determining adoption rates?

The paper is structured as follows: Section 3 provides information on the context of the rural extension program and the nature of the data collected for this study. Section 2 lays out the conceptual framework and hypotheses to be tested using empirical data. Section **??** provides the empirical specification applied to the experimental data set at hand. Section 4 gives the main results starting with descriptive statistics on the outcome variables in the baseline and post-test,then providing the main findings from the OLS estimation, and ending with robustness checks on the results. Section 5 concludes with main findings from the paper.

2 Conceptual Framework

2.1 The Model

This paper uses the conceptual framework provided by Isham et al. [2002] and looks at differences in rates of adoption of agricultural technology in the presence of an extension program, and where a certain group in the population can be identified as an excluded" minority and therefore may be experiencing difficulties in accessing information about an innovation. It considers the hypothesized adoption rates of the more advantaged (non-excluded) and disadvantaged (excluded) groups in the population, given the baseline adoption level of a technology, and then looks at the potential impact of a "treatment" that increases the availability of certain agricultural technologies in the villages.

A summary of the conceptual model is depicted in Figures 1a and 1b. The adoption pattern (cumulative distribution function for adoption) of the non-excluded group is depicted in blue, and the adoption pattern of the "excluded" group is in green, where the cumulative distribution function (CDF) of the "non-excluded" group stochastically dominates the "excluded" group. In other words, in any time period before both groups reach "saturation point", a higher percentage of the non-excluded group is expected to have adopted the technology. The S-shaped pattern of the adoption curve indicates that the rate of adoption of a technology depends very much on the initial (baseline) level of adoption for each group.

Figure 1a represents the early stages of adoption for a technology: here we expect to see that the more advantaged group has both a higher level of adoption, as well as a higher rate of adoption of the technology (a steeper slope on the CDF). In the early adoption stages, the excluded group may either not yet have started adopting the technology, or in any case would have lower levels of adoption compared to the non-excluded group. This delay may be a function of their expected returns to the investment or lack of resources/information about the technology and its validation. Figure 1b represents the later stages of a technology's adoption, where the excluded group is still expected to have a lower level of adoption, but their rate of adoption (slope of the curve) may now be *higher* compared to the non-excluded group. The impact of the treatment in all cases would be an increase in the adoption rate for both groups, and if the policies have been successfully inclusive, bringing benefits to the poor, we would expect to see that the impact of the treatment would be higher for the excluded group.

2.2 Empirical Specification

In order to test the model presented above, we can use the following empirical specification:

$$\Delta Y_i = \beta + \gamma\, Y_{i(t)} + \delta\left(T_{v(t+1)}\right) + \zeta Y_{i(t)} T_{v(t+1)} + \varphi Z_i T_{v(t+1)} + \Delta u_i \tag{1}$$

Where t is the year when the baseline data is collected in the experiment and t+1 is the year for the post-test data. The dependent variable in the equations (ΔY_i) is whether a certain technology is adopted by a household between time t and t+1. The dependent variable takes the value of 0 or 1. For each household i, the probability of adopting a certain technology in time t+1 depends on: whether they had adopted the technology in the earlier period $(Y_{i(t)})$; whether they have received a treatment (in the form of an agricultural extension program) in time t, $(\mathrm{T}_{v(t+1)})$; the interaction between treatment and the baseline adoption level $(Y_{i(t)} T_{v(t+1)})$; and an interaction term between treatment and household characteristics which provides information on the heterogeneous impact of the treatment on different households $(Z_i T_{v(t+1)})$.

The treatment intervention for increasing the adoption of villagers to the new technology takes place between t and t+1. Given the experimental set-up of the study, the treated group gets the intervention in t+1 while the control group does not. For the treated group: $T_{vt} = 0$ and $T_{v(t+1)} = 1$ and for the untreated group $T_{vt} = 0$ and $T_{v(t+1)} = 0$.

In this specification, β, the constant term, indicates the time trend in the diffusion of the technology in the absence of the treatment. We are able to measure this time-trend given the counterfactual measured by the control group in the time period of the treatment. β is expected to be positive if we assume there is on-going diffusion of the technology (increase in levels of use) outside of the treatment area. The coefficient γ is expected to be negative since the probability of adoption is –by definition– lower for a household that has already adopted the technology in a previous period.

If the treatment has had an impact on adoption rates in the project villages we should expect to see $\delta > 0$. The interaction term between initial levels of adoption and the treatment should yield a negative coefficient (ζ <0) since the treatment is likely to have a smaller impact on those who have already adopted the technology or in places where adoption rates are already high. To the extent that Z_i indicates variables of exclusion, we expect to see a positive coefficient on these variables (or the indexed exclusion variable) interacted with treatment, if the treatment has been "inclusive" and has reached the poor and excluded. A positive and significant coefficient for φ thus indicates (where Z_i are household characteristics that define exclusion and poverty), a pro-poor and inclusive expansion of the technology as a result of the treatment.

Another specification includes baseline characteristics of households (Z_i) in the model. While we normally expect household fixed effects to drop out of the model when we take the first difference, in this model we keep household characteristics, to allow the excluded and non-excluded groups to behave differently in their adoption patterns rates. The specification then becomes:

$$\Delta Y_i = \beta + \gamma\, Y_{i(t)} + \delta\left(T_{v(t+1)}\right) + \zeta Y_{i(t)} T_{v(t+1)} + \varphi Z_i T_{v(t+1)} + \eta Z_i + \Delta u_i \qquad (2)$$

This specification allows us to compare the adoption rates of the excluded and non-excluded groups in the absence of treatment. In this specification, we expect γ may take on a positive or negative value depending on the stage of adoption of the technology: in early stages of adoption the excluded may have lower rates of adoption (as in Figure 1 a in the conceptual framework diagrams) hence η would be expected to be negative for variables that proxy exclusion. For a technology that has already been around and been adopted by a larger percentage of the population, we may expect to see a steeper adoption curve for the excluded (Figure 1 b), in which case η might take on a positive value[1].

A final specification is run looking at the impact of the treatment on the socially excluded:

$$\Delta Y_i = \beta + \gamma Y_{i(t)} + \delta \left(T_{v(t+1)}\right) + \zeta Y_{i(t)} T_{v(t+1)} + \varphi Z_i T_{v(t+1)} + \eta Z_i + \pi S_i T_{v(t+1)} + \Delta u_i \tag{3}$$

Here, the S_i variable is a dummy variable for not having social interactions in the village, and the coefficient on the interaction term between social exclusion and the treatment indicates whether the socially excluded groups in the village were more or less likely to benefit from the program.

To summarize, the following propositions come out of the conceptual model and are tested in the empirical specification.

Proposition 1: The impact of the treatment program is likely to be an increase in the adoption rate for all groups ($\delta > 0$) (if the program is successful).

Proposition 2: The treatment is likely to bring about a higher increase in adoption rates for a technology in the earlier phases of diffusion (ζ <0).

Proposition 3: To the extent that the program is inclusive in its reach, we expect to see that the rates of adoption are higher with the program among the excluded group (where exclusion can be defined in terms of political/economic exclusion or social exclusion). ($\varphi > 0$)

Proposition 4: For a technology that is in the early phases of adoption, we expect the excluded group to have a lower *level* of adoption in the baseline and a lower *rate* of adoption between t0 and t1 than the non-excluded group ($\eta < 0$).

Proposition 5: For a technology that is in the later phases of adoption, we expect the excluded group to still have a lower *level* of adoption in the baseline but we expect the excluded

[1] While the results on exclusion are interesting to explore, it is important to note that there are likely to be issues of endogeneity related to omitted variables (as well as possibly reverse causality) here with the excluded not being able to adopt new technologies for other reasons that are not captures in the regression. So it is important to take these results related to exclusion with some caution and interpret them as associations rather than attribute causality to the interpretations.

group to have a *higher* rate of adoption than the non-excluded group ($\eta > 0$).

Table 1 summarizes the characteristics of households in treatment and control villages in the baseline. It is possible to observe that the percentage of household heads with no formal education (illiterate or with no diploma) is higher (35 percent) in treatment villages compared to control villages where the same percentage is around 20 percent. In treatment villages there is a higher percentage of households that were forced migrants and moved back recently to the villages: the percentage of household heads in treatment villages that report they were forced migrants is 53 percent in the baseline, whereas this value is lower at 33 percent in control villages (difference is significant with p-value<0.01). When we consider the asset profiles of the households in treatment and control villages, we can see similar profiles and the ethnic composition of the villages is also similar with mostly Kurdish speaking minorities living in these clusters of villages in Bitlis.

3 Data

3.1 The Context of the Progam

The data comes from a rural development program implemented by a Turkish NGO in the Bitlis province of eastern Turkey in primarily Kurdish-speaking villages. The eastern and south-eastern regions of Turkey, including Bitlis, have a long history of Kurdish ethnic insurgence dating from the 1930's, originating in the early days of the founding of the Republic of Turkey along lines of Turkish national identity. Conflict between the Turkish military and Kurdish PKK insurgents peaked in the mid-1990s, and the government took measures to clear out Kurdish villages in the region that were taken to be supporters of the PKK [Randal, 1998]. According to official statistics, between 1995 and 1998, the Turkish government emptied 3,000 villages, relocating close to 1 million people to urban centres in other parts of Turkey [2] [Baysal, 2008]. In 2005, the government started a compensation program to help restore life back to these villages. There was, however, a clear need to also bring economic/social livelihoods to this post-conflict area that had suffered for years from military tension and experienced negative growth rates, accompanied by high and stagnant levels of poverty.

[2] According to official statistics, population affected by forced migration is 953,680, while it climbs up to 1.5-3 million according to non-governmental organizations.

The Özyeğin Rural Development Program was launched in January 2009, against this background of underdevelopment, forced migration and high levels of poverty. The project started as a pilot in 6 six villages in the eastern Bitlis province of Turkey. At the launch of the program, the project villages had high levels of poverty, and unemployment, particularly among the youth. When the program was launched, the unemployment rate and the percentage of population looking for jobs were high in the villages[3]. Because of a lack of availability of local jobs, seasonal migration was rampant high among young men in the baseline in 2008[4]. The program was set-up as a post-conflict village livelihoods revitalization project with the aim of "*empowering villagers to return to their villages with economic means to support themselves through agriculture in a sustainable way*". In this regard, the pilot can be considered a post-conflict livelihoods and peace building project in the region. The Program was designed to reduce rural poverty in these villages by investing in the returns to the assets of the poor: mainly by means of investments in their productivity, through the extension of agricultural technologies to the villages.

Before the launch of the program, together with the NGO field team, I collected a baseline survey of households in the 6 treatment villages and also collected a non-randomized control sample from 6 villages in the neighbouring district. The baseline questionnaire included modules on use of agricultural technology, household economic welfare, use of health and education services, as well as a module on women's empowerment and use of maternal health care services. In December 2010, two years after the launch of the program, we ran a post-test in the same villages using a subset of the modules from the baseline survey. The quantitative survey was conducted as a census in the project and control villages (all households in the cluster of villages were interviewed). There were a total of 326 households in the baseline data, coming from 192 households in 6 treatment villages and 134 households in control villages. The panel survey was collected in 389 households since there were new households moving back in this period to the villages: the panel was collected from 227 treatment and 162 control households. In the analysis, only the 325 households that responded to both rounds of the survey were included in

[3]The percentage of working age male population (ages 15+) that were employed in project villages was 57.8 percent, while the unemployment rate has was 12.5 percent.

[4]About 14 percent of men in Project villages reported having to seasonally migrate outside of the province in order to find jobs within the past year. These men were mostly employed in the construction, services and manufacturing sectors and more than half of them worked in Istanbul.

the sample.

Table 2 provides balancedness tests comparing treatment and control villages and provides the t-tests for the differences in the means between treatment and control households across various household head characteristics. It is possible to see the differences in levels of education and the "forced migrant" status of the household head which come out as being significant differences between treatment and control samples.

The differences across treatment and control villages, at least in terms of forced migration status levels, is no coincidence. This is a direct function of the fact that the selection of villages was not random and the implementing NGO had already selected the treatment villages (based on need and the proportion of households returning to the village after forced migration in the 1990s) by the time the evaluation strategy was discussed. For lack of a completely randomized sample, the control villages were selected in the neighbouring district and are a cluster of villages that display similar characteristics: have a similar climate and agricultural crops and have a similar ethnic composition. In this regard, the control villages provide a comparison group for tracking the time trend for the outcome indicators [5].

The Özyeğin Rural Development program impact evaluation provides an opportunity to set hypotheses related to the diffusion of agricultural technologies where there are certain sub-population groups that may be excluded in political/economic or social ways from mainstream access to information. The program attempted to reach out to the excluded groups to increase their adoption of certain technologies and use of public services. Given the panel and experimental structure of the survey, the data collected from this program evaluation allows us to look at technological diffusion rates for households at different baseline levels of adoption and with different characteristics. We can look at the heterogeneous impact of the agricultural extension program implemented by this NGO on different household types and test the propositions listed in the conceptual model.

[5] Given the differences in the baseline across treatment and control villages, it was a good idea to control for baseline household characteristics in the empirical specification in order to reduce bias in the measurement of the treatment effect, which is already how the model is set up (in Equation 2).

3.2 Description of variables

Three different outcome variables Y_i are considered in the paper: (i) whether the household has inoculated fruit trees in the past 12 months, (ii) whether the household has vaccinated livestock against diseases in the past 12 months, and (iii) whether anyone in the household has used public agricultural consulting services (at the district level). The outcome variable ΔY_i is defined as a binary variable in the main results, whereby it takes the values 0 and 1. In the construction of the dependent variable, it is assumed that if a household has already adopted a technology in the past, they already have knowledge of it and would be able to apply it again, or that there is no return from the investment they have made. In this way, if the technology use takes on the value of 1 in t and then the household reports not using the same technology in t1, then the model assumes they still have access to the technology, and the change in their technology use is set equal to 0 (rather than -1).

The Filmer-Pritchett asset index is constructed using principal components analysis and considering a list of housing characteristics and assets [Filmer and Pritchett, 2001]. A higher value of the index indicates higher level of welfare (assets) for the household. The households in the sample (treatment and control villages) are split up into 5 equal groups of household quintiles, with the first quintile indicating the poorest 20 percent of households in terms of assets. The list of variables that are used for the construction of the asset index is listed in Table 3.

Exclusion is defined in the paper in political/economic or social terms. The main exclusion variable in the regressions is constructed as a dummy variable and takes the value of 1 if the household head either (i) does not speak any Turkish, (ii) has not completed any formal schooling, (iii) if the household is in the poorest asset quintile. This variable is constructed as proxy for political and economic exclusion of the household. The regressions consider these variables separately (columns 1-2 in Tables 5-7) as independent variables and also look at the combined "political/economic exclusion" variable as an independent variable (columns 3-4 in Tables 8-10.)[6].

[6]Due to high correlations across these variables, there is a problem with multicollinearity and we lose significance of these variables when they all enter the regression as separate independent variables. This is why an exclusion" proxy variable is constructed as a single proxy variable merging these three exclusion characteristics, in order to illustrate the heterogeneous impact of the program on the excluded.

Social exclusion is defined as the household not having any social interactions with the rest of the households in the village. The data is collected in a social networks module that asks each household head in the village, which households they have "frequent" interactions with and which households in the village they have "rare/occasional" interactions with. The second kind of interaction is coded in the data as a "weak link" in the network. Such links are important for the transfer of information across households; hence we use this variable to construct the social exclusion variable for the household[7].

4 Results

4.1 Descriptive Statistics

The descriptive analysis in Table 4 and Figure 2 provide some descriptive insights on agricultural adoption rates in the data before launching on the interpretation of the regression results:

First of all, adoption levels in the baseline between treatment and control villages did not vary: Agricultural technology use and utilization of public agricultural extension services vary at the baseline by household characteristics and the technology in question: In treatment villages where the intervention took place, 21.6 percent of households had inoculated fruit trees and 48.3 percent of households had vaccinated livestock in 2008 (compared to 23.1 percent and 50.8 percent respectively in control villages). The difference in adoption rates across the treatment and control groups was not statistically different in the baseline. The use of public agricultural services was also quite low in both project and control villages: 18.9 percent of treatment households and 19.7 percent of control village households had utilized such consulting services in the past year when baseline data was collected (See Table 4).

Second, in the baseline, in both treatment and control villages, we find that the excluded group has lower adoption levels for all dependent variables. Figure 2 summarizes visually the adoption rates in treatment and control villages before and after the program, for the

[7]Since weak social ties are particularly important for the diffusion of knowledge and information [Granovetter, 1973], in this paper we consider these types of social ties across households rather than strong ties that may be based on kinship and family relationships. Socially excluded households in the village, may be less likely to have heard of agricultural extension programs, and may therefore have lower levels of adoption in the baseline. They may also have a lower likelihood of benefiting from the NGOs intervention, since they have weak social interactions and may be unaware socially of the treatment that is taking place at the village level.

"excluded" and "non-excluded" households[8]. This pattern of the non-excluded having higher levels of adoption in the baseline holds for all three dependent variables in the analysis. This is in line with our expectation from the conceptual model Figures 1a and 1b where the cumulative distribution function for the technology adoption rates of the non-excluded group stochastically dominates the CDF of the excluded group.

Third, for both the excluded and non-excluded groups in treatment villages the adoption level increases in this time period, and in all cases the difference-in-differences between the treatment and control groups is positive. This is in agreement with Proposition 1 in the conceptual model. For the excluded group, however, the increase in adoption levels for inoculation of fruit trees as well as vaccination of animals is higher than for the non-excluded group, indicating that the policies implemented by the NGO were inclusive and helped reach out to the poor and lower educated members of the community on these two indicators (also in line with Proposition 2 in the conceptual model). However, the impact of the program on the excluded group, in terms of expanding reach to public services seems more limited: in terms of utilization of consulting services the program does seem to succeed in rates of access however not necessarily in an inclusive, pro-poor fashion. This is an interesting finding that will also be confirmed below in regression results.

Finally, it is important to note that the baseline adoption levels of these technologies are very different and therefore we should expect to see different diffusion patterns (and rates of adoption) among the excluded and non-excluded groups: While vaccination of animals was already adopted by close to half of the households in the baseline, inoculation of fruit trees and utilization of consulting services had only been adopted by about 1 in 5 households. We expect therefore that the diffusion patterns of the two technologies would be different after the treatment (following Propositions 4 and 5 in the conceptual framework respectively).

4.2 Main Results

The results of the OLS regressions for equations 1 and 2 are presented in Tables 5-7. In columns 1-2 the household characteristics for exclusion are taken as separate variables: these include the

[8]The definition of exclusion is based on economic and political exclusion. The variable is defined as being either in the poorest asset quintile, having no formal education or not speaking the official language of the country (Turkish).

household being in the poorest asset quintile, the household head not speaking Turkish, and the household having no formal schooling or being illiterate. In Columns 3-4 of these tables, the exclusion variable is reduced to a dummy variable that takes on the value of 1 if any of the exclusion characteristics are in place. Column 5 in all of the tables runs the specification in Equation 3 that includes the “social exclusion” variable.

The samples in the regressions in this section were limited to households that could potentially benefit from the treatment. Note that while the total sample of households that responded to both rounds of the panel were 325 households, only 249 households (76.6 percent of the total sample) had fruit trees or could benefit from inoculation, and only 185 households (56.9 percent of total sample) had livestock and could benefit from an expansion in vaccination.

4.2.1 Inoculation of Fruit Trees: Early Stage Adoption

Table 5 provides results of the OLS regression for the dependent variable on inoculating fruit trees. Given that the inoculation of fruit trees was a technology adopted by 22 percent of households in the baseline (in treatment and control villages overall), we expect to see a pattern here of early adoption (See Figure 1a). In the results we find that $\gamma <0$, indicating that higher levels of adoption in the baseline is associated with lower probability of adopting the technology during the treatment period. This is consistent with the model since we would only expect to see a positive coefficient on γ in the very early stages of adoption (as diffusion gains momentum). The treatment is associated with an increase in the rate of adoption by 26.2-31.4 percentage points depending on the specification (see Table 5 Columns 1-5). This fulfils proposition 1 in the conceptual framework ($\delta > 0$) and indicates that the program was successful in increasing the adoption rate in the treatment villages overall. For higher levels of initial adoption, the impact of treatment is smaller ($\zeta <0$) as predicted by Proposition 2. (This result makes intuitive sense since with higher levels of adoption, there are a smaller number of households to have adopted the technology, and hence it becomes more difficult to diffuse a technology for the NGO.)

We test the inclusiveness of the NGOs efforts for reaching the excluded groups ($\varphi >0$): in Column 2 and 4 the where specification follows Equation 2: we find that those with no formal education are more likely to have higher adoption rates as a result of the treatment (Column 2) and those in the “excluded” category (as defined by either being in the poorest quintile, having no formal education or no speaking Turkish) are more likely to adopt the technology in this time period by 22.7 percentage points (See Column 4). The variable that interacts treatment with exclusion takes a highly positive and significant value hence it is possible to say that Proposition 3 in the model also holds for this technology and that diffusion of the technology has been inclusive. On the other hand, the excluded in general are less likely to have adopted the technology in this time period: in columns 2 and 4, we can observe that the coefficient on the variable for being in the poorest quintile, and the coefficient on the "exclusion" variable are both negative. The "excluded" (in Column 4) are 14.4 percentage points less likely to adopt the technology in this time period compared to the non-excluded. This finding is consistent with Proposition 5 in the conceptual model, that the excluded have lower rates of adoption (as well as lower levels of adoption) in the early phases of diffusion of a technology.

Finally, we also test for the impact of treatment on the socially excluded (in Column 5). The results show that for such socially excluded households, the efforts of the NGO are not necessarily inclusive: while those who are excluded on the economic/political dimensions, benefit favourably from the NGOs efforts, the socially excluded are less likely to have increased adoption levels as a result of the program (the coefficient on social exclusion is -0.173 with p-value$<$0.10).

4.2.2 Vaccination of Livestock: Later Stage Adoption

The second set of OLS results are related to the vaccination of animal livestock in the villages against diseases and are presented in Table 6. As described in Section 4.1, the baseline adoption levels for animal vaccination are higher at close to half of the villagers in the baseline using this technology. In this regard, it can be considered a technology already in the later stages of diffusion (See Figure 1b), by the time the NGO intervention starts. The baseline level of adoption takes on a strongly negative coefficient in these regressions: for higher levels of baseline adoption, we expect to see a much lower rate of adoption during the treatment period: ($\gamma <0$). The impact of the NGOs efforts are not reflected on the results: the households located in the treatment villages are not more likely to adopt the technology and we also lose the results on the interaction terms between treatment and exclusion for this dependent variable: the treatment effect cannot be observed in these results in a statistically significant manner, and the excluded are also not more likely to adopt the technology as a result of the NGOs efforts.

(hence Propositions 1- 3 do not hold).

What we do observe is that for the excluded group the rate of adoption is higher (even without the treatment) and this is in accordance with Proposition 5 in the model, whereby we expect the excluded to have higher adoption rates and to catch up in the later stages of diffusion.

4.2.3 Use of Consulting Services: Early Adoption in the Case of Access to Public Services

The last set of results are presented in Table 7 where the dependent variable is whether anyone in the household has utilized publicly provided agricultural consulting services in the last year. In this case, the results closely resemble the early adoption period results for inoculation of fruit trees, though there is one difference: the treatment is not necessarily inclusive, particularly for the group that does not speak the official Turkish language. This intuitively makes sense since to make use of public services the ability to speak the official language would be essential.

Looking at these results in more detail: in the baseline we noted that about 20 percent of households were using these consulting services: hence we do expect the pattern of diffusion to be quite similar to the section on inoculation of fruit trees as the initial penetration rates are the same. In this set of results, again we find that baseline level of adoption is negatively correlated with adoption rates ($\gamma < 0$) and that treatment has a positive impact on adoption rates for all ($\delta > 0$) , and treatment is less likely to be as beneficial in places with higher levels of initial adoption ($\zeta < 0$). In the case of use of public services though, we find that treatment was *not* more likely to benefit the excluded, rather the non-excluded group benefited disproportionately in this regard ($\varphi < 0$) (Column 4). The exclusion variable for not speaking Turkish took on a highly negative and significant coefficient in these regressions where not speaking the official language was associated with a 23.3 percentage point reduction in the probability of increased use of consulting services (with p-value<0.05). Being excluded from social networks was once again associated with a lower level of increase in the adoption rate for these services.

4.3 Robustness Checks

In the current data set used for the study, there are a total of only 12 clusters (villages) and in the main results so far presented robust standard errors clustered at the village level are presented. Cameron et al. [2007] suggests that in applications with few clusters (5-30), standard asymptotic tests can over-reject considerably. The authors provide a technique for using bootstrap methods to get asymptotic refinement on the results. In this paper, we run the same specifications using these bootstrapped standard errors (with 100 bootstrap repetitions in the calculation) as robustness checks.

Most results reported are robust to this asymptotic refinement, though not all. Tables 8-10 provide the OLS results with bootstrapped standard errors. While the treatment effect of the program and the interactions between baseline adoption levels and treatment are robust to the adjustment using bootstrapped standard errors, we lose significance on some of the exclusion variables (ηZ_i) in the robustness checks. For instance, while being in the poorest quintile of assets was associated with lower adoption rates for inoculation of fruit trees (with p-value$<$0.10) (in Table 5 Column 2), we find that this is no longer the case with bootstrapped standard errors (See Table 8 Column 2). The results on the inclusion/exclusion of the treatment (the interaction between exclusion variables and treatment) are still significant after the standard errors are adjusted.

As a second robustness check, I run the same specification using dependent variables that are defined as a change in behaviour variable and take the values -1, 0 and 1. If the household adopts the technology in t+1 and did not use the technology in t, the outcome variable takes the value 1. If the household used the technology earlier and then stopped using the technology the outcome variable takes the value -1. If there has been no change in behaviour for the household, then the outcome variable takes the value 0. Hence there are 3 categories the dependent variable can take: -1 for a decrease in use of technology, 0 for no change in adoption status and 1 for an increase in the use of the technology. The main results on the impact of treatment and disproportionate impact on the excluded group remain robust to this specification as well.

5 Conclusion

This paper considers the impact of an agricultural extension program implemented in a post-conflict area in eastern Turkey. The paper builds on previous theoretical models of agricultural technology diffusion and tests some of the arguments in these models looking at the heterogeneous impact of the program on adoption rates of "excluded" and "non-excluded" groups in the villages. Using an experimental panel survey data of treatment and control households in the villages where the agricultural extension program is carried out, the paper explores heterogeneity in the adoption rates of technologies for different parts of the village population. The main results in the paper are consistent with the predictions of the model presented: for instance in the early stages of adoption, the existence of the agricultural extension program increased the adoption rates in the villages significantly for all households: treatment is associated with an increase in the rate of adoption of inoculation of fruit trees by 26.2-31.4 percentage points depending on the empirical specification. One also finds evidence of the "inclusiveness" of the NGO's efforts by looking at the heterogeneous impact of the program of adoption rates of the excluded group and find that those in the excluded group (defined as political and economic exclusion) have an even higher likelihood of adoption for this technology. An interesting descriptive finding in the paper that merits further study is the contrast in results for the politically/economically and socially excluded groups. The paper finds that while the politically and economically excluded groups, may be reached and can benefit from the inclusive policies in the villages, those in the "socially" excluded group and that do not have many social interactions with the rest of the village community remain excluded from the benefits of the program.

This paper considered the impact of an agricultural extension program in a post-conflict setting in eastern Turkey. It tested a model of agricultural technology diffusion by using an experimental panel survey that was conducted in project villages as well as control villages before and after program implementation.

The main propositions of the model were that if the extension program were successful, there would be an increase in the adoption rates of villagers in the treatment group, though the changes in adoption levels would vary by the phase of diffusion of the technology (early vs. late phases of adoption) and by the characteristics of the households (whether they were considered to be among an excluded or non-excluded group in the villages). We expected to see that for the technologies in the earlier phases of adoption, the excluded group would have lower levels and rates of adoption, while the non-excluded group (with higher assets, education and those who spoke the official language in the country) would have higher levels and rates of adoption. In the empirical findings, this was the case for two of the dependent variables: inoculation of fruit trees, as well as increased use of public consulting services. Both of these were used only by about one-in-five households in the baseline survey, and these technologies/utilization rates could be considered as being in the nascent stages of growth.

The extension program increased the adoption rates for inoculation of fruit trees by anywhere between 26.2 -31.4 percentage points. The impact of the program was higher among those with lower levels of initial adoption, and among the politically/economically excluded group. Among the excluded the likelihood of adoption was higher by an additional 22.7 percentage points as a result of the program. Consistent with the conceptual model, in the absence of the program though, the adoption rates of the excluded would have been lower for this technology in the earlier phases of adoption. The findings for the use of consulting services were similar (with strong impact of the program on overall adoption rates), however there was a difference in the reach of the program to the politically/economically excluded group: The program had no impact on improving access of the politically excluded to publicly provided agricultural services, while having a very strong and positive reach to the excluded group in the villages through its own private means (in the form of inoculation of fruit tress). This suggests that barriers to accessing mainstream information services is still limited in this post-conflict region particularly for those who do not speak the official language. The paper found that for vaccination of livestock, the impact of the program was negligible, and one could also not see a favourable impact of the program on the excluded. However, it was possible to see that the excluded group had higher catch-up rates in such a later-adoption stage technology (even in the absence of the program).

The paper also contrasted results of the impact of the program for the politically/ economically excluded group vs. the socially excluded groups in the villages and it found systematically that those who were socially excluded in the villages could derive less benefits from the program and were less likely to adopt even when the NGO program could be defined as inclusive in reaching the poor and more disadvantaged. In other words, from this descriptive analysis, it seems that lack of social capital on the part of a household impacts their likelihood of benefiting from such services, more so than their lack of access to physical capital (as proxied by the asset index) or human capital. This is an interesting descriptive finding of the paper that certainly merits further investigation.

The empirical analysis in this paper can be taken further in several ways: first of all, the "exclusion" variable used in the paper was a crude definition constructed using several existing variables in the data set relating to wealth (asset index), education and ability to speak the official language. While this serves as a decent proxy for exclusion in this region, it would be much better to have a more detailed – and preferably categorical - variable on exclusion. This could be collected using self-reporting, as well as using objective data on the number of visits to government offices, voting history and degree of engagement in political/social affairs.

Second, it would be good to repeat a similar analysis where the adoption levels are reported as continuous variables, where we can also take the quadratic form of the baseline adoption levels. This would enable us to emulate the S-shaped diffusion function and thus fit the functional form described in the conceptual model better. It would also be good to have larger sample sizes in the data, that would allow the construction of village level baseline adoption variables. Both of these independent variables would help explain the model better.

Finally, it would be interesting to further pursue the results presented in this paper on social exclusion and the inability of the program to reach the socially excluded (while being perfectly inclusive of the politically and economically excluded groups). It is obviously very difficult to set-up an experimental study that would give causal interpretations on this social exclusion variable (since such set-up would have serious ethical drawbacks), but it may be possible to have further qualitative measures of social exclusion included in the data that would perhaps make the correlation results associated with this variable more consistent and reliable.

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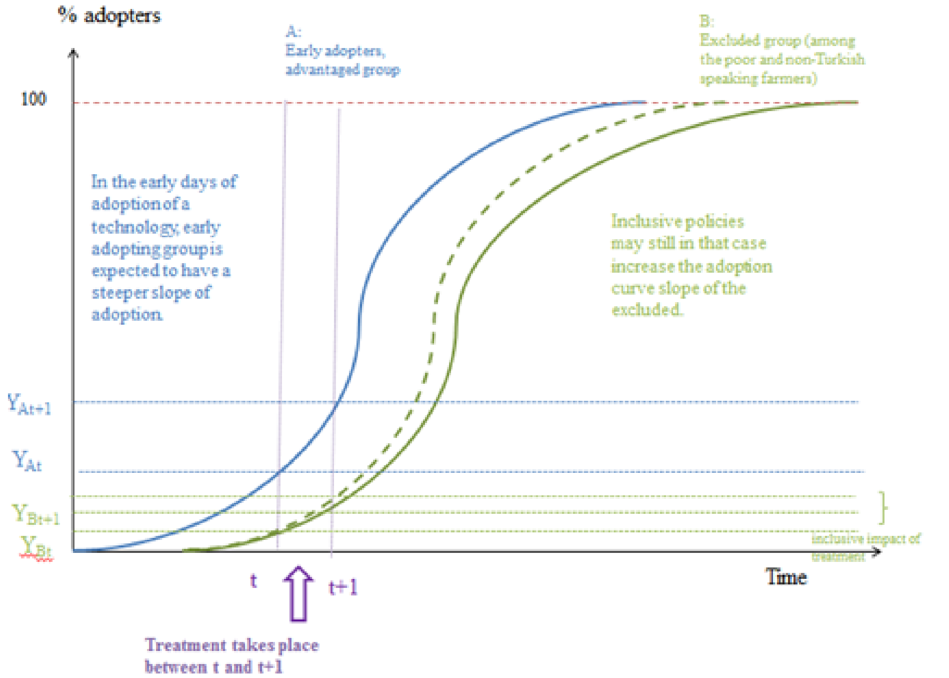
Figure 1: Conceptual Model for Agricultural Technology Diffusion

(a) Earlier Stages of Adoption



(b) Later Stages of Adoption

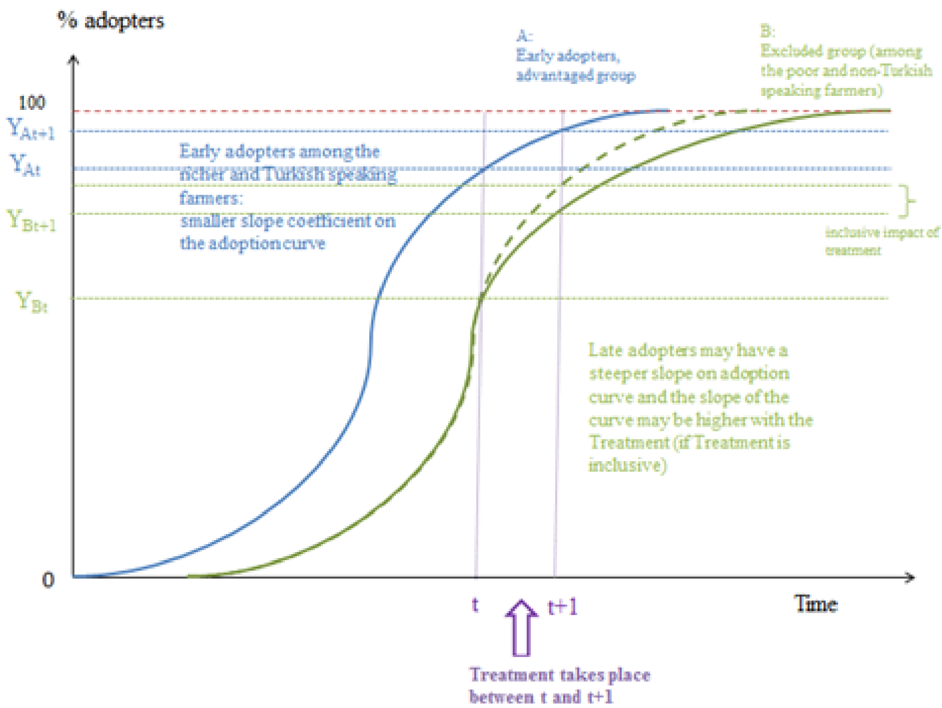
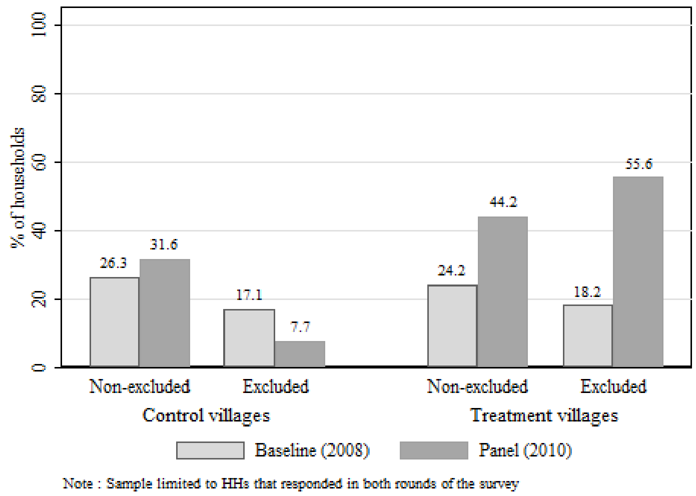
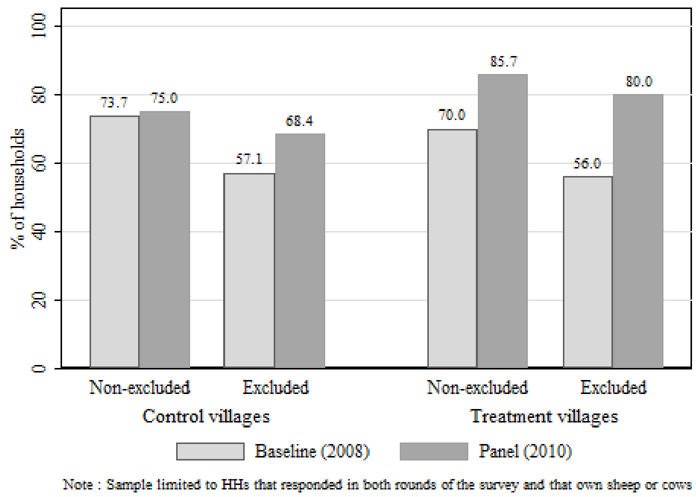


Figure 2: Changes in Agricultural Technology Adoption and Use of Consulting Services in Treatment and Control Villages

(a) Percentage of households that inoculated fruit trees



(b) Percentage of households that used preventive vaccination



(c) Percentage of households that visited the district or province agricultural offices

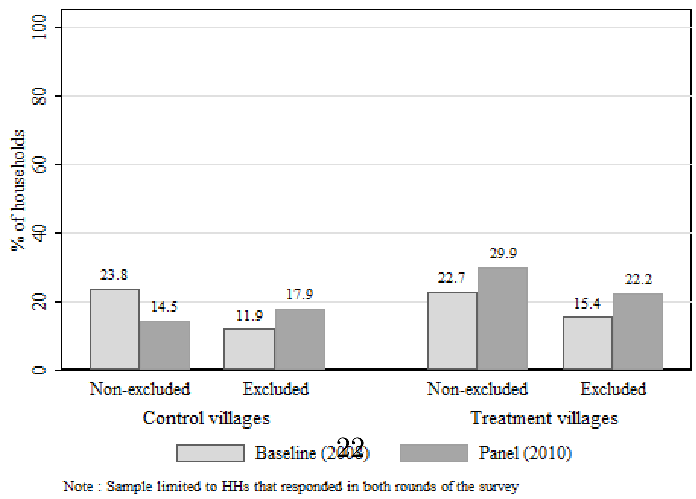


Table 1: Summary Statistics in Baseline for Treatment and Control Villages

	Household in Treatment Village					
	Control villages		**Treatment villages**		**Total**	
	Col %	95% CI	Col %	95% CI	Col %	95% CI
Asset Quintiles						
Asset Quint 1 (n=66)	24.1	[17.5,32.1]	17.6	[12.8,23.7]	20.2	[16.2,25.0]
Asset Quint 2 (n=65)	25.6	[18.8,33.7]	16.1	[11.5,22.0]	19.9	[16.0,24.6]
Asset Quint 3 (n=65)	18.0	[12.4,25.6]	21.2	[16.0,27.6]	19.9	[15.9,24.7]
Asset Quint 4 (n=65)	13.5	[8.7,20.5]	24.4	[18.8,30.9]	19.9	[16.0,24.6]
Asset Quint 5 (n=65)	18.8	[13.0,26.4]	20.7	[15.6,27.1]	19.9	[15.9,24.7]
Total (n=326)	100.0		100.0		100.0	
Educational Attainment of HH Head						
Illiterate or no diploma (n=91)	19.7	[13.7,27.4]	35.1	[28.6,42.3]	28.7	[24.0,33.9]
Primary school (n=192)	65.9	[57.4,73.5]	56.8	[49.5,63.8]	60.6	[55.1,65.8]
Basic education or Junior High School (n=18)	9.1	[5.2,15.4]	3.2	[1.5,7.1]	5.7	[3.6,8.8]
Senior High School or Above (n=16)	5.3	[2.5,10.8]	4.9	[2.5,9.1]	5.0	[3.1,8.1]
Total (n=317)	100.0		100.0		100.0	
Does not speak Turkish						
Speaks Turkish (n=307)	98.5	[94.1,99.6]	95.1	[90.9,97.5]	96.5	[93.9,98.1]
Does Not Speak Turkish (n=11)	1.5	[0.4,5.9]	4.9	[2.5,9.1]	3.5	[1.9,6.1]
Total (n=318)	100.0		100.0		100.0	
Was a forced migrant						
HH head was not a forced migrant (n=180)	66.9	[58.4,74.4]	47.2	[40.2,54.2]	55.2	[49.8,60.5]
HH head was a forced migrant (n=146)	33.1	[25.6,41.6]	52.8	[45.8,59.8]	44.8	[39.5,50.2]
Total (n=326)	100.0		100.0		100.0	
Exclusion variable)						
Non-excluded (n=189)	63.2	[54.6,71.0]	54.4	[47.3,61.3]	58.0	[52.5,63.2]
Excluded (n=137)	36.8	[29.0,45.4]	45.6	[38.7,52.7]	42.0	[36.8,47.5]
Total (n=326)	100.0		100.0		100.0	

Source: Bitlis Baseline data

Table 2: Balancedness Tests Comparing Treatment and Control Villages

Variable Name	**Treatment**	**Control**	**T-test for difference in the means**
Asset index	3.937	3.812	-1.111
	-1.027	-0.958	[0.267]
Poorest Quintile	0.176	0.241	1.423
	-0.382	-0.429	[0.156]
Richest Quintile	0.207	0.188	-0.427
	-0.406	-0.392	[0.670]
No formal Education	0.351	0.197	-3.029***
	-0.479	-0.399	[0.003]
Primary School	0.568	0.659	1.646
	-0.497	-0.476	[0.101]
Basic Education	0.032	0.091	2.228**
	-0.178	-0.289	[0.027]
Secondary School or higher	0.049	0.053	0.175
	-0.216	-0.225	[0.861]
Does not Speak Turkish	0.049	0.015	-1.619
	-0.216	-0.122	[0.106]
Forced Migrant	0.549	0.331	-3.969***
	-0.499	-0.472	[0.000]
Exclusion Variable	0.456	0.368	-1.575
	-0.499	-0.484	[0.116]

Notes: The standard deviations are provided below (Column 1-2) and the p-values for the t-test are provided in [bracket]. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Source data: Bitlis Baseline Survey

Table 3: Household Characteristics and Assets Used in the Construction of the Asset Index

Household Assets	Refrigerator
	Oven
	Iron
	Microwave oven
	Laundry machine
	Dishwasher
	Radio
	TV
	Satellite
	Cable TV (Digiturk)
	Computer
	Landline phone
	Mobile Phone
	Bicycle
	Private Car
	Minibus
Household Characteristics	Number of Rooms
	Number of Living Rooms
	Number of Kitchens
	Number of Toilets
	Number of Baths
	Number of Animal Barns

Table 4: Summary Statistics for the Adoption of Agricultural Technologies

	Mean					
	Baseline Inoculation (%)	Baseline Vaccination (%)	Baseline Consulting (%)	Panel Inoculation (%)	Panel Vaccination (%)	Panel Consulting (%)
Asset Quintiles						
Asset Quint 1 (20%)	13.5	35.8	15.4	30.8	57.7	28.8
Asset Quint 2 (20%)	24.1	46.6	19.7	20.4	67.3	16.0
Asset Quint 3 (20%)	19.0	55.0	16.9	35.0	65.0	13.3
Asset Quint 4 (20%)	19.4	42.9	11.3	52.6	75.4	15.8
Asset Quint 5 (19%)	33.9	63.9	32.3	49.1	72.7	34.5
Total (100%)	22.3	49.2	19.3	38.1	67.8	21.5
Educational Attainment of HH Head						
Illiterate or no diploma (28%)	21.2	40.0	15.1	42.9	62.3	15.6
Primary school (60%)	21.5	52.8	20.0	34.1	68.9	21.2
Basic education or Junior High School (5%)	26.7	60.0	12.5	68.8	87.5	25.0
Senior High School or Above (5%)	38.5	53.8	46.2	30.0	50.0	50.0
Total (100%)	22.4	49.5	19.3	38.6	67.4	20.9
Does not speak Turkish						
Speaks Turkish (96%)	23.2	49.8	19.4	37.8	66.8	21.5
Does Not Speak Turkish (3%)	0.0	27.3	18.2	50.0	90.0	0.0
Total (100%)	22.3	49.0	19.3	38.3	67.7	20.7
Exclusion variable)						
Non-excluded (57%)	25.3	56.8	22.7	37.7	72.2	22.1
Excluded (42%)	17.8	37.8	14.2	38.7	61.3	20.7
Total (100%)	22.3	49.2	19.3	38.1	67.8	21.5
Household in Treatment Village						
Control villages (40%)	23.1	50.8	19.7	23.5	62.6	15.7
Treatment villages (59%)	21.7	48.0	19.0	48.7	71.5	25.8
Total (100%)	22.3	49.2	19.3	38.1	67.8	21.5

Source: Bitlis Baseline data

Table 5: OLS estimation for Increase in Adoption of New Technologies in Agriculture (Inoculation of Fruit Trees)
(Dependent variables: Increase in inoculation of fruit trees (0,1 binary variable))

	(1) inoculation	(2) inoculation	(3) inoculation	(4) inoculation	(5) inoculation
Baseline adoption level: Inoculation	-0.195***	-0.203***	-0.192***	-0.206***	-0.206***
	(0.0182)	(0.0201)	(0.0189)	(0.0257)	(0.0258)
Household in Treatment Village	0.262***	0.271***	0.268***	0.281***	0.314***
	(0.0305)	(0.0288)	(0.0306)	(0.0285)	(0.0182)
Baseline adoption level (Inoculation) x Treatment	-0.359***	-0.351***	-0.345***	-0.331***	-0.342***
	(0.0470)	(0.0480)	(0.0410)	(0.0446)	(0.0471)
Poorest Asset Quintile X Treatment	-0.0491	0.0279			
	(0.0580)	(0.0666)			
No formal education x Treatment	0.0913	0.180*			
	(0.0515)	(0.0926)			
Does not speak Turkish X Treatment	-0.0469	0.0179			
	(0.151)	(0.163)			
Poorest Asset Quintile		-0.0770**			
		(0.0322)			
No formal education		-0.0891			
		(0.0768)			
Does not speak Turkish		-0.0648			
		(0.0597)			
Exclusion Variable x Treatment			0.0827*	0.227**	0.237***
			(0.0410)	(0.0745)	(0.0743)
Exclusion				-0.144**	-0.144**
				(0.0621)	(0.0623)
Social exclusion x Treatment					-0.173*
					(0.0911)
Constant	0.195***	0.231***	0.192***	0.242***	0.242***
	(0.0182)	(0.0363)	(0.0189)	(0.0398)	(0.0399)
Observations	247	247	249	249	249

Standard errors in parentheses
Source data: Bitlis Baseline and Panel 1 Surveys. Robust standard errors clustered at the village level.
* p¡0.10, ** p¡0.05, *** p¡0.01

Table 6: OLS estimation for Increase in Adoption of New Technologies in Agriculture (Vaccination of Livestock)
(Dependent variables: Increase in vaccination of livestock (0,1 binary variable)) The sample for animal vaccination regressions is limited to households that own a sheep or a cow.

	(1) vaccination	(2) vaccination	(3) vaccination	(4) vaccination	(5) vaccination
Baseline adoption level: Vaccination	-0.850***	-0.838***	-0.850***	-0.844***	-0.844***
	(0.0541)	(0.0590)	(0.0538)	(0.0518)	(0.0519)
Household in Treatment Village	-0.0188	-0.0241	-0.0149	-0.0223	-0.0189
	(0.0314)	(0.0298)	(0.0303)	(0.0290)	(0.0220)
Baseline adoption level (Vaccination) x Treatment	0.0536	0.0420	0.0444	0.0382	0.0367
	(0.0902)	(0.0937)	(0.0866)	(0.0855)	(0.0831)
Poorest Asset Quintile X Treatment	0.00358	-0.0536			
	(0.0890)	(0.0935)			
No formal education x Treatment	0.0268	-0.0134			
	(0.0368)	(0.0472)			
Does not speak Turkish X Treatment	0.101	0.0250			
	(0.0631)	(0.0746)			
Poorest Asset Quintile		0.0572*			
		(0.0260)			
No formal education		0.0401			
		(0.0291)			
Does not speak Turkish		0.0759*			
		(0.0389)			
Exclusion Variable x Treatment			0.0302	-0.0397	-0.0402
			(0.0434)	(0.0469)	(0.0450)
Exclusion				0.0699***	0.0699***
				(0.0176)	(0.0177)
Social exclusion x Treatment					-0.0206
					(0.0580)
Constant	0.850***	0.827***	0.850***	0.829***	0.829***
	(0.0541)	(0.0610)	(0.0538)	(0.0538)	(0.0539)
Observations	185	185	186	186	186

Standard errors in parentheses
Source data: Bitlis Baseline and Panel 1 Surveys. Robust standard errors clustered at the village level.
* p¡0.10, ** p¡0.05, *** p¡0.01

Table 7: OLS estimation for Increase in Use of Consulting Services
(Dependent variables: Increase in Use of Agricultural Consulting Services(0,1 binary variable))

	(1) consulting	(2) consulting	(3) consulting	(4) consulting	(5) consulting
Baseline consulting services utilization level	-0.133***	-0.124***	-0.131***	-0.114***	-0.114***
	(0.0263)	(0.0275)	(0.0262)	(0.0210)	(0.0210)
Household in Treatment Village	0.0856***	0.0885***	0.0780***	0.0690**	0.0878**
	(0.0253)	(0.0230)	(0.0246)	(0.0289)	(0.0361)
Baseline consulting services utilization level x Treatment	-0.105***	-0.113***	-0.109***	-0.125***	-0.115***
	(0.0316)	(0.0327)	(0.0345)	(0.0308)	(0.0330)
Poorest Asset Quintile X Treatment	-0.00235	-0.0906			
	(0.0574)	(0.0753)			
No formal education x Treatment	-0.141**	-0.179			
	(0.0560)	(0.111)			
Does not speak Turkish X Treatment	-0.0877*	0.145			
	(0.0448)	(0.0939)			
Poorest Asset Quintile		0.0882*			
		(0.0483)			
No formal education		0.0375			
		(0.0953)			
Does not speak Turkish		-0.233**			
		(0.0824)			
Exclusion Variable x Treatment			-0.131***	-0.223**	-0.214**
			(0.0356)	(0.0769)	(0.0753)
Exclusion				0.0917	0.0917
				(0.0682)	(0.0683)
Social exclusion x Treatment					-0.114**
					(0.0471)
Constant	0.133***	0.107***	0.131***	0.0982***	0.0982***
	(0.0263)	(0.0266)	(0.0262)	(0.0206)	(0.0207)
Observations	253	253	254	254	254

Standard errors in parentheses
Source data: Bitlis Baseline and Panel 1 Surveys. Robust standard errors clustered at the village level.
* p¡0.10, ** p¡0.05, *** p¡0.01

Table 8: Robustness checks:OLS estimation for Increase in Adoption of New Technologies in Agriculture (Inoculation of Fruit Trees)
(Dependent variables: Increase in inoculation of fruit trees (0,1 binary variable))

	(1) inoculation	(2) inoculation	(3) inoculation	(4) inoculation	(5) inoculation
Baseline adoption level: Inoculation	-0.195***	-0.203***	-0.192***	-0.206***	-0.206***
	(0.0522)	(0.0570)	(0.0395)	(0.0541)	(0.0565)
Household in Treatment Village	0.262***	0.271***	0.268***	0.281***	0.314***
	(0.0368)	(0.0374)	(0.0347)	(0.0434)	(0.0289)
Baseline adoption level (Inoculation) x Treatment	-0.359***	-0.351***	-0.345***	-0.331***	-0.342***
	(0.0794)	(0.0754)	(0.0601)	(0.0622)	(0.0723)
Poorest Asset Quintile X Treatment	-0.0491	0.0279			
	(0.0698)	(0.0964)			
No formal education x Treatment	0.0913	0.180			
	(0.0631)	(0.118)			
Does not speak Turkish X Treatment	-0.0469	0.0179			
	(0.150)	(0.120)			
Poorest Asset Quintile		-0.0770			
		(0.0594)			
No formal education		-0.0891			
		(0.0924)			
Does not speak Turkish		-0.0648			
		(0.0937)			
Exclusion Variable x Treatment			0.0827*	0.227**	0.237**
			(0.0447)	(0.113)	(0.0938)
Exclusion				-0.144	-0.144
				(0.102)	(0.0889)
Social exclusion x Treatment					-0.173*
					(0.0953)
Constant	0.195***	0.231***	0.192***	0.242***	0.242***
	(0.0204)	(0.0530)	(0.0270)	(0.0778)	(0.0570)
Observations	247	247	249	249	249

Standard errors in parentheses
Source data: Bitlis Baseline and Panel 1 Surveys. Robust bootstrapped standard errors clustered at village level using Cameron et al (2007)
* p¡0.10, ** p¡0.05, *** p¡0.01

Table 9: Robustness checks: OLS estimation for Increase in Adoption of New Technologies in Agriculture (Vaccination of Livestock)
(Dependent variables: Increase in vaccination of livestock (0,1 binary variable)) The sample for animal vaccination regressions is limited to households that own a sheep or a cow.

	(1) vaccination	(2) vaccination	(3) vaccination	(4) vaccination	(5) vaccination
Baseline adoption level: Vaccination	-0.850***	-0.838***	-0.850***	-0.844***	-0.844***
	(0.0801)	(0.0765)	(0.0858)	(0.0689)	(0.0773)
Household in Treatment Village	-0.0188	-0.0241	-0.0149	-0.0223	-0.0189
	(0.0455)	(0.0320)	(0.0390)	(0.0325)	(0.0303)
Baseline adoption level (Vaccination) x Treatment	0.0536	0.0420	0.0444	0.0382	0.0367
	(0.129)	(0.0985)	(0.109)	(0.0913)	(0.103)
Poorest Asset Quintile X Treatment	0.00358	-0.0536			
	(0.0906)	(0.0951)			
No formal education x Treatment	0.0268	-0.0134			
	(0.0360)	(0.0425)			
Does not speak Turkish X Treatment	0.101	0.0250			
	(0.0789)	(0.0747)			
Poorest Asset Quintile		0.0572			
		(0.0411)			
No formal education		0.0401			
		(0.0346)			
Does not speak Turkish		0.0759			
		(0.0500)			
Exclusion Variable x Treatment			0.0302	-0.0397	-0.0402
			(0.0363)	(0.0548)	(0.0541)
Exclusion				0.0699**	0.0699**
				(0.0328)	(0.0330)
Social exclusion x Treatment					-0.0206
					(0.0551)
Constant	0.850***	0.827***	0.850***	0.829***	0.829***
	(0.0801)	(0.0800)	(0.0858)	(0.0750)	(0.0830)
Observations	185	185	186	186	186

Standard errors in parentheses
Source data: Bitlis Baseline and Panel 1 Surveys. Robust bootstrapped standard errors clustered at village level using Cameron et al (2007)
* p¡0.10, ** p¡0.05, *** p¡0.01

Table 10: Robustness checks: OLS estimation for Increase in Use of Consulting Services
(Dependent variables: Increase in Use of Agricultural Consulting Services(0,1 binary variable))

	(1) consulting	(2) consulting	(3) consulting	(4) consulting	(5) consulting
Baseline consulting services utilization level	-0.133**	-0.124**	-0.131**	-0.114***	-0.114***
	(0.0540)	(0.0603)	(0.0559)	(0.0371)	(0.0375)
Household in Treatment Village	0.0856*	0.0885***	0.0780*	0.0690*	0.0878*
	(0.0471)	(0.0300)	(0.0470)	(0.0408)	(0.0497)
Baseline consulting services utilization level x Treatment	-0.105*	-0.113*	-0.109*	-0.125***	-0.115*
	(0.0568)	(0.0627)	(0.0632)	(0.0404)	(0.0679)
Poorest Asset Quintile X Treatment	-0.00235	-0.0906			
	(0.0588)	(0.104)			
No formal education x Treatment	-0.141**	-0.179			
	(0.0555)	(0.153)			
Does not speak Turkish X Treatment	-0.0877*	0.145			
	(0.0480)	(0.0913)			
Poorest Asset Quintile		0.0882			
		(0.0892)			
No formal education		0.0375			
		(0.150)			
Does not speak Turkish		-0.233**			
		(0.0929)			
Exclusion Variable x Treatment			-0.131***	-0.223**	-0.214*
			(0.0390)	(0.108)	(0.114)
Exclusion				0.0917	0.0917
				(0.0966)	(0.106)
Social exclusion x Treatment					-0.114**
					(0.0573)
Constant	0.133**	0.107*	0.131**	0.0982***	0.0982***
	(0.0556)	(0.0558)	(0.0559)	(0.0364)	(0.0365)
Observations	253	253	254	254	254

Standard errors in parentheses
Source data: Bitlis Baseline and Panel 1 Surveys. Robust bootstrapped standard errors clustered at village level using Cameron et al (2007)
* p¡0.10, ** p¡0.05, *** p¡0.01