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INNOVATION ADOPTION AND LIQUIDITY CONSTRAINTS IN THE PRESENCE OF GRASSROOTS EXTENSION AGENTS: EVIDENCE FROM THE PERUVIAN HIGHLANDS

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Abstract

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JEL Classification: N/A

Keywords: Innovation adoption, liquidity constraint, Trust, credit

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Innovation Adoption and Liquidity Constraints in the Presence of Grassroots Extension Agents: Evidence from the Peruvian Highlands*

by

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1. Introduction

To analyze the role of the wealth constraint in mitigating innovation adoption, this paper uses a technology diffusion program based on the work of business-oriented grassroots extension agents in the Peruvian Highlands. Taking advantage of a multiplicity of innovations with different characteristics and of specific information about innovation suppliers who can grant seller credit, we show that the wealth constraint operates in a limited manner. Moreover, due to higher trust associated with greater familiarity, households are better able to adopt costly and indivisible innovations when a supplier/lender resides in their own community.

The world is now confronted with the challenge of having to raise agricultural productivity significantly so as to allow production to match the increasing demand arising from population growth and greater prosperity. It is an alarming fact that almost all recent increases in the world's cereal output came from rich countries, and much of this was a result of increased acreage, a possibility almost foreclosed in developing countries (FAO, 2009). Increasing agricultural yields is also one of the most effective means of reducing poverty because the poor are concentrated in rural areas and non-agricultural opportunities are limited in developing countries. In conditions of acute land pressure and/or poor soil fertility, yield increases will not happen unless technical progress takes place on a large scale.

It would be wrong to believe that slow growth in land productivity is necessarily caused by a short supply of technical innovations. For example, despite the release of nearly 1,700 improved wheat varieties in developing countries during the period 1988-2002, only a relatively small number have been adopted on a substantial scale by farmers (Dixon et al., 2006, p. 489). A large majority of them remain on the shelves of big international organizations, such as the Institutes belonging to the CGIAR (Consultative Group for International Agricultural Research). There are two main explanations for under-utilization of new technologies: technical innovations are inappropriate in the sense of being unsuited to the micro-environmental conditions faced by potential users; and these users are unwilling or unable to adopt them. If the first explanation has been used in some of their works (see, for example, Griliches, 1957), economists have largely focused their attention on a variety of factors that come under the second explanation.

These factors include information problems and lack of education (Foster and Rosenzweig, 1996; Weir and Knight, 2000; Dimara and Skuras, 2003; Munshi, 2008;

Adegbola and Gardebroek, 2007), credit constraints (Bhalla, 1979; Croppenstedt *et al.*, 2003; Barrett et al., 2004; Gine and Klonner, 2005; Minten et al., 2007; Miyata and Sawada, 2007), consumption risks (Dercon and Christiaensen, 2008; Gine and Yang, 2009; Foster and Rosenzweig, 2009), poor learning effects due to low density of social networks (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010), and problems of access to, and timely delivery of, modern inputs, which are often associated with poor infrastructure (Suri, 2009; Moser and Barrett, 2006).

Precisely because there are so many potential factors at play, methodological problems are likely to be serious. For example, when assessing innovation behaviour, it is particularly important to allow for incomplete information of potential adopters, so as to avoid selectivity bias (Feder et al., 1985; Rigby and Caceres, 2001). It is true that the use of sample separation and the modelling of innovation adoption as a multistage (usually a two-stage) decision process are explicitly aimed at surmounting the selectivity bias.[1] The difficulty remains, however, that a proper instrument satisfying the exclusion restriction may not be available.

A way out of this difficulty is provided by random experimental designs. Thus, Duflo, Kremer, and Robinson (2008), by applying treatment randomly across a farmer's plots, have shown that offering Kenyan farmers the option of buying fertiliser immediately after the harvest when liquidity constraints are most relaxed has the effect of increasing significantly the proportion of farmers using this modern input (at the full market price, but with free delivery). In this case, the obstacle to fertiliser use lies in savings difficulties rather than in information problems about its potential benefits, or supply constraints impinging on the local availability of crucial inputs (see also Carter et al., 2013, 2015).

A flurry of such experimental studies is currently undertaken under the Agricultural Technology Adoption Initiative (ATAI) of the Gates Foundation. They all aim at testing the impact of various types of interventions: social networks, collateralized loans, time-limited discounts on the price of fertilizers (with a few weeks' window right after the harvest), price subsidy schemes for the purchase of new seeds, introduction of new credit, savings, and insurance products, provision of targeted agricultural extension work involving community

[1] The first stage corresponds to the process of acquisition of the minimum information necessary to evaluate and assess the innovation. It is typically modelled by assuming that everybody has heard of an innovation, so that awareness results from an active and costly process of information collection only (see Saha et al., 1994, Dimara and Skuras, 2003, for more details). Note that stages preliminary to the actual adoption-decision process need not be associated with information acquisition only: they may concern access to credit or crucial inputs such as seeds or fertilisers, whose distribution may be highly imperfect (as is done in Coady, 1995; and Shiferaw, et al., 2008).

demonstration plots, supply of toll-free access to agricultural information via mobile phone, provision of input marketing and delivery services, supply of special devices to help farmers apply fertilizers effectively, etc.

Although our study does not follow an experimental approach and does not use randomisation, it avoids some important drawbacks of the multistage modelling of the adoption decision process. Indeed, we exploit the occurrence of an external shock under the form of a NGO (Non-Governmental Organisation) intervention aimed at training local extension agents who would then be able to disseminate information and distribute modern inputs to potential users of the Peruvian Highlands. The environment in which the supply of innovations occurs is thus made homogenous along the key dimensions of information, (basic) training and input distribution. By estimating the effect of the shock on innovation adoption among households of varying initial wealth or income, we are thus able to control for important confounding factors.

There still remain several reasons why wealth or income may affect innovation adoption behaviour: liquidity constraints, risk aversion, and scale constraints. More precisely, poorer households may be deprived of the wherewithal needed to purchase the monetary inputs embodied in the innovations; or they have this wherewithal yet are unwilling to take the associated risk; or else, they do not have a sufficient scale of operation to make the innovations profitable. An important characteristic of our adopter dataset is that it provides information about a rather large number of innovations on offer under the program. This allows us to differentiate the effect of the wealth or income constraint according to the type of innovations and to examine the influence of specific characteristics, in particular the costliness of embodied inputs and the degree of their divisibility. A priori, if the liquidity explanation holds, we expect that costly and indivisible innovations are disproportionately adopted by richer households.

Information about extension agents or innovation suppliers, and its articulation with key characteristics of would-be adopters, constitute another innovative feature of our work. To our knowledge, the present study is the first systematic attempt to examine the role of supply factors, including their interaction with demand factors, in the adoption of innovations. We are thus able to test whether the proximity of extension agents who can possibly grant seller credit for purchases of costly inputs encourages adoption of costly innovations among poorer households.

Our central findings are: (1°) the income or wealth effect operates only in a limited manner; and (2°) the most plausible mechanism behind the income constraint, insofar as it binds, is the lack of liquidity that it causes. Three innovation features explain why shortage of liquidity exerts only a limited impact: (i) some innovations are cheap in the sense that they do not embody (costly) monetary inputs; (ii) some other innovations are costlier but divisible; and (iii) extension agents may provide seller credit to help users finance the purchase of costly inputs.

Extension agents appear to have played two critical roles in our story. First, they have spread knowledge about available innovations and distributed the associated inputs. In our empirical investigation, we consider this role as well-established. Their second function is the provision of credit to adopters, which is of much interest to us since the income constraint possibly facing the latter can thus be mitigated. Our conclusion goes against the grain of the existing literature which provides a rather pessimistic assessment of the economic impact of agricultural extension in developing countries (see the review by Birkhaeuser et al., 1991). Two specific features of the extension program in our study area go a long way toward explaining this discrepancy. First, extension agents have been chosen by the local communities from their own ranks and a significant number of them operate in their native community. Second, they operate on a business basis (they sell their services at freely set prices) rather than being state employees or volunteers of private organisations. These two characteristics ensure a high quality of the services provided. Some recent experiences unfolding in Africa (in Kenya, for example) seem to be inspired by the same principles and to show promising results: extension effort enables smallholders to benefit from recent innovations adapted to their specific micro-climatic environment (Economist, March 20-26, 2016).

The rest of the paper is structured as follows. Section 2 describes the context of the study, placing emphasis on the role of the intervention of a non-governmental organization in activating the innovation market. It also provides basic information on our datasets, distinguishing between the supply and demand sides of this market. Section 3 consists of several parts: we begin by providing descriptive statistics that highlight the intensity and pattern of innovation adoption; we then assess the data available, emphasizing both their limitations and their originality; afterwards, we discuss the main empirical challenges that arise in our study setup; and, finally, we present the three empirical approaches used to isolate the effect of initial income on adoption behaviour. In Section 4, the results are presented and interpreted. This is done in successive steps, starting with the identification of individual innovations that are income-constrained, then proceeding by carrying out various robustness checks, turning to additional results obtained on the basis of cumulative models of innovation adoption, and finally examining the relationship between training and innovation adoption. In Section 5, we offer a broad look at the changes in household income and asset distribution to verify that they are in line with the results achieved in Section 4. Explicit reference is made to the debate around the Green Revolution in Asia. Section 6 concludes.

2. The survey area, the data, and the context of the study

2.1 Participatory extension and data about the supply of technical support services

The study area covers the two districts of La Encanada and Hualgayoq, which both belong to the province of Cajamarca, itself located in the northern sierra of Peru. Situated between 3,200 and 4,000 meters, the populations of these districts are among the most elevated communities in the whole country, hence their extreme isolation. The ecosystem of this part of the Andine Cordillera is characterized by a rainy and a dry season which both suffer from high variations of temperature during the day and extreme climatic conditions. Moreover, at these high altitudes, soils are poor and agricultural productivity is not only low but also subject to strong variations due to the risk of natural plant burning. Given the above characteristics of the physical environment, the dominant activity from which local inhabitants draw their livelihood is cow herding for milk and cheese production.

In order to increase animal productivity through better health practices (vaccination campaigns), the central government of Peru has initiated a program known as SENASA (Servicio Nacional de Sanidad Agraria) delivering subsidised veterinary services to local herders. This program yielded disappointing results, apparently for reasons that include low presence of government extension officers on the ground and deep distrust among local inhabitants. It is about at the same time that a Peruvian NGO “Soluciones Practicas” (Practical Action), henceforth called PA, stepped in with theme idea of upgrading technical practices among milk herders of the highlands. Drawing lessons from the failure of SENASA and other similar experiences (including its own earlier programs), the management staff of PA decided to adopt a market-based participatory approach grounded in the following principles. First, PA offered to twenty communities of the selected area to participate in a project of agricultural extension. All of them accepted. Second, each community had to supply a list of potential candidates to be trained as extension agents. Were allowed to be included in the list only permanent residents, selected through a democratic election process during a community assembly. A total of 69 candidates were submitted to the NGO.[2] Third, from this list, PA selected 42 people to be trained as extension agents (60 percent), called 'promotores'. Besides satisfying a number of criteria decided by PA (minimum age, minimum education, probity, etc.) and unknown to the communities, the trainees had to commit that, after their training, they would return to their native community in order to carry out their extension activities on a business basis.

Another objective of PA was to group extension agents in three associations (two for veterinary purposes and one for agricultural ones). Those groups would have to meet once a month and give the opportunity to its members to share new knowledge and experience but also their concerns and problems regarding their new activity. Furthermore, each association was provided with an initial amount of working capital so that it could start buying a stock of inputs and operate collectively as a rotating fund. Not only were members thus enabled to purchase products ahead of their sale and the payment of associated services, but special interventions by PA insured them against the risk of losses caused by customer defaulting. However, the veterinary rotating credit schemes collapsed in 2005-2006 as a consequence of rather familiar problems, embezzlement and lack of discipline on the part of certain members, in particular. Afterwards, the two associations have served only two functions: the pooling of product purchases (but the EA have to pay cash upon receiving the products ordered), and the exchange of technical and other information (in particular, regarding the creditworthiness of customers). In the agricultural association where defaulting on the obligation to return seeds after the harvest has been rather widespread, we estimate (on the basis of interviews with the agricultural agents) that about one-third of the seeds supplied to customers have never been returned. As a result, like what happened in the veterinary associations, the rotating fund could not be adequately replenished and eventually collapsed.[3]

The training program set up by PA was run by teachers coming from both the NGO itself and the university of Cajamarca, and it covered a period of 26 days. The courses, made compulsory for the extension agents, were entirely subsidised by PA. All the agents received the same basic training and they were also required to attend additional sessions in veterinary services or/and in agricultural support services. Started in July 2002, the basic training

[2] Interestingly, the number of candidates offered by each community did not vary by more than one unit.

[3] The default risk has been considerably enhanced as a result of unfair competition caused by the distribution of free seeds and free technical assistance by a big mining company (Yanacocha). This rivalintervention sparked a protest movement against the extension agents who stood accused of exploiting their communities.

program ended in September 2003. Afterwards, training continued in the form of occasional one-day follow-up sessions that were organised upon request from one of the associations of 'promotores', or from a subgroup of them. The PA's extension support program in the region ended in June 2007.

As a result of the above selection process, 25 percent of the communities representing 23 percent of the population were deprived of any extension agent. However, it is noteworthy that all these communities received regular visits of one to six agents during the period 2002-2007. A simple look at a map depicting the geographical dispersion of extension agents inside the project area suggests that the number of operating extension agents is not spatially correlated across the communities (map not shown).

The program thus produced an important but unintended feature: the trainees do not typically limit their services to their community of residence. They have a tendency to move to neighbouring communities to supply support services, and this creates a contamination effect. Contrary to expectations, the average number of innovations adopted per household in 2007 does not significantly differ between communities where (at least) one extension agent resides and the remaining communities.[4]

In surveying the extension agents, we could track and interview as many as 39 of them (out of 42). Out of these 39 agents, 32 are completely specialised in either veterinary or agricultural support services, while the remaining 7 provide both types of services. It is noteworthy that the three agents whom we could not trace back had actually left the area. We are therefore dealing with the entire population of extension agents actively operating in the surveyed communities.

2.2 Data about the potential users of technical innovations

In the twenty communities covered by the program, all residents have been informed about the PA initiative through their participation in the local popular assembly (the

[4] Besides offering individualised services to potential users (information, inputs and, possibly, credit), extension agents provided additional training to their own communities in the form of monthly sessions typically delivered during the community assembly. Since each man aged between 18 and 65 years and belonging to the community must attend the local assembly, the training given on this occasion was expected to help reinforce the dynamism and cohesion of the community. With the help of PA and under the leadership of the 'promotores', major portions of the irrigation system could thus be improved in each community benefitting from the physical presence of a 'promotor'. It is therefore not surprising that the quality of the irrigation system (our measure of irrigation quality will be explained later) was found to be significantly higher in these communities in the year 2007.

‘asemblea de ronda’) which also elected the program trainees. According to the record of PA, this corresponds to a population of 2,021 households. From this population, a random sample of 405 household heads has been drawn by the NGO staff so as to include a proportion of (about) one-fifth of each community’s population. Key characteristics of these potential innovation adopters have been collected just before the project, in year 2002. This information was completed by a second wave of surveys done in 2007, after the project, and collected by an independent survey firm with the help of local extension agents. Lastly, the baseline and endline databases were collected at the beginning of the rainy season and contain the same set of information on assets (cowherd and other animals, land pasture, irrigation infrastructure, etc), income sources (dairy products, improved pasture, handicraft, vegetables, etc), and prices and quantities for each income source. Regarding the latter measures, households were also asked to provide information on the dry season.

3. Descriptive statistics and methodology

3.1 The intensity and pattern of innovation adoption

Eleven innovations aimed at improving either the health of the cowherds (veterinary services) or the productivity of the pastures (agricultural services) have been actively propagated by the extension agents. They are listed here in an order whose meaning will soon become clear: (1) hygienic measures to be applied during milking operations; (2) double cow milking per day (instead of one); (3) multiple ploughing; (4) use of organic fertilisers; (5) use of lime to reduce acidity of the land; (6) improved seeds for pasture cultivation; (7) vaccination of cows according to a fixed calendar; (8) use of ensilage; (9) use of hay bundles; (10) supplementary nutriments with vitamins; (11) precocious weaning (to put the new-born calves on an improved diet).

A systematic pattern of innovation adoption emerges from the data, as seen from Table 1, a double-entry table in which each type of innovation adopted in 2007 is related to the number of innovations adopted. Innovation types are shown in the columns while frequencies are displayed in the rows. From cells (6,1) and (5,1), for example, we read that 74 households using innovation (1) in 2007 have adopted a total of 6 innovations, while 57 of them have adopted 5 innovations.

First, we see that only 5 out of 405 households (1.23%) had not adopted any innovation in 2007 (as compared with a proportion of more than 60% in 2002), which is suggestive of a large impact of the PA program. At the other end of the spectrum, only 4 households had adopted all the available innovations in 2007, and the modal value of the number of innovations adopted is 6. In the aggregate, 2,317 innovations have been adopted, representing almost 6 innovations per household on an average, compared to less than one in 2002 (0.7). The rate of use of the innovation potential –that is, the ratio of the aggregate number of innovations actually adopted by all sample households to the maximum number of adoptable innovations (=11x405)– was 52 percent in 2007, as against 5.97 percent in 2002 (see Appendix B). This comparison is legitimate since each available innovation had been adopted by at least one household in 2002.

Second, as indicated in the penultimate row, the most frequently adopted innovations are, by decreasing order of importance, innovations (3), (1), and (4). In particular, the twenty households which have adopted ten innovations out of eleven have all chosen innovations (1), (3), and (4), but also innovations (5) and (6) while their adoption behaviour differs regarding the other innovations. Third, in the last row we have ranked the innovations by decreasing order of priority in adoption. To obtain their rank, we have looked at the most frequently adopted innovation when a household adopts successively one, two, three, and up to eleven innovations in total, taking into account all the innovations most frequently adopted in the previous rounds. We have actually numbered the innovations so as to reflect their ranking according to this last criterion. By construction, therefore, the figures located on the descending diagonal are higher than, or equal to, any figure that appears on its right and belongs to the corresponding row.

INSERT TABLE 1 ABOUT HERE

From the above, we know which innovations are most frequently adopted and in which sequence they tend to be adopted overall. A different but related issue is whether some innovations are (perfect) complements. To measure complementarity, we compute a matrix in which the frequencies of all pairwise combinations of adopted innovations are displayed (see Table 2). Groups of innovations that tend to be jointly adopted appear in dark grey colour while those with the opposite characteristic appear in light grey colour. There are two main insights to be gained from this exercise. First, there are four innovations that tend to be jointly adopted: innovations (3), (4), (5), and (6). Second, only innovations (4) and (5) are close to being perfect complements: a comparison of columns (4) and (5) thus reveals that differences in adoption frequencies are minimal whichever the row considered.

INSERT TABLE 2 ABOUT HERE

To measure complementarity even more rigorously, we can look at sensitivity and specificity statistics, as done in Appendix A for all conceivable pairwise combinations of innovations adopted. We find that the probability of adopting (5) conditional on having adopted (4) is 0.92 (sensitivity) while the probability of not adopting (5) conditional on not having adopted (4) is 0.93 (specificity). This is according to expectation since the application of lime and organic fertilizers are joint ways of reducing acidity of pasture soil, with the application of lime preceding the use of organic fertilizers. Innovations (3) and (6) also evince a good measure of complementarity albeit in a less clear fashion than (4) and (5): for example, innovation (6) has been adopted 304 times but in only 260-254 times has it been adopted jointly with innovations (4) and (5), respectively. Sensitivity and specificity characteristics confirm that (3) and (6) are imperfect complements to (4) and/or (5) and to each other.[5]

On the basis of Appendix A, we have computed the minimum values of the sensitivity and specificity statistics for each pairwise combination of adopted innovations. Displayed in Table 3, these values are the most relevant measures of pairwise complementarity. Innovations (4) and (5) clearly come out as the most complementary innovations in our sample. Yet, if we fix the threshold of (near-) perfect complementarity at min{sensitivity, specificity}=0.95, no pair of innovations satisfies the definition. The same conclusion is obtained if we consider that two innovations are (near-) perfect complements if less than 5 percent of the agents who adopted one of them did not adopt the other: indeed, more than 6 percent of the herders who adopted (4) did not adopt (5).

INSERT TABLE 3 ABOUT HERE

[5] Respectively, these statistics are 0.85 and 0.83 for (4) conditional on (3); 0.86 and 0.54 for (6) conditional on (5); 0.83 and 0.51 for (6) conditional on (4); 0.81 and 0.95 for (5) conditional on (3); 0.82 and 0.88table for (6) conditional on (3).

3.2 Empirical challenges: assessing the data

Thanks to the design of the PA program, we naturally control for several potential determinants of non-adoption of new technology. In particular, the sample households have all received basic information about the extension program, the inputs involved are well distributed, and the way to use them are well communicated by extension agents to potential users. Moreover, property rights are individualised and well-established (including on the pasture lands) so that land tenure insecurity cannot impede innovation adoption. An important remaining cause for low adoption rates is insufficient wealth among a significant part of the population of potential adopters. Nonetheless, the correlation between the number of innovations adopted in 2007 and initial monetary income of the sample households is only 0.27. This implies that hardly more than 7 percent of the variation in the number of innovations adopted is explained by initial wealth differences. We are therefore confronted with a double task: to explain why the wealth constraint plays such a minor role in our study area and, to the (limited) extent that it operates, to determine whether it reflects a liquidity problem, risk aversion, or wealth-dependent profitability of innovations.

To have a better grasp of the methodological issues that answering such questions involves, we first need to take stock of the data at hand. As the discussion below indicates, the data have limitations that are the reverse side of their richness.

The main limitation arises from the fact that partly because of the aforementioned observation that innovations may be complementary and adopted simultaneously, it is difficult to individualise their specific returns. Actual costs are also hard to impute: although we know the number of new innovations adopted by each household and, thanks to access to the diaries of several extension agents, the unit monetary cost of each innovation, we are unable to infer the amounts actually spent on innovations during the period 2002-2007. The reason is that the quantities of inputs purchased by the households may differ markedly from the quantities prescribed for optimal use by these agents.[6] Households may thus decide to either apply a particular innovation over a restricted portion of their grazing area or herd (the innovation is divisible), or to apply sub-optimal doses of the corresponding inputs to their whole grazing area or herd (the innovation is adopted but not used optimally). If poorer households are more likely to thus divide or under-use their innovations, the effect of initial wealth on innovation adoption (measured by the number of innovations adopted) is diluted.

[6] Note also that expenditures on a given innovation can vary from year to year.

Interestingly, divisibility or under-utilization of innovations are not important enough to break the relationship between the number of innovations adopted and terminal incomes or productivities. Thus, the correlation of the former with the terminal monetary income of the household is 0.3266 (significant at the 99 percent confidence level) while the correlation with the average physical productivity of the cowherd (measured in 2007 in litres of milk per cow) is 0.3874 (again strongly significant).

Note that we ignore not only the precise amounts and values of the material inputs acquired for each adopted innovation but also the quantities of labour associated with them. Fortunately, labour hiring is practically non-existent among our sample households (only two out of 404 households reported having recourse to hired hands), so that there is no problem of under-estimating monetary expenditures on that count. Traditional inter-household labour exchanges remain the dominant way of complementing family labour in the study area.

Clearly, we are unable to precisely assess the cost-effectiveness or profitability of the innovations.[7] This said, the information we collected from extension agents (henceforth called EA) enables us to characterize the different innovations in a way that will prove extremely useful in interpreting our results. Therefore, even though it can be skipped for the time being, the short description provided below will constitute a precious aide-memoire for subsequent discussions.

<u>Innovations 1 and 2</u> (hygienic measures and double milking) are veterinary innovations that require additional labour and care but do not involve the purchase of material inputs. Therefore, we consider them as cheap innovations in terms of monetary inputs.

<u>Innovation 3</u> (multiple ploughing) is an agricultural innovation that requires additional labour and the complementary use of draught animals and a plough. Its adoption may thus be hampered by lack of access to an indivisible production factor, either because the household does not own a pair of oxen or because it does not have the wherewithal to rent it in. Moreover, this innovation would be too costly to apply to a small area of pasture land, so that it is unlikely to be profitable for small landholders.

<u>Innovation 4</u> (organic fertilizers) is an agricultural innovation that essentially requires the application of additional labour and care. It is divisible and its replication over time does not

[7] In principle, we could compare the effects on final incomes of various combinations of innovations, thereby inferring the marginal impact of any particular innovation (provided that all possible combinations are observed). In practice, however, owing to the large number of innovations and the limited size of our sample, such an exercise is not feasible.

necessitate the intervention of an EA. If an adopter needs to initially pay for the service of an EA in order to be taught the way to use it, no cash money is later required since no external input is involved.

Innovation 5 (application of lime) is an agricultural innovation involving the market purchase of an input. Moreover, it is technically divisible although we cannot rule out that scale economies make its application over a whole pasture area more profitable.

Innovation 6 (improved seeds) is an agricultural innovation that is divisible and does not involve any upfront cash expenditure. This is because seeds are advanced by the EA and returned in kind after the harvest on the (improved) pasture land. In other words, seeds are typically given on credit to adopter households.

Innovation 7 (vaccination) is a veterinary innovation that is both costly and indivisible. The reason why it is indivisible has to do with the organisation of its supply. Indeed, the vaccines are administered in three consecutive stages and for all the customers of the same community simultaneously. On a given day, the extension agent asks them to bring their animals to a central place in the village where they are being inoculated. This modality ensures not only that the correct doses are applied but also that the vaccination schedule is well respected. When a herder signs for vaccination, he commits to the complete set, hence the impossibility to "divide" the innovation through sub-optimal use. On the other hand, division through application to a portion of the herd is also precluded: externalities in vaccination justify the contract obligation to apply the innovation to the entire herd.[8] The diaries of the extension agents to which we had access show that, indeed, all the prescribed doses of the vaccine were duly administered to all the animals owned by the clients. The cost of the vaccine represents about 7 percent of the average yearly household income in 2002, but the relative burden rises to 22 percent if we consider only the lowest quartile of the initial

[8] Externalities exist because the vaccines are not 100 percent effective: there is a positive probability that a vaccinated individual is affected by a communicable disease transmitted through other non-vaccinated individuals belonging either to the same household's herd or to the herds of other households in the community. It is usually estimated that about 80-85 percent of a herd need to be vaccinated if the probability of catching a disease for any herding unit is to be reduced to something close to zero. In strategic terms, because the efficacy of vaccines is limited, thus giving rise to externalities, a coordination problem arises that is overcome thanks to the authority of the extension agents. As our interviews revealed, the latter were all convinced that externalities are indeed present and they therefore acted upon this belief. The two vaccines sold by them are the *triclabendazol* administered four times a year as a protection against the *faciola hepathica*, and the *albendazol prosanteles* and the *febendazol* administered five to six times a year as protections against the *redodondas*. It bears emphasis that, as our interviews revealed,

income distribution and to 20 percent if we consider only the households below the median income.

Innovation 8 (ensilage) is an agricultural innovation (a method ensuring that crops destined for animal feed are conserved in humid state) that requires a moderately expensive material input (plastic bags) and is highly divisible. In our study area, herders purchase the animal feed in a ready-made form from the EA.

Innovations 9 (fodder mixes) and 10 (supplementary nutrients), respectively an agricultural and a veterinary innovation, are again innovations that require moderately expensive material inputs and are divisible.

Innovation 11 (precocious weaning) is a veterinary innovation that not only necessitates the purchase of a costly input (the substitute nutrient for young calves) but also leaves limited possibilities for divisibility. This is because once a calf is weaned from the mother's milk substitute nutrients must be delivered on a regular basis. Another important feature of innovation 11 is that the embodied inputs are widely acquired outside the network of EAs and are typically paid in cash upfront

In the light of the above information, it appears that adoption of innovations 7 and 11 (and, plausibly, innovations 3 and 5 as well) should be most seriously constrained by wealth or liquidity while, at the other extreme, adoption of innovations 1 and 2 should be least constrained. Innovations 4, 6, 8, 9, and 10 lie in a sort of grey intermediate zone.

3.3 Empirical challenges: estimation issues

There are two main empirical challenges that we need to confront: how to measure the liquidity or wealth constraint, and how to disentangle the liquidity shortage hypothesis from alternative explanations based on either risk aversion or innovation profitability caused by scale economies?

Regarding the first question, we will use the household's monetary income as a proxy for liquidity. Computed on a monthly basis as the gross proceeds from the sale of milk and cheese, as well as some miscellaneous products, this income is a good proxy for the household savings that may be potentially used as working capital for the purpose of adopting innovations. To overcome the obvious problem that innovation adoption and income are simultaneously determined, we use an historical measure of income, i.e. the (gross) income of the household in 2002, as a proxy that is directly entered into the regression equation (we label it *income_02*). Yet, this does not solve the problem of omitted variables. In particular, some unobserved heterogeneity may exist in the form of individual characteristics of the agents that both determine their income, including past income, and their current innovation adoption behaviour. The effect of liquidity would then be confounded with the influence of personal attributes such as willingness to innovate and skill level, which are plausibly correlated with income.

To minimize the risk of biased estimates caused by omitted variables, we rely on a proxy measure of the innovativeness, skills, and entrepreneurial predisposition of the household heads. This measure, the number of innovations used in 2002 (labelled *innov_02*), has the advantage of being uncorrelated with the level of income in the initial period. Bearing in mind that comparatively few innovations were adopted in that early period, and comparing the average monetary income per head of adopter households with that of non-adopter households, the difference turns out to be negligible (701 soles for the former as against 685 soles for the latter).[9] Because most innovations used in 2002 were actually cheap, the absence of correlation between income and innovation adoption in that year (the correlation coefficient is equal to 0.04) is not surprising. By contrast, as pointed out earlier, the same correlation measured in 2007 is much higher and statistically significant. Presumably, this difference is related to the fact that costly innovations have been adopted in significant numbers during the period 2002-2007.

Turning now to the second issue, the well-known difficulty of differentiating the effect of risk aversion from that of a liquidity shortage, we propose to use a variable that may act as a proxy for risk aversion. This variable indicates whether a household was a producer of milk (or high quality cheese) or of low quality cheese in the initial year. The distinction is important because producers of low quality cheese present the double characteristics of being relatively poor and exposed to large income variations. On the one hand, the average monthly income of a cheese producer in 2002 was 430 soles as against 743 soles for milk producers and, on the other hand, the inter-seasonal income variation is 33 percent for cheese producers compared to 20 percent for milk producers (the inter-seasonal variation in the price of cheese is as high as 50 percent, compared to less than 5 percent for fresh milk). There are two reasons why the production of fresh milk for sale is more profitable and brings more stable incomes than the production of low-quality cheese. First, thanks to the existence of long-term contracts signed with purchasing companies (Nestlé and Gloria), milk prices are more stable

[9] The same conclusion obtains if we correlate the number of innovations adopted in 2002 with the following asset measures: grazing land area owned in 2002 by the household, the number of cows per head owned, and the type of irrigation used in the household farm.

than cheese prices which vary according to spot demand in local markets.[10] Second, fresh milk carries a higher price per raw litre produced. If a number of producers specialize in cheese production, it is typically because they do not reach the production threshold (10 litres per day) required by these companies while they do not have access to any other distribution channel. They are thus caught in a poverty trap.

To sum up, because we are able to identify a special category of producers who are both poor and exposed to large risks, therefore presumed to be comparatively risk-averse, we can isolate the possible impact of risk aversion on innovation adoption. If all producers were aggregated, a confounding effect might be at work in the sense that we could attribute the impact of low incomes on innovation adoption to a liquidity problem rather than to risk. Indeed, insofar as the inputs associated with the new technologies must be paid upfront while the returns are uncertain, it would be impossible to make out whether the wealth effect arises from credit imperfections or from absent insurance. The liquidity constraint bites if, in the absence of credit, the potential adopter does not have funds prior to the realization of the gains from using the modern inputs associated with a new technology. But risk aversion is the problem if, in the absence of insurance, he is unwilling to borrow, or to use his own funds, to purchase the inputs required for the uncertain investment that a new technology represents (Foster and Rosenzweig, 2010).

The second effect potentially confounded with the liquidity constraint has to do with innovation profitability. It is suggested by the (significant) positive and expected correlation (0.45) between initial income and initial herd size of the households: rather than indicating the presence of a liquidity constraint, a positive effect of initial income on innovation adoption could reflect the impact of increasing returns to scale, in which case initial income would be a proxy for innovation profitability which we do not measure. In order to check for this possibility, we follow two different methods. First, we add the initial herd size of the household as a control in all the regressions and observe whether the initial income effects are affected. Second, we substitute initial herd size for initial income and examine whether results are similar or significantly different. If results are similar, there would be a strong presumption that the effect of initial income is an effect of initial physical wealth.

[10] A minimum price is guaranteed by these companies against the promise to deliver at least 10 liters per day. After evaluation, a company may decide to raise the producer price if it is satisfied with the quality (fat content) of the milk supplied. Note that neither company offers extension services to its suppliers.

Before describing our estimation approaches, a last methodological issue of the missing variable type must be mentioned. To be able to measure the income effect properly, personal characteristics of the household, the education level of the head in particular, need to be controlled for. This is because wealth or income may be significantly correlated with education so that, in the absence of education controls, a positive income effect may actually represent a relationship between education and innovation adoption (Foster and Rosenzweig, 2010).

Unfortunately, information about the age and education of the household head was missing in our complete dataset of 405 households. Confronted with such a serious, potentially fatal difficulty, we decided to return to the field and exert maximum effort to obtain information about these key missing variables. Operating within severe time and money constraints, we could collect the required information for about half the initial sample size (204 households). Our econometric models will therefore be estimated twice, first on the basis of the complete sample but with incomplete information about household characteristics and, second, on the basis of the restricted sample but with more complete information. The comparison is legitimate because the restricted sample does not seem to suffer from any selection bias compared to the original sample: the average values and densities of all the variables used do not differ significantly between the two samples (results not shown).

3.4 Empirical strategy: three approaches to testing

Given the complexity of the problem at hand, we resort to a multi-pronged empirical strategy that proceeds in several successive steps.

<u>In step 1</u>, the purpose is to identify the role of the income effect for each individual innovation. Since an innovation is always (or almost always) adopted in combination with a number of other innovations, we carry out a simultaneous estimation of eleven Seemingly Unrelated Regression Equations (SURE) in which the dependent variable is a dummy equal to one when innovation x has been adopted, with x varying from 1 to 11. Since the unobservables in each equation are plausibly correlated, this econometric model is appropriate in our setup.[11] Since we know that innovations (4) and (5) are perfect (or near-

[11] Ideally, we should estimate each equation controlling not only for the number of innovations adopted in 2002 and for whether the particular innovation considered was already adopted in that year (which we do), but also for the types of innovations initially adopted. In this way, relations between

perfect) complements, we estimate a single equation for their adoption, and the dependent (binary) variable is set to one if they are adopted simultaneously, and to zero otherwise.

In step 2, on the basis of the findings obtained under step 1, we test for the presence and the strength of the income effect when several innovations are adopted simultaneously. Indeed, lack of savings or working capital may inhibit not only the adoption of costly innovations considered separately (if they are indivisible) but also that of a great number of innovations which are not necessarily costly. When attention is focused on innovations whose separate adoption is not constrained by initial wealth (according to step 1), we want to check whether the cumulative adoption of several of them can give rise to a wealth constraint. And when attention is focused on innovations whose separate adoption is constrained by initial wealth, we want to check whether the wealth effect is confirmed and strengthened when an increasing number of them are adopted.

In the basic model of innovation adoption that we use in both steps 1 and 2, all determinants consist of demand, household-related characteristics. In a variant of this model, supply factors will be introduced in the form of a variable indicating the presence of (at least one) EA living in the community to which each household belongs. The type of EA considered matches the innovation (veterinary or agricultural) and, in the case of innovation (7), the dummy identifies the presence of (at least) one veterinary EA who sells the vaccination services (since not all veterinary EA do it). Interacting this supply-side variable with household initial wealth, a demand-side variable, we want to check whether and how the initial income constraint is affected by the actions of EAs. Moreover, from our dataset about innovation suppliers, we know that EAs have varying levels of income and wealth, which potentially constrain their business and their ability to extend credit to innovation adopters. It is therefore possible to determine if the initial income constraint is relaxed or tightened as a result of the close presence of EAs who themselves differ in their amount of wealth.

A priori, we are rather agnostic about the direction of the interaction term between supply and demand variables. There are two opposite effects and it is impossible to predict a priori whether one dominates the other. On the one hand, the close presence of (rich) extension agents might work in favour of richer villagers: this will happen if these agents have more cosy relationships with owners of large herds because they perceived them as more profitable and/or more entrepreneurial clients. On the other hand, (rich) extension agents are able to provide seller credit when they supply costly innovations and, therefore, their close presence

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innovations (complementarity or substitutability) could be taken into account. This is not feasible, though, because of the large number of innovations and the limited size of our sample.

might attenuate the impact of the liquidity constraint on poor herders. Physical proximity and community feelings would play an important role if they help foster more intimate relationships and thereby result in greater trust. A positive sign associated with the interaction term would mean that the former effect dominates the latter, and the innovation profitability explanation is likely to be more relevant, while a negative sign would point to the converse situation, implying that the liquidity explanation is more plausible.

In step 3, an additional, indirect test of the operation of a liquidity constraint is carried out. From our dataset about innovation adopters, we know the rate of attendance of each household head to special information and training sessions organized by PA during the years 2002-2007. It appears that only a minority of them have participated in such sessions and that some heads who did failed to adopt costly innovations**.** The question then arises as to whether poorer herders are disproportionately represented in the latter category of herders. If yes, assuming that attendance to optional training sessions reflects a willingness to innovate, a plausible interpretation is in terms of demand rationing arising from lack of liquidity: herders who wanted to adopt sophisticated innovations but failed to do it tend to be those who could not mobilize the money required.

4. Results

Before we present our results, two remarks are in order. First, since we may suspect substantial variations between communities in variables that we do not observe, community fixed effects are always introduced in our regressions. Moreover, standard errors are clustered at the community level. Second, while in some models the dependent variable is continuous and consists of the number of innovations adopted, in other models, the dependent variable is dichotomous and identifies a particular category of adopters (for example, adopters of the cheapest innovations only). In still other models, the sample is truncated so as to remove a special category of adopters (those of the most constraining innovations, in particular). In all the regressions, the linear probability model is used.

Table 14 in Appendix B displays the names and descriptive statistics of our main variables. Tables 15-16 present statistics for EA-related variables, and Table 17 for innovation adoption.

4.1 Identifying the income-constrained innovations

Bearing in mind the discussion toward the end of Section 3.1 where we rejected perfect complementarity for any pair of innovations, we opt for the simultaneous estimation of eleven individual regressions (one for each innovation) to identify innovations that are wealth-constrained. We use the SURE model but identical results are obtained by using a multivariate probit model or a simple OLS model. The dependent variable is a dummy equal to one when the household had adopted the innovation concerned, say *x*, in year 2007, and to zero otherwise. Since we try to understand the determinants of adoption of *x* during the critical period 2002-2007 (after the beginning of the PA program and the EA operation), a dummy indicating whether that innovation had already been adopted in year 2002 is included in the list of regressors (labelled *innovx_02*). Tables 4 and 5 are based on the complete sample (405 households) while Tables 6 and 7 are based on the restricted sample (204 households). Regressions in Tables 4 and 6 correspond to the basic model whereas regressions in Tables 5 and 7 include a supply-side variable corresponding to the interaction between the EA dummy (whether an extension agent of the type corresponding to the innovation, agricultural or veterinary, is living inside the community) and the initial wealth variable.[12] All independent variables bear names that are immediately intuitive once we know that the ending *02* (*07*) designates measures recorded for the initial (terminal) year (2002 and 2007, respectively.[13]

INSERT TABLES 4 AND 5 AROUND HERE

Let us begin our presentation of the results by examining Tables 4 and 5. Tables 6 and 7 will be commented later when we carry out robustness checks. From Table 4, it is apparent that only two innovations, (5) and (11), give rise to an income effect: in both cases, indeed, the coefficient of the initial income variable is positive and statistically significant (at 95 and 99 percent confidence levels, respectively). Surprisingly, the coefficients of the initial income variable for two costly innovations, (3) and (7), although positive, are not significant.

When the effect of an EA's close proximity is taken into account (see Table 5), the picture dramatically changes. Thus, adoption of both innovations (3) and (7) now appears to depend

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[12] Since the community fixed effects are maintained, we do not introduce the EA dummy separately.

[13] The only variable that requires some explanation is the irrigation control. We use binary variables representing the four irrigation systems observed in the study area: natural irrigation, water conveyed by a central canal, access to a secondary channel infrastructure, and irrigation through sprinkling. The reference category is the first system and the three dummy variables are denoted by *irrigation_1*, *irrigation_2*, and *irrigation_3*.

positively and significantly (at 95 percent confidence level) on the household's initial income while the coefficient of the interaction term is negative in the two corresponding regressions. In the case of innovation (7), the latter coefficient is significantly different from zero, and its size exceeds the size of the coefficient of the initial income variable. The sum of the coefficients of the two variables is not significantly different from zero, however. This implies that, in communities where a veterinary EA who supplies innovation (7) resides (that is, in 40 percent of them), there is no income constraint preventing poorer households from vaccinating their herd. By contrast, this constraint operates in the other communities.[14] These other communities can be of two types: either there is at least one veterinary EA coming from another community to vaccinate the local herds (in 45 percent of the communities), or there is none so that vaccination cannot take place (in the remaining 15 percent).[15]

In the case of innovation (3), the coefficients of the initial income variable and the interaction term are of about the same size and opposite signs (+0.78 for the former and -065 for the latter). Its behaviour is thus close to that of innovation (7).

Innovations (5) and (11), on the other hand, feature a positive interaction term, yet it is not significant. In both cases, due to strong multicollinearity between the initial income variable and the interaction term, the coefficient of the first variable ceases to be significant: the initial income effect is diluted by the presence of the interaction term. When, instead of estimating two separate equations for independent adoption of innovations (4) and (5), we estimate a single equation for the simultaneous adoption of both (so that we estimate ten instead of eleven adoption equations), the coefficient of initial wealth does not turn out to be significant.[16] Moreover, the results about the adoption of all the other innovations stand unaffected (results not shown).

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[14] Bear in mind that innovation (7) is the only innovation which, given the cost involved, is not necessarily supplied by an EA of the required specialization (only about 60 percent of veterinary EAs supply it). Hence the need to define our dummy measuring the EA presence in the way indicated. For all the other innovations, it is sufficient to define the dummy as the presence in the community of an EA of the specialization corresponding to the innovation concerned.

[15] Further probing reveals that EAs tend to select richer customers for vaccination only when they do not live in the user community. We thus re-estimated the model by defining the EA dummy in such a way that its value equals one when there is at least one veterinary EA who either resides in the community to which a herder belongs, or comes from another community to serve him, and to zero otherwise (no EA has turned up). What we find is that the wealth effect is no more mitigated (and the effect of wealth itself is weakly significant).

[16] In this instance, we introduce two dummies to represent intial adoption : one dummy indicates whether innovation (4) was already adopted in 2002, and the other whether innovation (5) was adopted. The reference category is therefore the situation in which none of them was initially adopted.

On the basis of our rich dataset reporting the activities and characteristics of almost all the EAs (39 out of 42), we can report a number of key findings directly relevant to the present analysis. First, a large proportion of EAs sell their services on credit, typically without interest. The repayment term is 15 days in 40% of the cases and one month in the remaining 60%. Second, many EAs complained about loan delinquency and mentioned the need to resort to rationing practices: 37% of the veterinary EA admitted to limiting the scope of their activities and 61% of them to catering to a fixed set of carefully selected customers (these two answers obviously overlap). Third, and relatedly, the EAs themselves are constrained by liquidity. This is especially true of veterinary EA who have to finance the purchase of costly products ahead of delivery to customers. In order to economize on transaction costs, purchases are pooled inside one of their two professional associations.

Fourth, we show in Appendix C that the business turnover of the EAs (the aggregate value of their services), measured in 2007, is constrained by the available liquidity proxied in different ways. Moreover, poorer EAs tend to limit their services not by reducing the number of their customers but by decreasing the average price or value of the services provided. Since product quality is uniform and the available product units are standardized so that prices are unique, reduction of service value cannot take the form of substitution of low quality for high quality products. In other words, liquidity-constrained EAs bring down the value of their services by generally eschewing costly innovations and concentrating on those requiring comparatively cheap inputs. (Incidentally, this explains why a significant fraction of veterinary EAs do not offer vaccination services.)

Since EAs are themselves liquidity-constrained, we cannot rule out the possibility that (poor) customers have a better chance to have their own liquidity constraint relaxed if the EA living in their community is (are) comparatively rich. To test for this possibility, we re-run our regressions by re-defining the EA dummy (and the interaction term) as follows: it is equal to one if at least one EA (of the corresponding type) living in the community has an initial income higher than the median income of the EAs (variant A) or, alternatively, if at least one EA living in the community belongs the upper 25 percent of the initial income distribution of EAs (variant B).

There are three noteworthy findings emerging from the new regressions (results not shown). First, the coefficient of the initial income variable becomes significant for innovation (5) and highly significant (under variant A) for innovation (11), meaning that the dilution effect due to the presence of the interaction term is strongly reduced.[17] Second, the effect of initial income becomes non-significant for innovation (3) and is just significant for innovation (7). Third, the interaction term remains non-significant for innovations (5), (11), and (3) while it ceases to be significant for innovation (7), whether we consider variant A or B. From this evidence, we can therefore conclude that what matters for relaxing the liquidity constraint of poor herders is the close presence of an EA, not the fact that he is comparatively wealthy.

4.2 Robustness checks (1)

When we add initial herd size as a control and re-estimate our regressions, results about the effects of initial income and its interaction with EA presence appear to be essentially unaffected, and the same holds true if we add initial land size (results not shown). As for the effect of initial herd size itself, it comes out only for innovations (1) and (6). When we alternatively re-estimate the SURE models after replacing the initial income variable by initial herd size, including in the interaction term, our results are deeply altered in the following sense: unlike what was obtained with the initial monetary income variable, there is no significant effect of initial herd size on adoption for innovations (5) and (11) in the absence of the interaction term, and no significant effect of the same for innovation (7) in the presence of this term (results not shown). Moreover, regarding innovations (3) and (7), the coefficient of the interaction term is not significant.

There might still be a worry that the interaction effect simply reflects wealth differences between communities where (at least) one EA resides and those where no EA resides. More precisely, if EAs tend to live in relatively poor communities, we expect the interaction between wealth and the EA’s close proximity to be negative even in the absence of the kind of mitigating role we have attributed to them. As it turns out, not only is the average initial income identical between the above two types of communities but the income distributions also closely coincide, especially in their lower parts.

There exists another possible interpretation of the interaction effect that differs from the liquidity constraint hypothesis. It runs as follows. Since the EAs are themselves involved in the cattle rearing business, -they actually draw three-fourths of their total income from their

[17] For innovation (11), the magnitude of this coefficient is about the same between the reference model (in which we are only interested in the living presence of an EA in the community) and variant B while it increases perceptibly between the reference model and variant A. The magnitude of the coefficient for innovation (5) is broadly unaffected.

cattle rearing activities while the remaining one-fourth is generated by their extension activities-, they are likely to be dynamic milk producers who have adopted (almost) all the available innovations. Other herders living in the same community would be subject to a demonstration effect that reduces the perceived uncertainty of the returns on innovative behaviour. To the extent that they are relatively risk-averse, the poorer herders are especially affected, and we would expect them to better overcome their resistance against adoption than poorer herders living in communities where there is no resident EA. If we follow this line of interpretation, it is risk aversion rather than lack of liquidity that would explain the interaction effect. For this alternative explanation to be valid, however, we should observe a negative interaction effect in regard of a rather wide range of innovations, which is not at all what our results show.

Finally, it must be noted that all the above results are obtained in the presence of the *milk_producer* dummy (equal to 1 when the household produces fresh milk or high quality cheese) the coefficient of which is generally non-significant. If, as suggested earlier, we interpret that binary variable as a proxy for risk aversion, the implication is that the effects of initial income and close proximity of EA arise from liquidity rather than risk considerations.

4.3 Robustness checks (2)

Because of missing age and education data in the complete sample, we need to check whether the above findings are not spurious in the sense that the effect of initial income is wrongly attributed to a liquidity problem. This would be the case if initial income were systematically correlated, positively with education and negatively with age. We have therefore re-run our SURE regressions on the basis of a restricted sample for which we measure the age and education of the household head. In both cases, the measure is continuous (in number of years).

INSERT TABLES 6 AND 7 AROUND HERE

The most important lesson emerging from a comparison of Tables 6-7 with Tables 4-5 is that neither age nor education of the head disturbs the results obtained on the basis of the complete sample. When we consider the basic model (see Table 6), we again find that an income effect exists for innovations (5) and (11), and this is despite the fact that education positively and significantly influences adoption. The effect of initial income for innovation

(7) remains insignificant but the effect for innovation (3) is now significant. Education also has a significant and positive impact on the adoption of innovations (3), (4) and (6), yet no impact on adoption of innovation (7) whose implementation is the entire responsibility of the EA in charge. Finally, a new innovation, (4), appears to give rise to a liquidity constraint and the influence of education is again positive and significant.

When the interaction term is added to the list of regressors (see Table 7), we reach the same conclusion that no big change is brought to the picture obtained earlier. In particular, the initial income and the interaction effects continue to hold for innovation (7) as before: the coefficients are of opposite signs and their sum is not significantly different from zero. For innovation (3), the interaction term remains non-significant. On the other hand, the dilution of the income effect persists for both innovations (5) and (11). As for innovation (4), the effect of initial income is confirmed. However, when we re-estimate the model by estimating a single equation for the adoption of innovations (4) and (5) together, the coefficient of initial wealth is no more significant. And the same holds true for both innovations (4) and (5) when they are clubbed together in the model where the interaction term is absent. It is noteworthy that the results about the adoption of all the other innovations stand unaffected when we allow for the complementarity of innovations (4) and (5), regardless of whether the interaction term has been introduced or not (results not shown). Lastly, when the EA dummy is re-defined to take the wealth of the EAs into account under variants A and B, the three findings previously stated continue to hold, yet the income effect for innovation (3) is now almost significant.

4.4 Summary and discussion

The central results presented so far can now be summarized as follows. Innovations (3), (5), (7), and (11) give rise to a liquidity constraint. For innovation (7), however, the constraint vanishes in communities where at least one (veterinary) EA practicing that innovation is living. Put in another way, demand for innovation (7) is constrained by wealth or liquidity only when the EA comes from outside of the community, indicating that external EAs tend to select their customers on the basis of their wealth or income. Moreover, the beneficial effect of the close proximity of an EA does not depend upon his initial income level: both relatively poor and relatively rich EAs cater to customers in their village community regardless of their wealth status. There are thus three types of innovations: those which give rise to no liquidity problem; those which always give rise to such a problem; and those which cause liquidity constraints only when the operating extension agent comes from another community. Innovations (1), (2), (6), (8), (9) and (10) belong to the first category; (3), (5) and (11) belong to the second; and (7) belongs to the third. Innovation (4), whose adoption appears to be constrained by liquidity when the head's education is controlled for, belongs to the second category. Its close complementarity with (5), which is costly, seems to account for its status.

The constraining character of innovations (3), (4)-(5), (7) and (11) is broadly in accordance with the expectations stated in Subsection 3.2. It might seem surprising that the mitigating role of EAs living in the community of the cattle herders is clearly at work only for innovation (7), vaccination. That innovation, however, has two particular characteristics that are worth bearing in mind here. First, it is considered the most profitable by the veterinary EAs who are therefore eager to supply it to customers whenever their own financial basis allows them to do so. Second, because individually applied vaccines are not completely reliable, it gives rise to an important network externality: over a rather high range of adoption, its benefit increases with the size of the local adopter group (see supra, footnote 8). Since the EAs also own cattle which they want to best protect against the risk of communicable diseases, they have a personal interest in vaccinating as many cows as possible inside the community where they live. This implies that they make special efforts to reach out to poorer herders when the latter belong to their own community. One obvious way to persuade them to adopt the innovation is by offering them credit. The risk of the EA is rather low since he can rely on local trust as well as on local reputation and sanctioning mechanisms to enforce repayment promises. Hence the negative sign of the interaction term for innovation (7) when the EA dummy is defined by the living presence of a veterinary agent inside the community of the herder household. Note that the examination of the EA diaries confirms that seller credit is most often granted when herders purchase vaccines.

Because vaccination has the effect of significantly reducing cattle mortality (Bonjean, 2014), it is a disappointing finding to see it ranked only seventh in the adoption order (see Table 1). As suggested here, the limited adoption of vaccination is caused by the absence of seller credit in communities where no EA resides.

Innovation (11), which is also costly and profitable, is usefully contrasted with innovation (7). On the one hand, precocious weaning does not give rise to any externality and, on the other hand, the embodied inputs are widely acquired outside the network of EAs and are typically paid in cash upfront (see Subsection 3.2). The income constraint therefore bites and there is no mitigation effect.

4.5 Additional results from cumulative models

In the following analysis, we first look at the liquidity problem when all innovations are considered. We then focus attention on those innovations which appear to give rise to a liquidity constraint according to the results obtained in the preceding subsection. Finally, we consider innovations with the opposite characteristic.

In Table 8, the dependent variable is simply the number of innovations that were adopted in 2007 by the household, controlling for the number of those that had been adopted in 2002. In columns (1) and (2), results of the basic model are presented, using the complete and the restricted samples, respectively. In columns (3) and (4), the interaction term is added, again using the two samples alternatively. Note that the dummy reflecting the role of the EA may be defined in two different ways when all the innovations are taken into account: it is equal to one when there is at least one EA of each type in the community, or it is equal to one when there is at least one EA of either type (agricultural or veterinary). Results are quite close and we only present those obtained under the former definition. In all estimates, the coefficient of the initial income variable turns out to be highly significant and positive whereas the interaction term is not significant when introduced.

INSERT TABLE 8 AROUND HERE

In Table 9, we repeat the same exercise but concentrate on the innovations that can potentially create a liquidity problem because they are costly. In the first four columns, we show the estimates obtained when the dependent variable is the number of innovations adopted in the following list: innovations (3), (5), (7), and (11). The sequence of models used is the same as in Table 8. We find that the initial income has a strongly significant influence on the adoption of costly innovations: richer households are able to adopt a larger number of these innovations. When the role of EAs is taken into account and education of the head is measured (see column (4)), the interaction term is statistically significant and has a negative sign: the presence of at least one EA (of each type) in the community has the effect of halving the effect of initial income on the adoption of 'costly' innovations. This last finding is not surprising insofar as innovations (3) and (7) are included in the list of costly innovations. Note that the income effect also comes out if we enlarge the list of costly innovations to include innovation (4), or if we restrict it by excluding innovation (7), for which evidence of the mitigating role of physically close EA has been well established. Finally, in columns (5) and (6), the dependent variable is alternatively defined as the number of innovations adopted among innovations (4), (5), and (11), instead of (3), (5), (7), and (11). Since the physical proximity of EAs does not have a mitigating effect in the case of these three innovations, no interaction term is included as regressor. Whether based on the complete or the restricted sample, the estimates show that, again, a strongly significant income effect is present (results not shown).

INSERT TABLE 9 AROUND HERE

It could be argued that, in the presence of divisible innovations, a simple counting is not an appropriate measure of innovation adoption behaviour. Yet, similar results are obtained if we replace the continuous dependent variable (the count of costly innovations) by a dichotomous variable equal to one if the household has adopted at least one innovation in the above lists, or if it has adopted at least two or at least three of them (results not shown). Those households, indeed, tend to be richer than the others.

Note carefully that in all the above estimation models (as well as in those discussed below), the results do not change if we add initial herd size as a control. As for the dummy *milk_producer*, it is always present in the regressions presented in this subsection 4.3.

The next exercise consists of looking at the adoption behaviour pattern that is obtained when adopters of the costly innovations are excluded from both the complete and the restricted samples. The objective here is to determine whether the adoption of a cumulative number of non-costly innovations gives rise to a liquidity problem. We start by removing adopters of innovation (11) who represent 56 out of 405 households in the complete sample, and 30 out of 204 households in the restricted one, that is, a proportion of roughly 14 percent in both samples. The dependent variable is the total number of innovations adopted by households which have adopted any number of innovations except innovation (11). Due to the removal of the adopters of (11) in the truncated samples, the counting of innovations not only excludes that particular innovation but also the lower-rank innovations used by these adopters. Results are shown in the four columns of Table 10 where the order of presentation is identical to that followed in the previous tables.

INSERT TABLE 10 AROUND HERE

It is striking that the income effect has vanished. The coefficient of initial income nevertheless retains its positive sign and its magnitude is not much affected by the truncating of the sample. If we truncate the sample further by excluding adopters of innovations (4) and (5), which are complementary, the magnitude of the income coefficient is reduced by at least half while non-significance persists (results not shown).[18] Innovation (11) thus appears as the critical innovation that drives a large part of the liquidity effect result. A comparison between the initial incomes of adopters and non-adopters of innovation (11) confirms the above conclusion: the income of the adopters (1,110 soles) exceeds that of the non-adopters (760 soles) by almost 50 percent, and the t-test of difference of means is highly significant. By contrast, the difference between the initial incomes of adopters and non-adopters of innovation (5) is much smaller (821 against 775 soles, that is a gap of only 6 percent), and is statistically non-significant. To understand the pivotal role of innovation (11), it is important to again bear in mind that the embodied inputs are widely acquired outside the network of EAs and are typically paid in cash upfront.

Finally, we look at the effect of initial income while considering the lowest end of the innovation spectrum. The idea here is to single out the households which have failed to adopt any innovation except the cheapest ones. More precisely, the dependent variable is a dummy equal to one when the household has adopted either no innovation at all (this is the case for only five households), or innovations (1) and/or (2) to the exclusion of any other innovation (among innovations (3) to (11)). It is equal to zero otherwise. Results are displayed in Table 11. When the interaction term is omitted (see the first two columns), the coefficient of initial income is statistically different from zero, yet it is now negative: exclusive adopters of the lowest-ranked, cheap innovations tend to be initially poorer than the other adopters. Moreover, they have a lower level of education and are younger.[19]

INSERT TABLE 11 AROUND HERE

As a final check, for each of the estimated models commented in Section 4, we use a stepwise procedure in order to verify the absence of an omitted variable that would explain at once the effects of all relevant variables, including the key variable of interest (wealth or

[18] This removal is not without problem, however. Because of the high number of adopters of innovations (4) and (5), the sample sizes are considerably reduced when these adopters are left out.

[19] When the interaction term is included, these results continue to hold except for the fact that the income effect is no more significant.

income, our proxy for liquidity). More precisely, for each model we estimate an initial regression featuring only wealth and the number of innovations adopted in 2002. Controls are then added successively in the subsequent regressions. The variables measuring the household's predisposition to innovate are entered first, followed by other household-level determinants –physical assets such as size of the grazing area possessed, type of specialization (milk or low-quality cheese producer), gender of the head, size of the household, age and education of the head– and a location-specific variable (status of the irrigation system). What we find is that the coefficient of the wealth variable is stable across the different specifications (results not shown), which strengthens our confidence that there is a causal relationship between wealth and innovation adoption

4.6 Relationship between training and innovation adoption

The organisation in charge of the innovation diffusion program has set up five training sessions aimed at providing more information about the use of the available innovations. Attendance was free and voluntary and, as it turned out, about 30 percent of the sample household heads (124 of them) attended at least one such training session. Out of these 124 heads, as many as 68 dropped out after the initial session, thus leaving only 56 persons who attended at least two sessions. Two additional pieces of evidence are worth emphasizing. First, there is no significant difference in initial incomes between those who did not attend and those who did attend at least one training session (or between those who did not attend more than one session and those who did). And, second, not all of those who did participate in the training events adopted costly innovations. Thus, 7 out of the 124 household heads who did attend at least one training session did not adopt any innovation among innovations (3), (4), (5), (7), and (11). The same is true for 1 out of 56 heads who attended at least two sessions. If we restrict our attention to adoption of the critical innovation (11), however, we find that 103 persons who attended at least one training session (83 percent), and 44 persons who attended at least two such sessions (79 percent), did not adopt that particular innovation.

Since there is good ground to believe that attendance is a good indicator of the willingness to innovate, we presume that those household heads who did not innovate were hampered by financial constraints. To determine whether this is true, a straightforward test consists of comparing the average initial incomes of the trainees who did innovate with those who did not. Simple t-tests of difference of means have been carried out and are reported in Table 12.

INSERT TABLE 12 AROUND HERE

Again, the result is striking and confirms what has been found in the preceding subsection. It is only with respect to innovation (11) that the initial income of the household appears to be a constraint on adoption. In this case, the constraint is reflected in the fact that poorer households are disproportionately represented in the category of herders willing but unable to adopt that innovation.

5. Changes in income and asset distributions: a retrospective look at the Green Revolution

We have thus established that, thanks to the cheapness of some innovations, the divisibility of most of them, and the possible mitigating role of the EAs, innovation adoption has not been much affected by the liquidity constraint except in the case of the highest-ranked innovation. This result, however, does not guarantee that the household income distribution has not changed much after the start of the PA program. As a matter of fact, poorer adopters may well have acquired smaller doses of the divisible innovations, thereby causing a decrease of their terminal incomes relative to those of richer adopters.

A simple computation of the Gini coefficients for both the initial and terminal years, 2002 and 2007, reveals that inequality in household monetary incomes has only slightly increased, from 0.540 to 0.567, and this increase is statistically non-significant. Clearly, the liquidity constraint has not been a major obstacle against increases of income among the majority of the sample households. The same conclusion obtains when the initial and final distributions of average productivity of cowherd are compared. Moreover, the value of the Gini coefficient appears to have slightly declined when the distribution of cowherds (or cowherds per capita) or the distribution of grazing land areas (or grazing land areas per head) are considered. The only dimension along which the inter-household distribution has undergone a dramatic evolution is the area of improved pastures: the Gini coefficient has decreased from about 0.89 to 0.54 when this variable is measured on an aggregate basis, and from 0.91 to 0.58 when it is measured on a per capita basis. It is striking that the proportion of households owning improved pastures has risen tenfold, from 9.2% in 2002 to 90.6% in 2007. Note that the diffusion of improved pastures is the result of adoption of innovations (4), (5), and (6), which have been widely adopted as indicated by their ranks in the adoption ladder.

In a companion paper, Bonjean (2014) has shown that the lack of significant increase in income inequality is to be largely attributed to the action of the EAs in favour of the poorer cattle herders. The mitigation effect went through two different channels: a quantity and a price channel. The quantity effect essentially arose from a comparatively large increase in the cowherd size among poorer households, itself caused by reduced mortality of the cattle following vaccination. On the other hand, the price effect is associated with the quantity effect insofar as herders who succeeded in increasing their milk sales above the threshold of 10 litres a day could benefit from a perceptible price rise thanks to their securing access to better-paying purchasing companies (Nestlé, Gloria, and smaller undertakings). It is therefore the EAs' support for the widespread adoption of the critical innovation (7), vaccination, among cattle herders of their own community that appears as the key inequality-dampening factor in the PA program.

Our study therefore contributes to the debate around the equity effects of technological change in poor rural areas. This debate can be traced back to the Green Revolution when strong fears were expressed that inequality would be exacerbated after the introduction of the major technical advances involved (comprising high-yielding seed varieties, fertilizers, and irrigation water). The new technology, so the argument ran, would be monopolised by large farmers who have greater financial capacity –they can therefore bear the higher cost of cultivation per land unit and invest in fixed capital assets−, greater risk-bearing ability, and better access to information and knowledge than financially constrained and poorly educated or ill-informed smallholders (see, e.g., Falcon, 1970; Cleaver, 1972; Griffin, 1974; Farmer, 1977; Dantwala, 1985; Lipton and Longhurst, 1989). Unconvinced by these arguments, however, a number of economists preferred to stress the accessibility (at least, after some time) and divisibility of the technological components of the Green Revolution (see, in particular, Hayami and Ruttan, 1971, Chap. 11; Bliss and Stern, 1982; Adams, 1995; Hayami, 1997: 177-80). As a result of these characteristics, adoption rates should not markedly differ between rich and poor farmers, and the risk that the former would buy up the lands of the latter, thus leading to growing land concentration, was likely to be averted.

The pessimistic scenario has been largely invalidated by the facts: the evidence failed to confirm that the Green Revolution technology caused an increase in the income distribution. In one of the few available studies based on repeated surveys of the same area, the study of Palanpur (Uttar Pradesh, India), the conclusion was reached that "in short, the Green Revolution has not been a major force of rising inequality... there is no evidence of any overall influence of technological change in the direction of increasing inequality" (Lanjouw and Stern, 1998: 406).[20] Hayami and Ruttan (1971: 337, 340, 345), who looked carefully at the Asian situation, concurred that neither farm size nor tenure had been a serious constraint to adoption of the Green Revolution technology: this technology represented a neutral technological change with respect to farm scale in the sense that both small and large farms achieved approximately equal gains in efficiency. For the authors, therefore, the danger of growing income inequality in rural areas does not arise from new technology but from insufficient progress in its development and diffusion relative to the rapid increase of population pressure on land (see also Hayami, 1984; Feder, 1985). The situation in the Punjab (India) seems to bear out the above diagnosis: differences by size class in total bio-chemical inputs per acre were not significant, suggesting that small farmers did not have much difficulty obtaining purchased inputs (Dantwala, 1985: 117, citing a study by Bhalla and Chadha, 1981; see also Chaudhry, 1982, for Pakistan). In the same line, a study of North Arcot District (Tamil Nadu state, India) concluded that, following the introduction of high-yielding rice varieties, the relative income and consumption expenditure of the large farms declined while that of the landless labourers increased to achieve parity with the small paddy farms (Hazell and Ramasamy, 1991, Chap. 3: 49-51).[21]

6. Conclusion

Under a program aimed at activating a market for technical innovations in conditions of highly imperfect credit and insurance markets, cattle herders from a remote and poor area in the Peruvian Highlands were offered a range of new techniques. Diffusion has been helped by extension agents residing in the communities so that these herders were reasonably well informed about techniques appropriate to their local environment. One key remaining constraint on innovation adoption, after we check for the possible role of wealth-dependent

[20] This conclusion is nevertheless qualified once the time sequence of the effects of technical change is taken into account: if by the mid-seventies the distribution of income had not widened as many had feared, in the mid-eighties the distribution of land cultivated did exert a disequalizing impact following further agricultural intensification.

[21] Interregional distribution of income is another matter, though. It may indeed worsen if some regions enjoy natural and infrastructural conditions suitable for the new technology package while others do not, say because they are not well-endowed in regard to rainfall and irrigation. Think, for example, of the contrasted picture drawn by Hayami and Kikuchi (1981, chs. 8 and 9) between a village located in the coastal plain of West Java, in which modern rice varieties were quickly diffused, and a village located in the mountain valley in which these varieties failed to be adopted. This issue is all the more serious as the rural poor are often concentrated (for historical reasons) in the less favoured ecological zones (Scobie and Posada, 1984).

profitability, is lack of liquidity. As it turned out, it is essentially at work for a few innovations only. There are three reasons for such limited operation of the liquidity constraint: (i) innovations may be cheap in the sense that they do not embody (costly) monetary inputs; (ii) innovations may be divisible; and (iii) the extension agents may provide seller credit to help users finance the purchase of these inputs. A central finding is that, for two innovations that are costly and indivisible, extension agents have helped mitigate and even cancel the disadvantage of low income but only when they work and reside in the same community as the (poor) adopters. In other words, for these innovations, the liquidity constraint binds when the operating extension agent comes from another community (so that trust is not sufficient to justify a credit risk).

This finding therefore confirms a basic intuition on which the technology diffusion program rested from the very start: extension work should be performed by motivated agents native from, and permanently residing in the user community. Interestingly, one of the two innovations for which explanation (iii) holds involves an important externality and is comparatively profitable (vaccination) while the other one is associated with complementary indivisible assets which the extension agents own and can lend (multiple ploughing). As for the most important innovation causing a liquidity problem (precocious weaning) regardless of the role of extension agents, it is largely indivisible, and it embodies costly inputs that are widely acquired outside the network of these agents. Another innovation creating liquidity problems, lime application, is relatively costly and highly complementary with another innovation, the application of organic fertilizers.

Distribution of income has not changed much under the impact of the program and, if anything, distribution of productive assets has become more equal. Our results therefore evoke the relatively egalitarian process underlying the Green Revolution as it has taken place in Asian agriculture, in particular. In our study area, a central role has been played by extension agents recruited from the user communities themselves, and acting as private business operators rather than as salaried staff (or volunteers) of private or public organisations. This particular mode of operation has helped promote equality of access to available innovations through supply of basic information and modern inputs, and through provision of seller credit to poor adopters for the most critical innovation. Such a conclusion goes against the rather pessimistic assessment of the economic impact of agricultural extension that emerges from much of the past literature. It is noteworthy, however, that pessimistic conclusions have been reached on the basis of ill-conceived extension programs.

Finally, innovation adoption is significantly influenced by education yet not for all innovations. Those for which education plays a perceptible role tend to require a lot of individual care and good management ability: multiple ploughing, application of organic fertilizers and lime, use of improved seeds and supplementary nutrients, and precocious weaning. It is noticeable that vaccination of the animals does not figure out in the list. This is because the operation involved, which takes place at a few discrete times, is the entire responsibility of the extension agent in charge. Herders just have to take their animals to him.

TABLES

Table 1: Types of innovation most frequently adopted by rural producers (2007)

	Type of innovation											
Nr of innovations adopted	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	Total
0	0	0	0	0	0	0	0	0	0	0	0	5
1	9	0	1	0	0	1	0	0	0	1	0	12
2	20	8	6	4	0	1	0	1	0	4	0	22
3	27	4	29	12	8	18	1	2	0	4	0	35
4	29	11	37	24	23	18	5	1	0	2	2	38
5	57	21	63	58	52	49	5	2	2	7	4	64
6	74	57	84	77	73	75	25	8	3	20	8	84
7	51	48	58	56	54	58	43	15	7	18	5	59
8	33	22	33	32	33	33	25	18	13	11	11	33
9	29	30	31	30	31	29	28	24	26	13	8	31
10	18	17	18	18	18	18	15	16	15	13	14	18
11	4	4	4	4	4	4	4	4	4	4	4	4
Nr of adopters*	351 (50)	222 (32)	364 (70)	315 (22)	296 (1)	304 (36)	151 (13)	91 (4)	70 (6)	97 (26)	56 (6)	405
Order of importance	2	6	1	3	5	4	7	9	10	8	11	
Rank order of adoption	1	2	3	4	5	6	7	8	9	10	11	

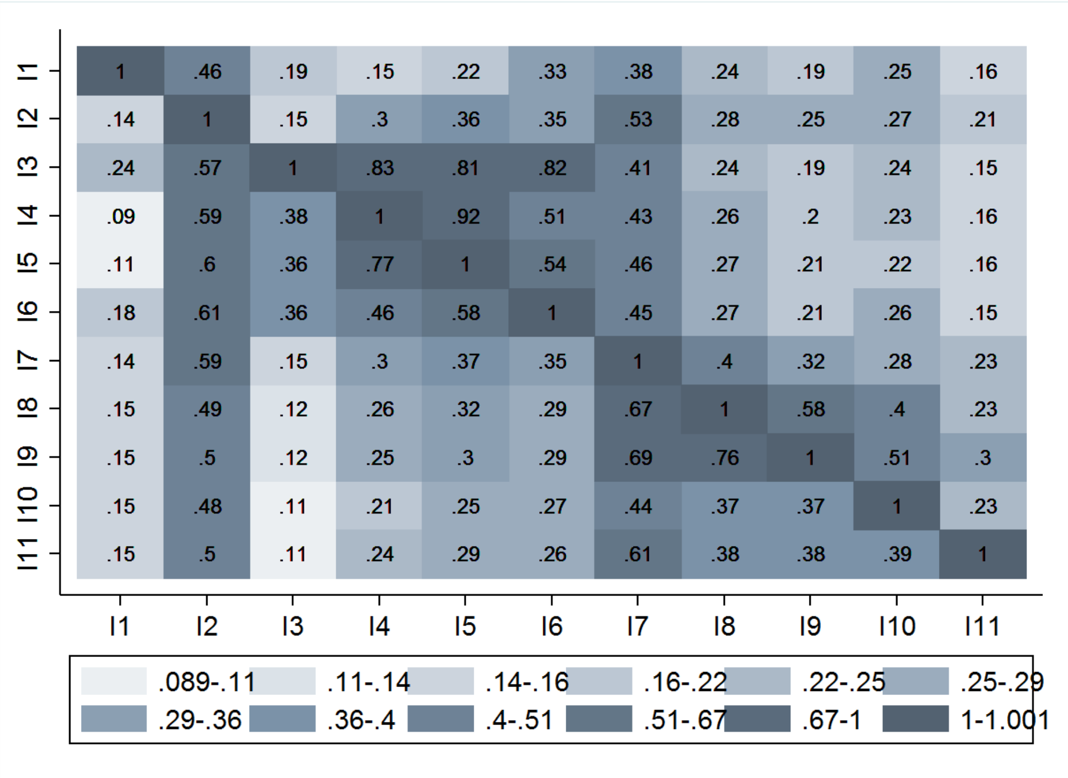
* The figures between brackets indicate the number of adopters in 2002.

Table 2: Frequencies of joint pairwise adoption of innovations

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11
I1	351										
I2	193	222									
I3	320	208	364								
I4	269	187	308	315							
I5	254	178	294	290	296						
I6	268	185	299	260	254	304					
I7	133	117	148	137	135	138	151				
I8	84	62	87	82	81	81	61	91			
I9	66	55	69	63	63	65	48	53	70		
I10	88	61	89	73	66	78	43	36	36	97	
I11	55	47	54	50	48	47	34	21	21	22	56

0-50 | 50-100 | 100-150 | 150-200 | 200-250 | 250-300 | 300-350 | 350-400

Table 3: Minimum values of sensitivity and specificity statistics for pairwise innovation adoption



	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11
I1	1	.46	.19	.15	.22	.33	.38	.24	.19	.25	.16
I2	.14	1	.15	.3	.36	.35	.53	.28	.25	.27	.21
I3	.24	.57	1	.83	.81	.82	.41	.24	.19	.24	.15
I4	.09	.59	.38	1	.92	.51	.43	.26	.2	.23	.16
I5	.11	.6	.36	.77	1	.54	.46	.27	.21	.22	.16
I6	.18	.61	.36	.46	.58	1	.45	.27	.21	.26	.15
I7	.14	.59	.15	.3	.37	.35	1	.4	.32	.28	.23
I8	.15	.49	.12	.26	.32	.29	.67	1	.58	.4	.23
I9	.15	.5	.12	.25	.3	.29	.69	.76	1	.51	.3
I10	.15	.48	.11	.21	.25	.27	.44	.37	.37	1	.23
I11	.15	.5	.11	.24	.29	.26	.61	.38	.38	.39	1

Table 4: Determinants of adoption when innovations are considered separately - Basic Model and Complete Sample

	diffinnov1	diffinnov2	diffinnov3	diffinnov4	diffinnov5	diffinnov6	diffinnov7	diffinnov8	diffinnov9	diffinnov10	diffinnov11
income_02	0.367	0.240	0.411	0.427	0.728**	0.322	0.546	0.158	0.275	0.300	1.133***
	(0.32)	(0.38)	(0.27)	(0.33)	(0.35)	(0.36)	(0.38)	(0.37)	(0.34)	(0.35)	(0.31)
female_head_02	-0.024	-0.048	-0.027	0.042	-0.016	0.051	0.011	-0.142**	-0.152**	-0.052	-0.088
	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.05)
innovation_dummy_02	-0.905***	-0.584***	-0.946***	-0.844***	-0.910***	-0.863***	-0.423***	-0.382**	-0.291**	-0.303***	-0.307**
	(0.07)	(0.07)	(0.04)	(0.06)	(0.23)	(0.08)	(0.11)	(0.17)	(0.13)	(0.08)	(0.13)
innovations_number_02	-0.000	0.025	0.006	-0.008	-0.002	0.001	-0.014	-0.013	0.033*	0.031	0.012
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
hhold_size_02	0.042	-0.027	-0.019	-0.004	-0.041	-0.027	-0.116**	-0.063	-0.116**	0.059	-0.073
	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
milk_producer_02	0.060	0.093*	0.016	0.027	-0.008	0.064	0.025	-0.040	-0.040	0.008	0.058
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
irrigation_1_02	0.028	0.002	-0.004	-0.008	0.014	0.068	0.043	-0.065	-0.070	-0.041	0.053
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
irrigation_2_02	-0.037	-0.140	0.084	0.049	0.044	0.135	-0.034	-0.005	0.130	0.069	-0.100
	(0.07)	(0.09)	(0.06)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)
irrigation_3_02	0.160	0.206	0.105	-0.231	-0.153	0.189	0.493**	0.001	0.073	-0.159	-0.162
	(0.17)	(0.20)	(0.14)	(0.17)	(0.18)	(0.19)	(0.20)	(0.19)	(0.18)	(0.18)	(0.16)
grazing_area_02	-0.001	-0.011***	0.000	0.002	0.001	-0.003	-0.003	0.006*	0.003	-0.004	-0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.793***	0.550***	0.878***	0.759***	0.873***	0.358***	0.469***	0.280**	0.347***	0.006	0.131
	(0.12)	(0.15)	(0.11)	(0.13)	(0.13)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.12)
r^2	0.493	0.465	0.645	0.494	0.431	0.467	0.408	0.232	0.180	0.217	0.182
chi^2	411.570	352.024	946.718	558.644	314.771	390.403	287.779	126.677	89.459	107.253	92.703
N	405										

SURE model with Fixed Effects at community level

Standard errors in brackets

* p < 0.10 ; ** p < 0.05 ; *** p < 0.01

Table 5: Determinants of adoption when innovations are considered separately - Variant allowing for the role of EA and Complete Sample

	diffinnov1	diffinnov2	diffinnov3	diffinnov_4	diffinnov_5	diffinnov6	diffinnov7	diffinnov8	diffinnov9	diffinnov10	diffinnov11
income_02	0.394	-0.040	0.781**	0.594	0.408	0.686	1.241**	-0.344	-0.181	0.146	0.708
	(0.49)	(0.57)	(0.40)	(0.48)	(0.50)	(0.51)	(0.49)	(0.53)	(0.49)	(0.53)	(0.47)
EA_vete * income_02	-0.044	0.461								0.253	0.698
	(0.61)	(0.71)								(0.65)	(0.59)
EA_vagri * income_02			-0.654	-0.300	0.567	-0.645		0.889	0.814		
			(0.51)	(0.62)	(0.65)	(0.66)		(0.68)	(0.63)		
EA_vete_vaccination * income_02							-1.456**				
							(0.66)				
female_head_02	-0.024	-0.045	-0.032	0.039	-0.012	0.047	0.008	-0.136**	-0.147**	-0.050	-0.084
	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.05)
innovation_dummy_02	-0.904***	-0.583***	-0.944***	-0.837***	-0.902***	-0.865***	-0.443***	-0.380**	-0.301**	-0.304***	-0.289**
	(0.07)	(0.07)	(0.04)	(0.06)	(0.23)	(0.08)	(0.11)	(0.17)	(0.13)	(0.08)	(0.13)
innovations_number_02	-0.000	0.025	0.006	-0.009	-0.002	0.002	-0.010	-0.014	0.033*	0.030	0.010
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
hhold_size_02	0.042	-0.029	-0.016	-0.002	-0.044	-0.024	-0.118**	-0.068	-0.120**	0.059	-0.075
	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
milk_producer_02	0.061	0.090*	0.018	0.028	-0.010	0.066	0.031	-0.043	-0.043	0.006	0.054
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
irrigation_1_02	0.028	0.002	-0.004	-0.008	0.014	0.067	0.035	-0.064	-0.070	-0.041	0.054
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
irrigation_2_02	-0.036	-0.145	0.091	0.052	0.037	0.142*	-0.028	-0.016	0.121	0.067	-0.108
	(0.08)	(0.09)	(0.06)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)
irrigation_3_02	0.160	0.201	0.112	-0.227	-0.159	0.197	0.514***	-0.009	0.064	-0.162	-0.169
	(0.17)	(0.20)	(0.14)	(0.17)	(0.18)	(0.19)	(0.20)	(0.19)	(0.18)	(0.18)	(0.16)
grazing_area_02	-0.001	-0.011***	-0.000	0.002	0.001	-0.003	-0.004	0.007*	0.003	-0.004	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.794***	0.533***	0.903***	0.772***	0.850***	0.384***	0.546***	0.245*	0.314**	-0.004	0.106
	(0.13)	(0.15)	(0.11)	(0.13)	(0.14)	(0.14)	(0.15)	(0.15)	(0.13)	(0.14)	(0.12)
r2	0.493	0.466	0.646	0.494	0.432	0.469	0.414	0.234	0.181	0.217	0.185
chi2	411.542	351.860	951.161	556.050	315.855	392.967	296.451	129.062	91.077	107.206	94.610
N	405										

SURE model with Fixed Effects at community level
Standard errors in brackets
* p < 0.10 ; ** p < 0.05 ; *** p < 0.01

Table 6: Determinants of adoption when innovations are considered separately - Basic Model and Restricted Sample

	diffinnov1	diffinnov2	diffinnov3	diffinnov_4	diffinnov_5	diffinnov6	diffinnov7	diffinnov8	diffinnov9	diffinnov10	diffinnov11
income_02	0.673	0.527	1.078**	0.825*	1.213**	0.363	0.903	0.093	0.043	0.712	0.930*
	(0.49)	(0.58)	(0.43)	(0.49)	(0.51)	(0.61)	(0.60)	(0.58)	(0.52)	(0.58)	(0.49)
female_head_02	-0.123	-0.261**	-0.033	0.033	-0.046	0.115	-0.029	-0.202**	-0.209**	-0.111	-0.182**
	(0.09)	(0.10)	(0.08)	(0.09)	(0.09)	(0.11)	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)
innovation_dummy_02	-0.897***	-0.601***	-0.915***	-0.776***	0.000	-0.751***	-0.704***	0.000	0.000	-0.309**	-0.531*
	(0.10)	(0.12)	(0.07)	(0.08)	(.)	(0.12)	(0.15)	(.)	(.)	(0.13)	(0.30)
innovations_number_02	-0.036	0.009	-0.023	-0.027	-0.014	-0.038	-0.004	-0.004	0.018	-0.004	-0.026
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
hhold_size_02	0.030	0.006	-0.003	-0.025	-0.034	-0.060	-0.027	-0.030	-0.047	0.089	-0.028
	(0.07)	(0.09)	(0.07)	(0.07)	(0.08)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.07)
milk_producer_02	0.110*	-0.013	-0.070	-0.006	-0.036	0.056	0.001	-0.083	-0.072	-0.094	0.054
	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
irrigation_1_02	0.039	-0.098	-0.017	-0.007	0.016	0.109	0.063	-0.014	-0.032	-0.039	0.055
	(0.06)	(0.08)	(0.06)	(0.06)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)
irrigation_2_02	0.054	-0.274**	0.014	0.054	0.109	0.263**	-0.137	0.066	0.072	0.120	-0.225**
	(0.10)	(0.12)	(0.09)	(0.10)	(0.10)	(0.12)	(0.12)	(0.11)	(0.10)	(0.11)	(0.10)
irrigation_3_02	0.078	0.212	-0.038	-0.171	-0.107	0.015	0.601**	-0.085	0.017	-0.326	-0.257
	(0.19)	(0.23)	(0.18)	(0.19)	(0.20)	(0.24)	(0.24)	(0.23)	(0.21)	(0.23)	(0.19)
grazing_area_02	0.002	-0.008	0.005	0.003	0.003	-0.000	-0.003	0.012**	0.009*	0.002	-0.005
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
education	-0.003	0.001	0.015*	0.021**	0.026***	0.027**	0.003	0.010	-0.003	0.016	0.017*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
age	-0.001	-0.000	0.004**	0.004*	0.006***	0.002	0.002	-0.001	-0.003	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.948***	0.801***	0.634***	0.607***	0.580***	0.237	0.248	0.316	0.486**	-0.105	0.045
	(0.21)	(0.25)	(0.19)	(0.21)	(0.22)	(0.26)	(0.26)	(0.25)	(0.22)	(0.25)	(0.21)
r2	0.495	0.512	0.642	0.570	0.527	0.431	0.447	0.301	0.208	0.234	0.298
chi2	208.073	210.507	481.505	351.788	227.403	172.854	173.206	87.886	53.598	60.643	89.095
N	204										

SURE model with Fixed Effects at community level
Standard errors in brackets

* p < 0.10 ; ** p < 0.05 ; *** p < 0.01

Table 7: Determinants of adoption when innovations are considered separately - Variant allowing for the role of EA and Restricted Sample

	diffinnov1	diffinnov2	diffinnov3	diffinnov_4	diffinnov_5	diffinnov6	diffinnov7	diffinnov8	diffinnov9	diffinnov10	diffinnov11
income_02	0.499	1.122	1.688**	1.305*	1.207	1.253	1.768**	-0.490	-0.375	0.938	1.078
	(0.83)	(0.98)	(0.70)	(0.78)	(0.83)	(0.97)	(0.75)	(0.93)	(0.83)	(0.96)	(0.83)
EA_vete * income_02	0.263	-0.896								-0.342	-0.223
	(1.01)	(1.20)								(1.16)	(1.01)
EA_vagri * income_02			-0.969	-0.761	0.009	-1.415		0.924	0.662		
			(0.87)	(0.97)	(1.03)	(1.21)		(1.15)	(1.02)		
EA_vete_vaccination * income_02							-1.946*				
							(1.05)				
female_head_02	-0.120	-0.268***	-0.042	0.027	-0.046	0.102	-0.043	-0.194*	-0.204**	-0.113	-0.184**
	(0.09)	(0.10)	(0.08)	(0.09)	(0.09)	(0.11)	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)
innovation_dummy_02	-0.899***	-0.597***	-0.920***	-0.774***	0.000	-0.760***	-0.687***	0.000	0.000	-0.301**	-0.531*
	(0.10)	(0.12)	(0.07)	(0.08)	(.)	(0.12)	(0.15)	(.)	(.)	(0.13)	(0.30)
innovations_number_02	-0.035	0.009	-0.022	-0.027	-0.014	-0.036	-0.011	-0.004	0.018	-0.004	-0.026
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
hhold_size_02	0.026	0.019	0.014	-0.012	-0.034	-0.035	-0.017	-0.046	-0.059	0.094	-0.024
	(0.07)	(0.09)	(0.07)	(0.07)	(0.08)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.07)
milk_producer_02	0.109*	-0.010	-0.071	-0.006	-0.036	0.056	0.007	-0.083	-0.072	-0.094	0.054
	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
irrigation_1_02	0.040	-0.101	-0.022	-0.010	0.016	0.104	0.057	-0.010	-0.030	-0.040	0.054
	(0.06)	(0.08)	(0.06)	(0.06)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)
irrigation_2_02	0.050	-0.258**	0.028	0.065	0.109	0.285**	-0.123	0.052	0.062	0.126	-0.221**
	(0.10)	(0.12)	(0.09)	(0.10)	(0.10)	(0.12)	(0.12)	(0.12)	(0.10)	(0.12)	(0.10)
irrigation_3_02	0.079	0.209	-0.038	-0.173	-0.107	0.012	0.626***	-0.083	0.018	-0.327	-0.258
	(0.19)	(0.23)	(0.17)	(0.19)	(0.20)	(0.24)	(0.24)	(0.23)	(0.21)	(0.23)	(0.19)
grazing_area_02	0.002	-0.007	0.005	0.004	0.003	0.001	-0.003	0.011**	0.009*	0.002	-0.004
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
education	-0.003	0.001	0.015*	0.021**	0.026***	0.027**	0.004	0.010	-0.003	0.016	0.017*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
age	-0.001	-0.000	0.004**	0.004*	0.006***	0.002	0.002	-0.001	-0.003	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.944***	0.818***	0.652***	0.620***	0.579***	0.262	0.337	0.300	0.474**	-0.099	0.049
	(0.21)	(0.25)	(0.19)	(0.21)	(0.22)	(0.26)	(0.26)	(0.25)	(0.22)	(0.25)	(0.21)
r2	0.495	0.513	0.644	0.572	0.527	0.435	0.457	0.303	0.209	0.234	0.298
chi2	208.170	211.500	481.463	353.711	227.410	175.376	179.526	88.723	54.085	60.566	89.167
N	204										

SURE model with Fixed Effects at community level
Standard errors in brackets
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 8: Determinants of the number of innovations adopted - Basic Model and Variant, Complete and Restricted Samples

	innov_07			
income_02	5.034***	7.353**	5.590**	10.280**
	(1.59)	(2.59)	(1.96)	(3.93)
EA_veteoragri * income_02			-0.914	-4.407
			(2.60)	(4.42)
female_head_02	-0.407	-1.046	-0.413	-1.084
	(0.32)	(0.66)	(0.32)	(0.68)
innovations_number_02	0.360**	0.085	0.362**	0.088
	(0.14)	(0.21)	(0.14)	(0.21)
hhold_size_02	-0.364	-0.138	-0.361	-0.069
	(0.33)	(0.44)	(0.33)	(0.45)
milk_producer_02	0.261	-0.129	0.267	-0.117
	(0.29)	(0.33)	(0.30)	(0.33)
irrigation_1_02	0.014	0.072	0.013	0.055
	(0.34)	(0.32)	(0.34)	(0.31)
irrigation_2_02	0.171	0.107	0.182	0.180
	(0.46)	(0.52)	(0.45)	(0.50)
irrigation_3_02	0.413	-0.189	0.423	-0.210
	(0.82)	(0.66)	(0.83)	(0.69)
grazing_area_02	-0.016	0.020	-0.016	0.023
	(0.02)	(0.04)	(0.02)	(0.04)
education		0.124		0.123
		(0.08)		(0.08)
age		0.014		0.013
		(0.01)		(0.01)
Constant	6.127***	5.412***	6.132***	5.364***
	(0.67)	(1.36)	(0.66)	(1.32)
r2 within	0.078	0.094	0.078	0.096
N	405	204	405	204

OLS with Fixed Effects at community level and standard errors clustered at the community level

Standard errors in brackets

* p < 0.10 ; ** p < 0.05 ; *** p < 0.01

Table 9: Determinants of the number of costly innovations adopted - Basic Model and Variant, Complete and Restricted Samples

	costly35711				costly4511	
income_02	2.823***	3.928***	3.996***	6.242***	2.351**	3.006**
	(0.71)	(1.14)	(1.28)	(1.69)	(0.83)	(1.21)
EA_veteoragri * income_02			-1.927	-3.483*		
			(1.31)	(1.67)		
female_head_02	-0.083	-0.301	-0.096	-0.330	-0.030	-0.184
	(0.12)	(0.32)	(0.12)	(0.33)	(0.15)	(0.25)
innovations_number_02	0.081	-0.017	0.085	-0.015	0.039	-0.048
	(0.05)	(0.10)	(0.05)	(0.09)	(0.05)	(0.09)
hhold_size_02	-0.237	-0.106	-0.231	-0.051	-0.111	-0.093
	(0.19)	(0.22)	(0.18)	(0.21)	(0.16)	(0.12)
milk_producer_02	0.078	-0.071	0.089	-0.062	0.064	0.000
	(0.12)	(0.15)	(0.12)	(0.15)	(0.08)	(0.10)
irrigation_1_02	0.113	0.142	0.112	0.128	0.048	0.062
	(0.13)	(0.16)	(0.13)	(0.15)	(0.11)	(0.16)
irrigation_2_02	-0.022	-0.255	0.001	-0.197	-0.002	-0.069
	(0.16)	(0.16)	(0.17)	(0.17)	(0.26)	(0.25)
irrigation_3_02	0.257	0.219	0.277	0.203	-0.569	-0.566*
	(0.40)	(0.34)	(0.42)	(0.36)	(0.37)	(0.31)
grazing_area_02	-0.005	0.001	-0.006	0.003	-0.002	0.002
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
education		0.061*		0.060*		0.065*
		(0.03)		(0.03)		(0.03)
age		0.013*		0.013*		0.011*
		(0.01)		(0.01)		(0.01)
Constant	2.360***	1.679***	2.372***	1.641***	1.662***	1.141*
	(0.34)	(0.54)	(0.33)	(0.51)	(0.30)	(0.55)
r^2 within	0.065	0.109	0.068	0.116	0.048	0.106
N	405	204	405	204	405	204

OLS with Fixed Effects at community level and standard errors clustered at the community level

Standard errors in brackets

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 10: Determinants of the number of innovations adopted in the truncated sample - Basic Model and Variant, Complete and Restricted Samples

	innov_07			
income_02	2.634	2.893	3.737	6.952
	(2.18)	(2.41)	(2.28)	(5.90)
EA_veteoragri * income_02			-1.690	-5.015
			(3.09)	(6.01)
female_head_02	-0.351	-0.667	-0.353	-0.694
	(0.27)	(0.48)	(0.27)	(0.49)
innovations_number_02	0.192**	0.087	0.192**	0.079
	(0.08)	(0.16)	(0.08)	(0.16)
hhold_size_02	-0.228	0.126	-0.229	0.172
	(0.30)	(0.44)	(0.30)	(0.45)
milk_producer_02	0.192	0.134	0.195	0.128
	(0.28)	(0.29)	(0.28)	(0.29)
irrigation_1_02	-0.243	-0.620**	-0.242	-0.640**
	(0.25)	(0.25)	(0.25)	(0.25)
irrigation_2_02	0.328	0.688	0.338	0.751
	(0.47)	(0.72)	(0.47)	(0.71)
irrigation_3_02	1.189	0.292	1.216	0.338
	(1.08)	(0.72)	(1.10)	(0.77)
grazing_area_02	-0.014	0.034	-0.016	0.033
	(0.02)	(0.02)	(0.02)	(0.02)
education		0.054		0.054
		(0.05)		(0.05)
age		0.005		0.004
		(0.01)		(0.01)
Constant	5.016***	4.217***	5.029***	4.193***
	(0.51)	(1.07)	(0.50)	(1.06)
r2 within	0.041	0.095	0.041	0.099
N	349	174	349	174

OLS with Fixed Effects at community level and standard errors clustered at the community level

Standard errors in brackets

* p < 0.10 ; ** p < 0.05 ; *** p < 0.01

Table 11: Identifying adoptors of cheap innovations - Basic Model and Variant, Complete and Restricted Samples

	no_costly_07			
income_02	-0.283*	-0.831**	-0.334	-0.662
	(0.15)	(0.35)	(0.29)	(0.40)
EA_veteoragri * income_02			0.085	-0.255
			(0.36)	(0.66)
female_head_02	0.021	0.037	0.021	0.035
	(0.04)	(0.06)	(0.04)	(0.07)
innovations_number_02	-0.002	0.019	-0.002	0.019
	(0.01)	(0.03)	(0.01)	(0.03)
hhold_size_02	0.017	-0.003	0.016	0.001
	(0.03)	(0.04)	(0.03)	(0.04)
milk_producer_02	-0.023*	-0.006	-0.023*	-0.006
	(0.01)	(0.03)	(0.01)	(0.03)
irrigation_1_02	0.022	0.040	0.023	0.039
	(0.03)	(0.03)	(0.03)	(0.03)
irrigation_2_02	-0.057	-0.061***	-0.058	-0.057**
	(0.04)	(0.02)	(0.04)	(0.02)
irrigation_3_02	-0.104**	-0.031	-0.105***	-0.033
	(0.04)	(0.05)	(0.04)	(0.05)
grazing_area_02	-0.001	-0.002	-0.001	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)
education		-0.009*		-0.009*
		(0.00)		(0.00)
age		-0.002**		-0.002*
		(0.00)		(0.00)
Constant	0.037	0.200	0.036	0.197
	(0.08)	(0.12)	(0.08)	(0.12)
r2 within	0.020	0.056	0.020	0.057
N	405.000	204.000	405.000	204.000

OLS with Fixed Effects at community level and standard errors clustered at the community level

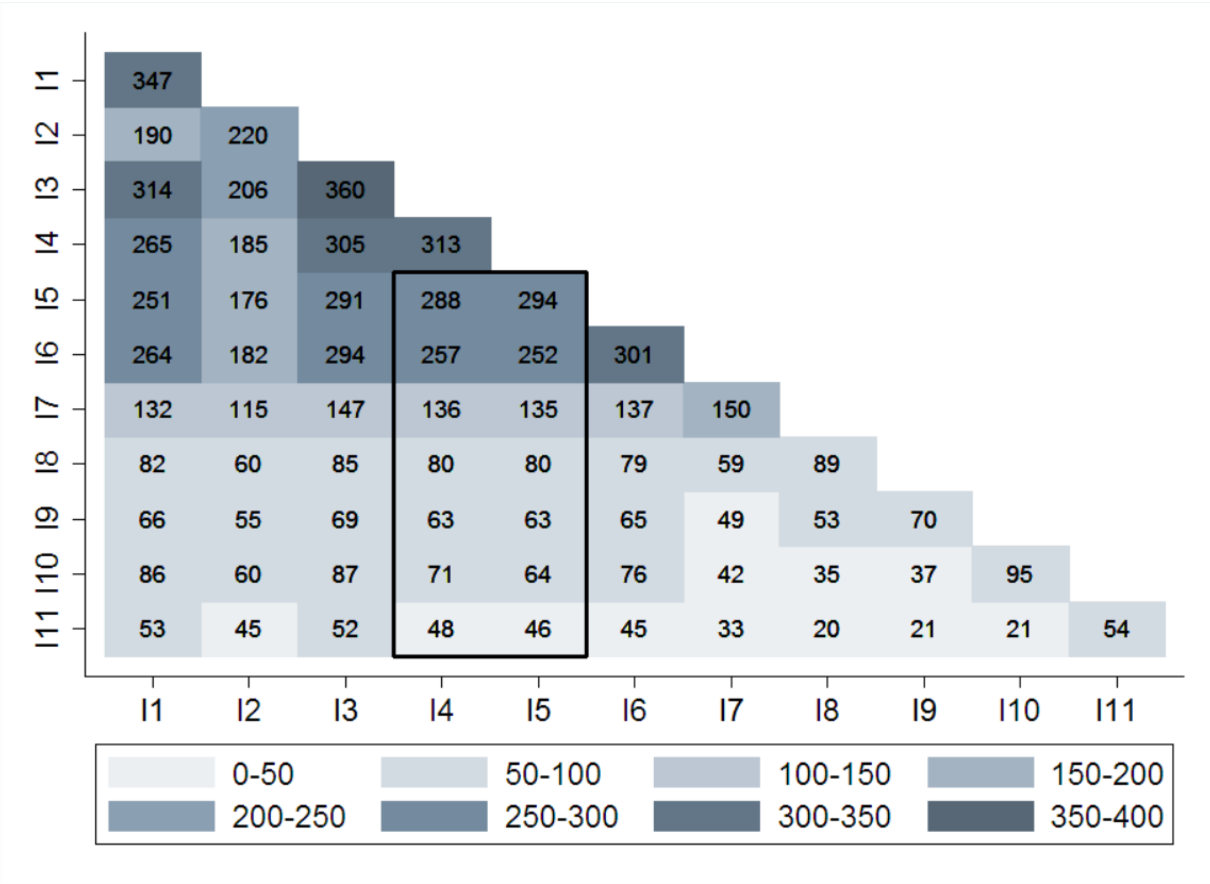
Standard errors in brackets

* p < 0.10 ; ** p < 0.05 ; *** p < 0.01

Table 12: Testing difference of (initial) mean incomes between trainees who did and did not adopt 'costly' innovations

Innovations that have been adopted or not adopted by:	Innovations (3), (4), (5), (7) and (11)	Innovations (5) and (11)	Innovation (11)
Heads who attended at least one training session (124)	NS	NS	S
Heads who attended at least two training sessions (56)	NS	NS	S

Figure 1: Frequencies of joint pairwise adoption of innovations



APPENDIX

APPENDIX A

Table 13: Sensitivity and specificity statistics for pairwise innovation adoption: probabilities of adopting innovation I_i (column) conditional on having adopted innovation I_j (row)

Specificity, Prob(I_i=0|I_j=0)

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}
I_1	1	.46	.19	.15	.22	.33	.67	.87	.93	.83	.98
I_2	.14	1	.15	.3	.36	.35	.81	.84	.92	.8	.95
I_3	.24	.66	1	.83	.95	.88	.93	.9	.98	.8	.95
I_4	.09	.61	.38	1	.93	.51	.84	.9	.92	.73	.93
I_5	.11	.6	.36	.77	1	.54	.85	.91	.94	.72	.93
I_6	.18	.63	.36	.46	.58	1	.87	.9	.95	.81	.91
I_7	.14	.59	.15	.3	.37	.35	1	.88	.91	.79	.91
I_8	.15	.49	.12	.26	.32	.29	.71	1	.95	.81	.89
I_9	.15	.5	.12	.25	.3	.29	.69	.89	1	.82	.9
I_{10}	.15	.48	.11	.21	.25	.27	.65	.82	.89	1	.89
I_{11}	.15	.5	.11	.24	.29	.26	.66	.8	.86	.79	1

Sensitivity, Prob(I_i=1|I_j=1)

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}
I_1	1	.55	.91	.77	.72	.76	.38	.24	.19	.25	.16
I_2	.87	1	.94	.84	.8	.83	.53	.28	.25	.27	.21
I_3	.88	.57	1	.85	.81	.82	.41	.24	.19	.24	.15
I_4	.85	.59	.98	1	.92	.83	.43	.26	.2	.23	.16
I_5	.86	.6	.99	.98	1	.86	.46	.27	.21	.22	.16
I_6	.88	.61	.98	.86	.84	1	.45	.27	.21	.26	.15
I_7	.88	.77	.98	.91	.89	.91	1	.4	.32	.28	.23
I_8	.92	.68	.96	.9	.89	.89	.67	1	.58	.4	.23
I_9	.94	.79	.99	.9	.9	.93	.69	.76	1	.51	.3
I_{10}	.91	.63	.92	.75	.68	.8	.44	.37	.37	1	.23
I_{11}	.98	.84	.96	.89	.86	.84	.61	.38	.38	.39	1

APPENDIX B: Descriptive statistics

Table 14: Descriptive statistics of household variables

Variable	Definition	Mean	Std. Dev.	Min.	Max.
innov1_02	adoption of the "hygienic measures" in 2002	0.125	0.331	0	1
innov1_07	adoption of the "hygienic measures" in 2007	0.427	0.495	0	1
innov2_02	adoption of the "double cow milking" in 2002	0.08	0.271	0	1
innov2_07	adoption of the "double cow milking" in 2007	0.271	0.444	0	1
innov3_02	adoption of the "multiple ploughing" in 2002	0.169	0.374	0	1
innov3_07	adoption of the "multiple ploughing" in 2007	0.443	0.497	0	1
innov4_02	adoption of the "organic fertilizer" in 2002	0.052	0.221	0	1
innov4_07	adoption of the "organic fertilizer" in 2007	0.78	0.415	0	1
innov5_02	adoption of the "lime to reduce the acidity of the land" in 2002	0.002	0.05	0	1
innov5_07	adoption of the "lime to reduce the acidity of the land" in 2007	0.362	0.481	0	1
innov6_02	adoption of the "improved seeds" in 2002	0.09	0.286	0	1
innov6_07	adoption of the "improved seeds" in 2007	0.37	0.483	0	1
innov7_02	adoption of the "vaccination according to a fixed calendar" in 2002	0.034	0.182	0	1
innov7_07	adoption of the "vaccination according to a fixed calendar" in 2007	0.185	0.388	0	1
innov8_02	adoption of the "ensilage" in 2002	0.012	0.11	0	1
innov8_07	adoption of the "ensilage" in 2007	0.109	0.312	0	1
innov9_02	adoption of the "fodder mixes" in 2002	0.015	0.121	0	1
innov9_07	adoption of the "fodder mixes" in 2007	0.086	0.281	0	1
innov10_02	adoption of the "supplementary nutrients" in 2002	0.063	0.243	0	1
innov10_07	adoption of the "supplementary nutrients" in 2007	0.117	0.321	0	1
innov11_02	adoption of the "precocious weaning" in 2002	0.017	0.13	0	1
innov11_07	adoption of the "precocious weaning" in 2007	0.066	0.249	0	1
innov_02	number of innovations adopted in 2002	0.673	1.122	0	7
innov_07	number of innovations adopted in 2007	5.705	2.33	0	11
no_costly_07	dummy taking value 1 if none of the innovations in the set 3-11 have been adopted in 2007	0.051	0.22	0	1
costly_07	number of innovations adopted in the set containing the innovations 3, 5, 7 and 11, in 2007	2.136	1.043	0	4
income_02	total monthly income in 2002, in 10,000 soles,	0.063	0.06	0	0.468
	average between the rainy and the dry season				
hhold_size_02	total number of members inside the household	1.726	0.34	0.693	2.565
female_head	the head of the household is a woman, in 2002	1.087	0.283	1	2
milk_producer_02	the household produces milk and sell it, in 2002	0.586	0.493	0	1
grazing_area_02	area of pasture in 2002	4.038	6.803	0	52
irrigation_1_02	the household's pasture are irrigated through natural irrigation only, in 2002	0.376	0.485	0	1
irrigation_2_02	the household has access to water conveyed by a central canal in 2002	0.176	0.381	0	1
irrigation_3_02	the household has access to a secondary channel infrastructure in 2002	0.064	0.245	0	1
irrigation_4_02	the household uses irrigation through sprinkling in 2002	0.01	0.099	0	1
irrigation_1_07	the household's pasture are irrigated through natural irrigation only, in 2007	0.182	0.386	0	1
irrigation_2_07	the household has access to water conveyed by a central canal in 2007	0.461	0.499	0	1
irrigation_3_07	the household has access to a secondary channel infrastructure in 2007	0.134	0.341	0	1
irrigation_4_07	the household uses irrigation through sprinkling in 2007	0.034	0.182	0	1
training	number of training session followed	0.462	0.801	0	5
training_d	at least one training session followed	0.3	0.459	0	1
education*	equivalent number of years of the highest level reached by the household head	4.507	2.896	0	11
age*	age of the household head, years	38.808	12.636	18	78
	* : variable for the reduced sample of 205 households				

Table 15: Descriptive statistics of the dispersion of the EA among communities

Variable	Definition	Mean	Std. Dev.	Min.	Max.
EA_vete	at least one EA specialized in veterinary practices lives in the community	0.741	0.439	0	1
EA_agri	at least one EA specialized in agricultural practices lives in the community	0.584	0.494	0	1
EA_vete_vaccination	at least one EA specialized in veterinary practices and supplying vaccination lives in the community	0.508	0.501	0	1
EA_vete_or_agri	at least one EA specialized in veterinary practices or in agricultural innovations lives in the community	0.741	0.439	0	1

Table 16: Descriptive statistics of EA variables

Variable	Definition	Mean	Std. Dev.	Min.	Max.
Age	age of the EA, years	34.475	6.643	25	57
Education	highest grade reached by the EA, year equivalent	3.632	1.036	2	6
Workshop	number of workshop supplied by the NGO the EA has been participating in	9.445	5.573	0	20
Mine	the EA is helped by the mining in supplying innovations	0.198	0.399	0	1
District	value 1 for Hualgayoc district	0.409	0.492	0	1
Domestic_income_07	domestic income of the extension agent in 2007, per year	6436.97	4103.847	480	30000
Value_services_07	income the EA gets from supplying services (profit)	168.152	265.996	0	1100
Meanvalue_clients_07	average value of the services the EA gives to one of his client, during the last month	10.965	11.332	0	40
Nr_clients_07	number of clients the EA served during the last month	23.194	20.919	1	80

Table 17: Descriptive statistics about innovation adoption in years 2002 and 2007

	2007	2002
Average number of innovations adopted per household	5.72	0.66
Modal value	6	0
Maximum value	11	7
Standard deviation	2.33	1.12
Proportion of non-adopter households	1.23%	62.72%
Rate of use of innovation potential	52.01%	5.97%

APPENDIX C: The liquidity constraints of extension agents

Extension agents themselves may have their activities constrained by liquidity. We test this hypothesis by estimating the impact of wealth on the scope of extension activities of the EAs, controlling for a number of personal and community-level characteristics. The model to be estimated has the following form:

$$Value_{of_{services_{07}}_{kj}} = \vartheta_0 + \vartheta_1 Wealth_{07_{kj}} + \vartheta_2 Community_{Income_{07_j}} + \vartheta M + \varepsilon_j$$

$$Value\_of\_services_{07_{kj}} = \theta_0 + \theta_1 Wealth_{07_{kj}} + \theta_2 Community\_income_{07_j} + \theta M + \varepsilon_j$$

where *k* and *j* index, respectively, the extension agent's household and his community, *Wealth_07* is a measure of the income (or capital assets) of the agent's household, *Community_Income_07* is the potential demand he faces in each village visited, and *M* is the matrix of personal characteristics.

Two key issues concern the way to measure the dependent variable, on the one hand, and the wealth or liquidity available to the extension agent, on the other hand. Since our objective is to assess the extent to which liquidity constrains the scope of business, we make the logical choice of using the total (monetary) value of the extension services supplied by the agent as our dependent variable. We label it *value_of_services*. As for our central independent variable, two different routes are trodden. In the first approach, we measure liquidity by using the current monetary income that the extension agent' household obtains from its domestic productive activities (sales of milk and cheese) only. We designate this variable by *domestic_income_07*, which is measured annually in this instance. The idea is that cash incomes currently earned from the sale of milk and cheese products can be easily used to finance expenditures involved in the purchase of inputs associated with extension service activities. The explanatory variable is thus considered as a mass of liquidity available to the head acting as an extension agent.

It could be objected that the above variable is likely to be endogenous to the value of extension services. There are two grounds on which such an objection could rest: (1°) incomes from extension services could be themselves invested in productive assets (a complementarity effect), and (2°) more intensive extension activities could be at the expense of domestic income-earning activities (a substitution effect). Upon careful look, such arguments are not very convincing, though. Regarding the complementarity effect, it is not very plausible to assume that productive investments made as a result of higher incomes from extension activities, assuming that they have actually occurred, could yield larger monetary benefits during the current period (think, for example, of the purchase of new seeds for pasture improvement). It is true that the purchase of a new cow could have immediate effects on domestic income, yet the expense involved (about 300 soles, on an average) is too high to be financed by an accumulation of savings over less than a year.[22] On the other hand, since women in age of working are specialised in the day-to-day handling of milk and cheese production within the household, it is difficult to see how greater extension activity on the part of the household head could cause a fall in domestic production.[23] We nevertheless check the robustness of our results by instrumenting the *domestic_income_07* variable by its five-year lagged value which is predetermined. The results remained unchanged, and the test of Durbin-Wu-Hausman supplies evidence supporting our belief that the current domestic

[22] Note carefully that this figure of 300 soles cannot be compared to the income data displayed in Table 10 because the latter have been estimated by using gross values.

[23] Bear in mind that there are only three women in our sample of 39 extension agents.

income from herding activities is not endogenous to the value of extension services (the test statistic is 1.33 which is associated with a p-value of 0.25).

In the second approach, we use physical assets as our wealth variable. To control for the effect of the size of the household or the workforce concerned, we measure physical wealth in per capita terms, using alternatively the number of women of working age (above twelve years old) and the total number of household members as the denominator. For the numerator, we use either the size of the cowherd or the pasture land area. The latter two variables are introduced separately because they are significantly correlated.[24] Whatever measure is used, the idea is that the size of physical assets is a proxy for the household's ability to own a working capital available for extension service activities. As a matter of principle, we believe that it is more meaningful to relate herding-related assets to the number of active women (in which case the variable is labelled *wealth1*) than to the total number of household members (*wealth2*) because domestic herding is the domain of women.

Let us now comment on the control variables that appear on the RHS of our regressions. Age of the extension agent is measured continuously, and is represented by two terms (*age* and *agesquare*) so as to allow for a non-linear effect. Two measures are employed to assess the influence of human capital: an ordered variable, labelled *education*, reflecting the level of formal schooling achieved by the agent, and the number of additional, optional training sessions or workshops organized by SP which the extension agent attended after year 2002. This second variable is named *workshop*. The formal education variable comprises six categories defined as follows: no education (value 1), primary school non-completed (value 2), primary school completed (value 3), secondary school non-completed (value 4), secondary school completed (value 5), and higher education, whether completed or not (value 6).

Besides age and education, the list of independent variables include the dummy *VET*, equal to one when the agent supplies veterinary services, and *nr_of_specialisations*, equal to one when the extension agent has more than one field of specialization (agricultural and veterinary), and to zero otherwise. Yet another dummy, labeled *mine*, indicates whether the agent is working for YANACOCHA mining company or not. This is useful information because a commonly heard opinion is that this company has recruited the most performing EAs to operate its aforementioned program. These EAs receive a fixed wage from YANACOCHA (bear in mind that the extension services delivered under this program are free of charge) and, in addition, they continue to operate as independent agents. The value of their incomes from extension has therefore been computed by summing up their wage and the value of their independently provided services.

Lastly, we control for location-specific effects in two ways. First, we use a district dummy, named *district*, which takes on value one when the extension agent resides in La Encanada district, and zero when he resides in Hualgayoq. Second, we measure the potential demand for an agent's services (denoted by *income_village_07*), as proxied by the sum of the (gross) incomes of all potential customers living in each village where he actually operates (this information is extracted from the adopter dataset). We decide not to aggregate all these incomes to obtain a single variable for each extension agent. Indeed, a preliminary analysis reveals a huge between-village heterogeneity that must be taken into account. Ignoring such heterogeneity would actually induce shrinkage of the standard errors and lead to overoptimistic conclusions. Hence, since most extension agents work in more than one village and an observation corresponds to the situation of a particular agent operating in one community only, many agents appear more than once in the dataset. To tackle this issue, we

[24] The correlation between land area per household member and the number of cows per member is 0.40 while the correlation between land area per active woman and the number of cows per active woman is 0.34. Finally, the correlation between land area and the number of cows is 0.24.

estimate the regression equation by clustering the standard errors at the level of the extension agent, which allows us to correct the inference. Furthermore, to guarantee the representativeness of our sample, we use the sampling weight set in the sample design stage while we estimate the regression.

Note that since several extension agents have two fields of specialization (none of them has three specializations), they appear twice in the dataset used for our regressions. To take this specific feature of the data into account, we estimate our regressions by attaching a sample weight of ½ to any agent who has two fields of specialization, so that his ultimate weight is unity. As it turns out, this weighting procedure does not yield different results from a simple procedure in which all observations receive the same weight (results not shown).

The estimates are presented in Table 3.1 which comprises four columns. In the first two columns, the liquidity effect is tested by using the current domestic income variable (through simple OLS and through an IV regression), while in the last two columns it is tested through the use of the physical asset variable (with the size of the cowherd measured per woman in age of working in the third column and per member of the household in the fourth column).

The existence of a liquidity effect, measured in terms of either current domestic income or physical assets (using cowherd size as the indicator of physical wealth), is largely borne out by the data: the coefficients of *domestic_income_07* and *wealth1* (but not the coefficient of the more questionable variable *wealth2*) are positive and significantly different from zero. Note that the size of the coefficient of the liquidity variable hardly varies when it is instrumented, yet the degree of its statistical significance improves from 95 to 99 percent (the p value is 0.035 with simple OLS and 0.002 with the IV method). Moreover, when we measure physical wealth as land area (per active woman or per household member) rather than as cowherd size, we find that its coefficient is positive and significantly different from zero (with a level of statistical significance equal to 90 percent). These latter results are not shown here.[25]

Note the strongly positive effect of the *mine* variable, indicating that agents recruited by YANACOCHA company obtain a higher total income from extension services than others. Interestingly, when we take the wage component out of total incomes from extension services, all the results displayed in Table 3.1 continue to hold. Results again persist if wages are added to incomes from domestic activities, considering that they, too, can be used to finance independent extension activities, and if the newly defined domestic income variable is interacted with the dummy *mine*.[26] Clearly, the EAs working for this company form a special, highly performing category of extension agents.

[25] Note that when wealth is measured as total pasture land area, its coefficient is again positive and significant (at 90 percent confidence level). On the contrary, when wealth is measured as total cowherd size, its coefficient is no more significantly different from zero.

[26] In the OLS estimate, we then find that the size of the coefficient of the domestic income variable increases slightly (from 0.017 to 0.019), that of the mine variable is substantially reduced (from 498 to 377), and that of the interaction term is not statistically different from zero (results not shown).

Table 15: Determinants of the value of extension services supplied and the impact of the wealth constraint

Dependent variable	Value_of_services_07			
	OLS	IV	OLS	OLS
VET	-41.867	-47.450	-84.533	-35.640
	(0.88)	(0.97)	(1.36)	(0.61)
Domestic_income_07	0.017**	0.020***		
	(2.15)	(3.08)		
Wealth1			77.253**	
			(2.40)	
Wealth2				75.789
				(1.15)
Age	-47.415*** -46.690***	-31.990*	-46.989***	
	(3.69)	(3.74)	(1.94)	(3.03)
Age_Square	0.684***	0.678***	0.499**	0.682***
	(4.11)	(4.27)	(2.46)	(3.46)
Education	84.286**	82.525***	71.938**	78.119**
	(2.67)	(2.79)	(2.55)	(2.07)
Workshop	24.848***	23.095***	11.951	30.905***
	(2.96)	(2.85)	(1.13)	(3.68)
Mine	498.242***	494.896***	479.554***	509.293***
	(16.71)	(15.65)	(12.01)	(14.04)
Nr_of_specializations	-61.673	-56.513	-33.654	-83.295
	(0.91)	(0.79)	(0.56)	(1.28)
District	81.363	91.787	115.820**	70.816
	(1.16)	(1.45)	(2.64)	(1.05)
Community_income_07	-0.240	-0.169	0.267	-0.316
	(0.65)	(0.54)	(0.66)	(0.71)
Constant	390.056	-133.828	-357.157	-82.049
	(1.58)	(0.56)	(1.16)	(0.30)
Observations	85	85	85	85
R-squared	0.90	0.90	0.91	0.89

Robust t-statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We may then want to identify the precise channel through which the liquidity constraint weighing on the EAs operates. Toward that end, we decompose the aggregate value of their services into a quantity and a price components, and we re-run the regression with exactly the same explanatory variables as those used in the above estimations, but with newly defined dependent variables. In the first series of regressions, the dependent variable is the number of services supplied by the agent and, in the second series, it is the average value or price of an extension service. The results (not shown) are rather neat when liquidity is measured in terms of domestic income: while the first estimation (number of services as dependent variable) does not yield any significant effect except for the *mine* variable, the second one (value of the average client) turns out to be a close replica of the estimation displayed in Table 3.1. The central conclusion to draw is that, when limited by his liquidity (yet not by his physical wealth), an extension agent rations his services not by reducing his number of customers but by decreasing the average price or value of the services offered them.

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