Working Paper Series

#2017-024

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UNU-MERIT Working Papers
ISSN 1871-9872

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Estimating the impact of sericulture adoption on farmer income in Rwanda: an application of propensity score matching

Alexis Habiyaremye*

June 6, 2017

Abstract

The adoption of an agricultural technology is often seen as a way to overcome the constraints imposed by the existing resources and/or production methods. As a small landlocked country, Rwanda sought to develop the capability to produce silk, a high value-to-volume ratio product, as a means to overcome the constraints of high transportation cost of exports. Sericulture was also seen as a handy strategy to boost rural farmer income by putting previously less productive land to use for mulberry plantations. Because sericulture was not introduced randomly, this study relied on observational data and applied propensity score matching to estimate its income and poverty reduction effects in 6 rural districts. The results indicate that sericulture adoption had beneficial effects both on increasing income and reducing poverty. The strengthening of related skills development and the supporting infrastructure remains crucial for the sericulture to successfully diffuse and yield economic benefits commensurate with its potential.

Keywords: Sericulture, Agricultural technology adoption, Propensity score matching

JEL Classification: C13, C15, O32, O38

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1 Introduction

The adoption of foreign agricultural technologies often occurs as a way to overcome the constraints posed by the limitations of existing resources and/or traditional production methods (Olson, 1992). In very densely populated and mountainous Rwanda, agricultural expansion in traditional farming activities is constrained by an unfavourable topographical configuration and dispersed human settlement patterns, which impede mechanisation and prevent the sector from reaping the benefits of scale economies.[1] To overcome the challenges posed by these constraints, a strategy based on sericulture adoption was seen as the most effective way to put the hitherto less productive land on sloppy hills to more profitable use.

With the high value to volume ratio of silk, sericulture adoption would give the land-locked country a handy advantage, enabling it not only to avoid the constraints of high transportation costs that have long hampered Rwanda's exports and made them uncompetitive in world markets, but also to diversify export revenue beyond traditional cash crops. Because of its low financial gestation period and high returns, the adoption of sericulture was also identified as an adequate way to more efficiently use scarce land resources and cheap labour to increase household income.[2] Sericulture development was thus identified as carrying the potential to play a key role in the transformation of the Rwandan rural economy by ensuring regular employment and steady returns as suggested by Lakshmanan et al. (1998).

The idea of enhancing farmers' income through silkworm rearing in Rwanda is however not a straightforward one. While various countries in Europe have successfully managed to adopt sericulture and establish local silk industry in the past, the

[1] Shortages of land and water, constant threat of soil erosion, farmers' limited access to credit, insufficient and poor-quality animal feed and regular disease epidemics with insufficient veterinary services are some of the other major constraints that restrict output expansion in this vital sector of the economy.

[2] Silk is a high value product in international markets and its demand is guaranteed.Its demand is strong, especially in India, where it consistently exceeds supply. Fresh silk cocoons can fetch a price between US$ 2.7 and US$ 7.5 per kilo, while silk yarn cost between $40 and $60 a kilo on international markets. The value of silk being tenfold that of cotton on world markets, a farmer adopting sericulture and using recommended standard practices was projected to add a net annual income of about FRW 1,000,000 (US$ 2,000) to his traditional revenue Mulberry trees take 6 months to grow after first planting and 3 months after pruning.

historical Chinese domination of silk production has only been challenged by Japan in the pre-WWII years. Nearly ten years after the initial introduction of sericulture in the country, its adoption has however stagnated and its poverty-reduction benefits are still difficult to predict. This study will aim to estimate the effects of sericulture adoption on enhancing farmer income and the effectiveness of using this foreign agricultural technology to reduce poverty. The study will also attempt to contrast the projected profitability of this agricultural technology adoption with the stagnation in its diffusion.

Given the high labour intensity of the sericulture industry, its adoption in Rwanda carried high expectations of employment creation, with hopes to absorb youth unemployment and offer rural women a suitable opportunity to improve household incomes. As shown by Qadri et al. (2010) and Praveena et al. (2011) in the case of India, sericulture can indeed be a viable source of employment, facilitate economic development, and thereby enable the improvement of living conditions in rural areas. Likewise, it is well known that sericulture has played an important role in the industrial development of countries like Korea and Japan (Kiyokawa, 1984). That is why the Government of Rwanda, in partnership with the local textile company, has sought to harness sericulture as an innovative form of land use that can contribute to the poverty reduction strategy by creating new employment opportunities and enabling poor farmers to generate higher incomes (Rajendran, 2011).

Because sericulture was introduced in the country in a non-random adoption process, giving preference to cooperatives, the appraisal of its welfare improvement effects cannot be easily done as when dealing with a randomized trial control. Having to rely on observational data, this study applies propensity score matching (PSM) and inverse probability-weighted estimations to assess the income-enhancing effects and poverty reduction impact of sericulture adoption. Silkworm rearing being a totally new phenomenon in the country with fairly unknown adoption risks, this assessment will provide a micro-level perspective on the economic benefits of a hitherto unknown production technique, using household survey data from a cross-section sample of 1343 rural households in 6 rural districts.

The adoption of sericulture in a country where no prior experience with any related production method nor any form of textile fibre production on large scale is a non-trivial novelty for the country. With the analysis sericulture adoption by Rwandan rural farmers, this study contributes to the existing agricultural technology adoption literature by empirically estimating income effects of a previously fairly unknown agricultural production method in low-skilled rural communities of a low-income, land-locked country. Silkworm rearing and spinning do not belong to the traditional activities of the Rwandan farming society and the benefits of sericulture adoption are therefore to be assessed with respect to traditional crops rather than directly comparable old production.

The paper proceeds as follows: the next section describes the basic features of the sericulture as an old Chinese agricultural technique and its embedding in the Rwandan national strategy for poverty reduction. It also draws on the literature to highlight the hurdles that must be overcome for an already existing (agricultural) technology or production method to be successfully adopted. Section 3 presents the evaluation methodology and the application of PSM procedure (Rosenbaum and Rubin, 1983) to make an assessment of the economic potentials of sericulture adoption and diffusion as an income diversification strategy in Rwanda. Section 4presents the household survey data used by this study and discusses the evaluation results while the final section draws some conclusions and formulates a few recommendations to enhance the success of diffusion.

2 Sericulture adoption and the promise of poverty reduction

2.1 From mulberry leaves to a silk gown

As a Chinese proverb goes, "with time and patience, a mulberry leaf becomes a silk gown". The process and the value chain through which this mulberry leaf becomes a silk gown is sericulture. It comprises diverse activities ranging from breeding and maintenance of silkworm races through the rearing of silkworm larvae for the production of cocoons, up to the reeling of silk yarns and the manufacturing of fabrics and finished silk products. Cultured silk production relies mainly on the rearing of domesticated silkworms (*Bombyx mori*), which for their metamorphosis spin cocoons made of raw silk. The silkworms feed preferably on white mulberry (*Morus alba*) leaves, but they may also eat the leaves of any other tree or shrub of the *Morus* family, like the *Morus rubra* or *Morus nigra*.

For the production of raw silk yarn, the silkworm eggs are laid on a specially prepared paper layer. The eggs hatch after incubation and the caterpillars (silkworms) are fed with fresh mulberry leaves. After about 35 days and four moltings, the caterpillars become about 10000 times heavier than their initial weight and begin spinning their cocoons. A straw frame is placed over the tray of caterpillars, and each caterpillar begins spinning a cocoon by moving its head in a pattern. Two salivary glands in the head of each silkworm produce liquid silk and force it through openings in the head, called spinnerets. Liquid silk is coated in sericin, a water-soluble protective gum, and solidifies on contact with the air. Within two to three days, the silk worm spins about one mile of silk filament to completely enclose itself in a cocoon. The silk farmers then kill most caterpillars by heat, leaving some to transform into moths to breed the next generation of caterpillars. It takes about 100 kg of mulberry leaves eaten by 3000 silkworms to produce one kg of silk.

To retrieve the silk threads, cocoons are soaked in boiling water to soften the sericin holding the silk fibers, which frees the silk filaments and readies them for reeling. This is known as the degumming process. The silk is obtained from the undamaged cocoons by brushing them to find the outside end of the filament. The fibers are then unwound and reeled with a hand spindle or by a reeling machine to produce a continuous thread. Since a single thread is too fine and fragile for commercial use, anywhere from three to ten strands are spun together to form a single thread of silk. The sericulture industry is thus a complex set of activities requiring not only patience and time but also ingenuity and hard work.

2.2 Sericulture adoption as a poverty-reduction strategy

Although the activities described above seem straightforward, the adoption of sericulture in a totally new socio-cultural environment is far from being an easy process. Some countries have succeeded in adopting and developing this industry, but many others, including the United Sates, have failed to keep it alive. As shown by Kiyokawa (1984), the sericulture industry requires much technology and an appreciable level of technical skills and financial investments to produce high quality, competitive silk. For this industry to thrive in a country, silkworm rearing and silk production must have linkages to a large variety of related businesses in the domestic market.

For example, in order to sustain sericulture production, linkages between organisations and traders who will purchase cocoons and the producing silkworm farmers are necessary. For their part, silk reeling companies producing raw silk must meet the quality requirements and the price demanded by process manufacturers of the textile industry that use this raw silk to produce fabrics. A well-established relationship of supply and demand from downstream to upstream, from processed products and sales to silkworm farmers, based on both domestic and international consumption needs, is therefore essential.

The high suitability of the Rwandan soil and climatic conditions for mulberry cultivation makes sericulture an environment friendly method of income generation for Rwandan farmers. The mulberry trees contribute to water conservation and soil protection against erosion on the many hill slopes that characterise the country's topography. The high value potential of silk and the optimal suitability of Rwanda's "Thousand Hills" for mulberry cultivation were seen as having the potential to transform otherwise underutilised land areas into highly productive mulberry and silkworm farms. The Rwandan government has consequently deployed massive support to shore up sericulture adoption and has integrated it in its priority clusters

Table 1: *Estimates of revenue from silk compared to traditional crops*

Crop	Revenue/ha/year	Profit	Profit margin %
Silk	4560000		41
Cassava	1750000	43.60	65
Potatoes	2000000	6.30	41
Coffie	1948800	5.60	39
Maize	750000	0.94	30
Beans	450000	0.91	14
Tea	819840	68880	8

Source:Karisimbi Business Partners analysis (Rwandan Development Board, 2013).

for development strategy. Sericulture development was integrated in the country's Vision 2020, a national development plan aimed to transform Rwanda from a low-income country into a knowledge-based economy by the year 2020. It was also incorporated in Rwanda's second Economic Development and Poverty Reduction Strategy (EDPRS2, 2013-2018).

The silk value chain has thus become a priority for government support. It was estimated that one hectare of mulberry can yields around 30 tons of leaves per year, which would produce around 750 kg of cocoons, giving 100 kg of raw silk (RDB, 2013). With current market price of USD 69/kilogram, this was a potential gross revenue of USD 6900 per year, per hectare. This revenue compares favourably with traditional crops, as can be seen in the revenue estimation displayed in Table 1. This was therefore expected to form an inducement to switch to sericulture production, especially considering land scarcity and profit potential. The aim of the adoption strategy was to reach 10000 hectares by the year 2020.

For the silk reeling industry to really be established and become a viable source of employment, the stimulation of a strong domestic demand, based on historical and traditional practices, is of crucial importance (JAICAF, 2007). In order to stimulate local demand and reinforce the capacity of silk production from locally produced raw materials, Utexrwa has attempted to revive and promote local traditions, such as ladies' traditional attire of imishanana, which will now be made of Rwandan silk (Rajendran, 2011). Production of silk handcrafts and souvenirs is also being developed to attract both local and export markets for fine silk products. Farmers were encouraged to form sericulture cooperatives and emphasis has been put on cocoon processing at cooperative and farmer level in order to promote downstream value addition in rural areas.

2.3 Hurdles to successful adoption and diffusion

The economic benefits of new agricultural methods and crop varieties to the adopting farmers have long been attested by a wide range of empirical studies (Hossain et al., 1994; Winters et al., 1998; De Janvry and Sadoulet, 2001; Irz et al., 2001). Such an agricultural innovation can also often serve to reduce downward risk and ensure food security in the presence of climate change hazards and other abiotic stress (Mottaleb et al., 2016). In addition, Emerick et al. (2016b) show that the adoption of a new agricultural technology can create a factor deepening effect, which crowds in new inputs and leads to improvement in agricultural practices.

Despite these seemingly obvious benefits of new agricultural technologies, however, slow diffusion rates appear to be more common than is usually thought, as remarked by Rosenberg (1972). Rwandan stagnation in sericulture diffusion is therefore far from being an unusual phenomenon. Most often, slow diffusion rates are due to the negligence of implementation agents, who complacently assume that good technologies will sell themselves since their benefits are obvious (Rogers, 1995; Toborn, 2011).

More theoretical arguments attribute slow diffusion mainly to micro-economic factors affecting the decisions to adopt (Hall and Khan, 2003). Such factors include adoption costs, profitability of the new technology with respect to the old ones, availability of complementary technical skills and inputs, the strength of the relation to the firm's customers, and the importance of network effects. For the successful diffusion of an adopted technology, another important consideration to be taken into account (in addition to information spread, costs and profitability) is the ability of the adopting entities in the local economy to absorb the new technological knowledge. Such ability is measured by four essential capabilities: production capabilities, investment capabilities, technical capabilities and linkage capabilities (Lall, 1992).

The epidemic (contagion) model of technology diffusion presented by Geroski (2000), for its part, explains the diffusion speed by the spread of information about the availability and the advantages on the new technology. Beaman et al. (2015) use such a contagion model based on network learning to show how variation in social learning parameters between adopters and potential adopters of a profitable agricultural technology results in sizable differences in adoption rates. As shown by Emerick et al. (2016a), in the absence of incentives for farmer-to-farmer learning, adoption of new agricultural technology can be significantly increased by organising information days whereby farmer visit fields in which the improved crop variety is demonstrated. Such a strategy is necessary to overcome the lack of incentives for farmer-to-farmer learning, as individual farmers who have adopted a new technology gain little from demonstrating it to their fellow farmers.

3 Estimating the effects of sericulture adoption on income and poverty reduction in Rwanda

3.1 Empirical strategy

Ideally, in order to establish a causal relationship between agricultural technology adoption and subsequent economic benefits, one would have to provide counterfactual evidence based on what the situation would be if the agricultural innovation had not been adopted (Rosenbaum and Rubin, 1983). Failure to distinguish between the causal effects of technology adoption and the effects of unobserved heterogeneity could produce biased estimates and lead to inadequate policy interpretations. This methodological difficulty is overcome through the use of the non-parametric propensity score matching (PSM) analysis developed by Rosenbaum and Rubin (1983) to account for endogeneity of the adoption decision. The PSM approach assumes that all variables influencing adoption and are correlated to outcomes are observable, and relies on the estimation of the probability to adopt the new technology conditional on the observed covariates (Dehejia and Wahba, 1999).

Despite the fact that PSM tries to compare the difference between the outcome variables of adopters and non-adopters with similar inherent characteristics, it thus cannot correct unobservable bias because it only controls for observed covariates to the extent that they are accurately measured. If there are unobserved variables that simultaneously affect the adoption decision and the outcome variables, such as tacit knowledge and technical skills of farmers, this can give rise to a selection bias or hidden bias problem, to which matching estimators are not robust (Rosenbaum, 2002).

To apply the PSM estimation of the treatment effect, we first specify a logit model defining household income and sericulture adoption equations as follows:

$$Y_i^s = \Psi_i^S(X_i) + \varepsilon_i^S, \qquad S = 0, 1 \tag{3.1}$$

$$S_i = \phi(W_i) + \zeta_i, \tag{3.2}$$

where S_i is an indicator variable taking the value 1 if the household adopts sericulture and 0 if it does not. Y_i^s represents the income of household i that has adopted sericulture S, thus household i has an income Y_i^1 if it adopts sericulture and Y_i^o if it does not adopt it. Household income depends on a number of observable and unobservable variables that are denoted respectively by X_i and ε_i^s with the latter having a mean of 0 and being uncorrelated with the X_i. Sericulture adoption S_i is dependent on a vector of observable variables W_i, which are a subset of X_i,[3] and other unobservable household characteristics captured by the random variable ζ_i.In order

[3]This means that the decision to adopt sericulture is modelled here as dependent on some of the same household characteristics that more generally determine income earning.

to determine the underlying causal relationship between sericulture adoption and income change we have to identify in a counterfactual framework what Rosenbaum and Rubin (1983) define as the *average treatement effect* (ATE), i.e the expected difference between the income of the households that have adopted sericulture and what their income would have been if they had not adopted it. ATE is thus defined as:

$$\alpha = E(Y_i^1 - Y_i^0). \tag{3.3}$$

The determination of the ATE is however made difficult by the fact that for each household, only one state Y_i^1 or Y_i^0 can be observed but not both.

What is observed can be formalised as:

$$Y_i = S_i Y_i^1 + (1 - S_i) Y_i^0 \quad S = 0, 1. \tag{3.4}$$

The expression for ATE can thus be rewritten as:

$$\alpha = P.[E(Y^1 \mid S = 1) - E(Y^0 \mid S = 1)] + (1 - P).[E(Y^1 \mid S = 0) - E(Y^0 \mid S = 0)] \tag{3.5}$$

where P is the probability is the probability of observing a household that adopted sericulture in the sample. This expression in equation (3.5) means that that the average treatment effect of sericulture adoption is the weighted average of the effect of sericulture adoption on the two categories of households:those who have adopted it (treatment group) and those who have not (control group), each weighted by its relative frequency. However, this is still not enough to estimate the the unobserved counterfactual states $E(Y^0 \mid S = 1)$ and $E(Y^1 \mid S = 0)$,which makes the he causal imputation difficult. This problem can nonetheless be solved by the use of econometric techniques, relying on some assumptions about the simultaneity of the determination of income and sericulture adoption.

These assumptions must be made about the correlation and distribution of the random components ε_i^S and ζ_i of equations (3.1) and (3.2), as well as about the specification and functional forms of the functions $\Psi(.)$and $\phi(.)$. With a judicious specification of the income determination and innovation adoption function, an unbiased estimate of the treatment effect can be calculated if random components are assumed to be orthogonal to the observed income determinants.

The primary assumption underlying the estimation if treatment effect is the *conditional independence assumption* (CIA), which assumes that the decision to adopt is random and uncorrelated with onserved income once we have controlled for observed income determinants X_i. Assuming that sericulture adoption is random after controlling for the observable variables X_i (*conditional independence*), and assuming the treatment effect is constant and independent of the values taken by the variables X_i (*common effect*), the treatment effect can be estimated as the coefficient of the binary variable in a linear ordinary least squares (OLS) regression in the following manner:

$$Y_i^1 = \Psi^1(X_i) + \varepsilon_i^1 = \delta^1 + \beta X_i + \varepsilon_i^1 \tag{3.6}$$

$$Y_i^0 = \Psi^0(X_i) + \varepsilon_i^0 = \delta^0 + \beta X_i + \varepsilon_i^0 \tag{3.7}$$

$$\alpha = E(Y^1 - Y^0) = \delta^1 - \delta^0. \tag{3.8}$$

Using these expressions and assuming linearity, the income equation(3.5) can thus be rewritten as:

$$Y = S(\varepsilon^1 = \delta^1 + \beta X_i + \varepsilon^1) + (1-S)(\varepsilon^0 = \delta^0 + \beta X_i + \varepsilon^0) = \delta^0 + \beta X + S(\delta^1 - \delta^0) + e \tag{3.9}$$

where $e = \varepsilon_i^0 + S(\varepsilon_i^1 - \varepsilon_i^0)$. Only under the assumptions of *conditional independence* and *constant effect*, the OLS can produce unbiased estimates of the treatment effect.The only remaining bias problem would be that the random coefficient is estimated without taking into account unobserved household-specific heterogeneity, which can lead to heteroscedasticity in the error terms. Failure to take into account this heterogeneity would indeed lead to inappropriate comparisons and inadequate interpretations. These assumption of conditional independence and common effects are thus too restrictive and often do not hold in the real world. In order to deal with this problem, it is necessary to relax the restrictive assumption of common effect and apply the non-parametric propensity score matching procedure (Rosenbaum and Rubin, 1983). As pointed out by Heckman et al. (1997) however, the relaxation of this assumption leads to reduced efficiency (larger standard errors) in the estimation.

3.2 Propensity score matching

The main feature of the PSM procedure is the creation of conditions for a randomised experiment in which evaluation is restricted to local comparison between adopting and non-adopting households having otherwise similar characteristics. Matching the adopters based on observed covariates might not be feasible or could be difficult when the set of covariates are large. In order to reduce this problem of dimensionality, Rosenbaum and Rubin (1983) suggested that instead of matching along the income covariates X_i, one can match along $p(X_i)$, a single index variable that summarizes covariates. This index is known as propensity score. PSM is thus as a method of sampling from a large pool of potential controls to produce a control group of modest size in which the distribution of covariates is similar to that of the treated group. The application of propensity score matching procedure must rely on the conditional independence assumptions, but since it compares households with similar income determinant it renders the assumption that technology adoption is uncorrelated with income more plausible.

Here, the usual procedure for propensity score matching is applied in two steps. First, a probability model for the adoption of sericulture technology is estimated to calculate the probability (or propensity scores) of adoption for each observation. Similarity of households is established through the closeness of scores on the probability to adopt sericulture, conditional on observable income determinant X_i. The conditional probability that household i adopts sericulture given its income determinants X_i is formally noted as:

$$p_i = p(X_i) = \Pr ob[S_i = 1 \mid X_i] \tag{3.10}$$

This is the propensity score that will allow to identify similar households for matching. The basic approach in matching is to numerically search for non-adopters who have a propensity score that is very close to the propensity score of the adopters. This is based on the underlying logical assumption that household with the same or similar propensity score should have the same distribution of X_i, irrespective of whether they are adopters or non-adopters of the innovation. This is what is called the *balancing property* and it is important to check for it after matching, to be sure that behaviour of farmers in each group is really similar (Mendola, 2007). The main purpose of the propensity score estimation is to balance the observed distribution of covariates across the groups of adopters and non-adopters (Lee, 2008). The balancing test is thus required after matching to be sure that the differences in the covariates in the two groups in the matched sample have been eliminated, in which case, the matched comparison group can be considered a plausible counterfactual construct (Ali and Abdulai, 2010).

Several versions of balancing tests exist in the literature, but the most widely used is the mean absolute standardized bias (MASB) between adopters and non-adopters suggested by Rosenbaum and Rubin (1985), in which they recommend that a standardised difference of greater than 20 per cent be considered as being too large and an indicator that the matching process has failed. Additionally, Sianesi (2004) proposed a comparison of the pseudo R^2 and p-values of the likelihood ratio test of the joint significance of all the regressors obtained from the logit analysis before and after matching the samples. After matching, there should be no systematic differences in the distribution of covariates between the two groups.

The treatment effect, given household characteristics is thus:

$$\alpha(X) = .\alpha = E(Y^1 - Y^0 \mid X) = E(Y^1 \mid S = 1, X) - .[E(Y^0 \mid S = 0, X)] \quad (3.11)$$

The average treatment effect is:

$$\alpha = E[\alpha(X)] \quad (3.12)$$

In the second step, each adopter is matched with his/her "closest" non-adopter with similar propensity score values, in order to estimate the average treatment effect for the treated (ATT)(Asfaw et al., 2015). Several matching methods have been developed to match adopters with non-adopters of similar propensity scores. Asymptotically, all matching methods should yield the same results. However, in practice, there are trade-offs in terms of bias and efficiency with each method Caliendo and Kopeinig (2008). One of these matching procedures is the nearest neighbour method (NNM) that simply identifies for each household the "closest twin"or "nearest neighbour" in the opposite adoption status; then it computes an estimate of the technological effect as the average difference of household's income between each pair of matched households (the weights are given by the relative frequency in the sample of adopters and non-adopters, respectively). A second method, namely the kernel-based matching (KBM) estimator, is more flexible than the former with respect to the specification of the propensity score. It follows the same steps as the nearest neighbour but the matching household is identified as the weighted average of all households in the opposite adoption status within a certain distance in the propensity score, with weights inversely proportional to the distance.[4]

The adoption effect for households with similar propensity scores can therefore

[4]Despite the popularity of the matching estimator among analysts, Heckman and Navarro-Lozano (2004) have pointed out that it may still carry some new sources of bias due to the selection of unobservables, the failure of common support condition, or the failure to control for local differences between treatment and control groups.

be rewritten as follows:

$$\alpha(p(X)) = E(Y^1 \mid S = 1, p(X)) - .E(Y^0 \mid S = 0, p(X)) \tag{3.13}$$

and the effect for the whole pupulation is

$$\alpha = E[\alpha(X)] \tag{3.14}$$

Despite the fact that propensity score matching tries to compare the difference between the outcome variables of adopters and non-adopters with similar inherent characteristics, it cannot correct unobservable bias because propensity score matching only controls for observed variables to the extent that they are accurately measured. If there are unobserved variables that simultaneously affect the adoption decision and the outcome variables, this can give rise to a *selection bias* or *hidden bias problem*, to which matching estimators are not robust (Rosenbaum, 2002).[5] Another necessary condition for the application of PSM is *common support condition,* which means that the propensity score must be bounded away from 0 and 1, Non-parametric matching methods can indeed only be meaningfully applied over regions of overlapping support as indicated by Heckman et al. (1997). This improves the quality of the matches as it excludes the tails of the distribution of $p(X)$, but it is done at the cost that sample may be considerably reduced. In this paper we use both the nearest neighbour method (NNM) and the KBM methods to match sericulture adopters and non adopters in order to determine the adoption effects on income and poverty reduction.

[5]The difference in difference matching estimator can allow to avoid time-invariant sources of bias, as shown by Smith and Todd (2003) and may perform better than PSM (Heckman et al., 1997). However, this estimator requires longitudinal data, which are not always available (with difference-in-differences estimators,the treatment impact is measured by the the difference between adopters and non-adopters in the after-before adoption comparison).

3.3 Inverse probability weighting approach

When applying the PSM approach, the difference in average treatment effects between the adopters and the non-adopters is calculated as the difference in outcomes between the matched groups. This estimation can be refined by subdividing the groups into layers (or strata) to be matched on the basis of propensity scores (stratification). With stratification by propensity scores, average effect is calculated within each layer and the causal difference is estimated as the average of the within-layer effects. As pointed out by Curtis et al. (2007), both matching and stratification for the construction of comparison groups have limitations that may constrain their practical application because matching algorithms frequently omit a significant proportion of the population when comparison groups are being constructed, thus limiting the ability to generalize from the results. Alternative methods that make more parsimonious use of observation data are therefore needed to overcome part of these limitations. As an alternative to matching or stratification, Cassel et al. (1983) and Rosenbaum (1987) among others, have recommended applying the semi-parametric inverse probability-weighted (IPW) estimators, which combine the strengths of robustness and parsimony. One of the advantages of this inverse probability-weighted approach over propensity score matching and stratification is that its estimator requires fewer assumptions about the distributional structure of the underlying data.

Inverse probability weighting relies on building a logistic (or probit) regression model to estimate the probability of the exposure observed for a particular individual in either treatment category, and using the predicted probability as a weight in subsequent analyses. Individuals with a high predicted probability of treatment receive a lower weight, compared with individuals with a low predicted probability. The goal is to estimate as closely as possible the counterfactual or potential outcomes if all farmers in the target population were assigned either category of treatment (adoption vs non-adoption). Thus, an individual with a low predicted probability of sericulture adoption, who actually adopted, will represent a larger group of individuals who did not adopt. In this study we will consequently also apply the inverse probability weighting estimation of the treatment effect as a supplemental robustness check on our PSM evaluation.

4 Data and results

4.1 Sampling

The household survey data used for this evaluation were taken from the 3rd round of Integrated Household Living Conditions Survey-EICV3 (Enquête Intégrale sur les Conditions de Vie des Ménages) completed in 2011. [6] This survey has collected valuable information on several factors related to the general socio-economic characteristics of respondents, which determine income and poverty. The collected information include age, gender, marital status, household size, education level, main and secondary occupations, household income, number and size of owned and cultivated land assets livestock ownership and source of income. For this study, a sample consisting of 1343 households based on EICV3 was selected for a further formal survey in six districts where sericulture has been introduced. The sampling framework is based on a multi-stage random sample of villages in the targeted districts. The areas covered by our study where sericulture cooperatives and individual farmers have started mulberry planting and cocoon production are located in the following districts: Nyaruguru (Southern Province), Bugesera (Eastern Province), Nyagahanga (Eastern Province), Karongi (Western Province), Nyanza (Southern Province) and Rushashi (Northern Province). Of the 1343 households in the survey 413 were identified as sericulture adopters.[7] In this study, adopters are classified as households who planted mulberry trees and used the leaves to rear silkworms, and non-adopters are those who did not participate in any activity related to sericulture. The sample targeted farming households in these districts in order to maximize the chances of having enough adopters in the study. For the sample households, additional infor-

[6] EICV data are available at the Rwandan National Institute of Statistics (www.statistics.gov.rw).

[7] The National Sericulture Centre (NCS), the unit of the Rwandan Ministry of Agriculture in charge of stimulating sericulture adoption, reported to be operating only four provincial centres and to have piloted sericulture activities in 40 cooperatives across the country, with membership of more than 2000 farmers (Rwanda Development Board, 2013).

mation was collected on household composition, membership of cooperatives and other rural associations, planted crop varieties and area planted, cost of production, yield data of their different crop types and ownership of non-farm assets. Further information was also gathered on indicators of access to public infrastructure and sources of information, contact with extension agents, farming experience and previous adoption of any other agricultural innovation. Information was collected the from the target households via personal interviews.

4.2 Some descriptive statistics

At the time of the survey, about 49 farming cooperative and several individual entrepreneurs in 19 districts and 47 municipalities are involved in mulberry cultivation. About 29 percent of the total sample of households are identified as sericulture adopters. This percentage is higher than the average national rate of sericulture adoption among farmers, which may introduce some auto-selection bias, but eve though PSM requires a randomised sample, we estimate the bias to be limited because of local randomisation. Table 2 presents the summary statistics of the households socioeconomic characteristics and the t-test for the differences between adopters and non-adopters.

For the farmers' characteristics in the sample, adopters tend to be on average 2 years younger than non-adopters. They also have on average less years of farming experience, which could imply that older farmers with longer experience in traditional crops are less likely to switch to this new form of farming activity. Non-adopter also have on average more land in use while adopters hold on average more assets, are significantly more likely to be members of cooperatives and have access to financial credit than non-adopters. Adopters are more likely to have previously adopted another agricultural innovation and tend to have more frequent contacts with extension agents but this latter can also be a consequence rather than a cause of sericulture adoption. Most non-adopters depend mainly on subsistence farming as their main source of income. As for the measures of poverty, adopters have a

Table 2: Descriptive statistics of sericulture adopters vs non-adopters

Income and adoption determinants	Adopters	Non-adopters	t-test difference
Characteristics			
Age head of household	43.60	45.3	-1.70**
Educational achievement (years of schooling)	6.30	5.70	0.60
Household size (no of persons)	5.60	6.40	-0.80
Gender head of household (1=male)	0.94	0.84	0.10*
Main occupation head of household (1=farming)	0.91	0.88	0.03
Years of farming experience	15.41	16.40	0.99**
Marital status head of hh (1=married)	0.89	0.79	0.10*
Land ownership			
Average size of owned land (ha)	0.41	0.45	-0.04*
Average size land in use (ha)	0.51	0.49	0.02
Land productivity (tons/ha)	4.52	4.97	-0.45
Number of land plots owned	3.02	2.65	0.37
Total assets owned (in thousands FRW)	883	778	54**
Association membership and access			
Membership of cooperatives	0.94	0.29	0.65***
Membership other associations	0.91	0.86	0.05
Contact with extension agents	0.89	0.53	0.36***
Access to credit	0.66	0.26	0.40***
Previous adoption of innovation	0.23	0.11	0.12**
Number of observations	413	930	

* = significant at 10%; **= significant at 5%; *** = significant at 1%

Table 3: Poverty measures for sericulture adopters and non-adopters

Poverty indicators among households in the 6 districts			
Poverty measures	Adopters	Non-adopters	t-test difference
Headcount ratio poverty	0.49	0.56	-0.07**
Headcount ratio extreme poverty	0.07	0.23	-0.16**
Poverty gap	0.16	0.33	-0.17**
Severity gap	0.07	0.18	-0.11***
Number of observations	413	930	

*= significant at 10%**=significant at 5%, ***=significant at 1%

As defined by the Rwandan national Institute of Statistics, the poverty line is set at an annual income of FRW 64,000 in 2001 prices while extreme poverty line is at FRW 45,000

significantly lower incidence of poverty than non-adopters. The head count ratio is significantly lower among the adopters, and the difference is even larger when extreme poverty is considered.

Subsistence crops are the main types of agriculture and cover the majority of the cultivated land, with only 4% of cultivated land planted with cash crops,mainly coffee and tea.

Table 3 compares the incidence of poverty, extreme poverty, the poverty gap, and the poverty severity of adopters and non-adopters which are computed using the Foster-Greer-Thorbecke (FGT) poverty measure (Mendola, 2007).[8]

In the areas of our studies which are located in the 4 provinces of the country, poverty is still highly prevalent among farmers and the depth and severity of the poverty indices show a sizable degree of propensity to fall below the poverty line and a disparity among the poor.

4.3 Results

For the first step of the PSM procedure, a logit model was used to predict the probability to adopt sericulture on the basis of the various household characteristics as regressors. Propensity scores estimates are then determined for both adopters and non-adopters. The common support condition is imposed and the balancing property is checked for the matched households. The logit results confirm the bal-

[8] In the areas of our study, which are spread over the 4 provinces of the country, poverty is still highly prevalent among farmers and the depth and severity of the poverty indices show a sizable degree of propensity to fall below the poverty line as well as a wide disparity among the poor.

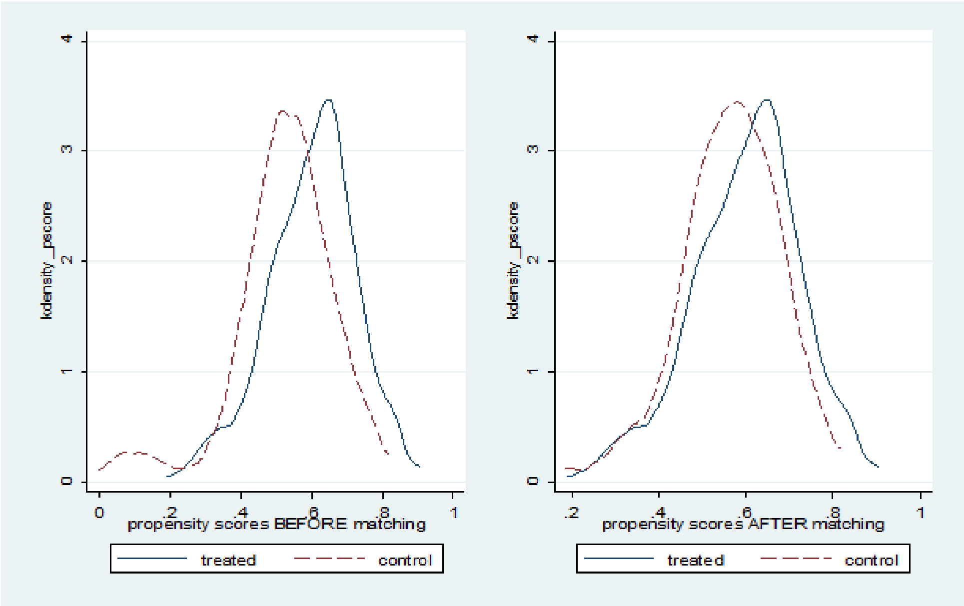

Figure 1: K-density distributions of propensity scores before and after matching

ancing property at 5% significance level. The density distributions of the estimated propensity scores for the two groups indicate that the common support condition is satisfied: there is substantial overlap in the distribution of the propensity scores of both adopters and non-adopters as indicated on the graphs displayed in Figure**??**.

The results of the logit estimation are presented in Table 4. The age of household heads, their marital status, access to credit and rural infrastructure and their membership in cooperatives are have a significantly positive effect on the probability to adopt sericulture. Frequency of contact with extension agents and previous experience with adoption of innovations are other factors that positively influence the likelihood of adopting sericulture.

Adoption is sometimes hampered not only by the inherent characteristics of the varieties themselves but also by lack of awareness of the end users of the technologies. To adopt the newly introduced agricultural techniques farmers need to be aware of the availability, feasibility and the profitability of sericulture. Education, contact with extension agents and membership in farmers' groups may be proxies for access to information. The first two variables are significant in explaining the variation in the adoption decision. Agricultural extension is the system of learning and building human capital of farmers through the provision of information and demonstrations, exposing farmers to technologies which can increase agricultural productivity and, in turn, income and welfare. Farmers who are frequently visited by extension agents tend to be more progressive and more likely to adopt mulberry cultivation as a new source of income.

The positive effects of average size of land in use and years of farming experience are only significant at 10% level, whereas household size and land productivity have a negative incidence on the adoption propensity (albeit only at 10% significance level for the latter). This might be due to the necessity for subsistence farmers to keep the more productive land in use for foodstuff production when they have large families rather than switch to mulberry cultivation and risk food shortage in the short run. Land productivity's negative association with sericulture adoption may also suggest farmers' inclination to commit land plots that were otherwise less productive for traditional crops for mulberry cultivation. The education level as well as membership in local farmers' organisations have surprisingly no significant influence on the adoption likelihood.

For the determination of the adoption effect, the matching is done through both the NNM and the KBM methods. To avoid geographical mismatches, the matching is done locally in each district and the sericulture effect is calculated separately for each of the 4 provinces. The sericulture adoption effects on household income are determined according to equation (3.8). The matching results displayed in table 5 indicate highly significant effects of sericulture adoption, both on income and poverty measures. The effects are fairly comparable between provinces.

Overall, matching estimates show that sericulture adoption has a positive and robust effects on household income and on poverty reduction although its effects are hard to measure given the still low level of sericulture penetration. Both match-

Table 4: Propensity score for sericulture adoption in the 6 districts

Logit propensity score for sericulture adoption		
Variables	Coeff	(std errors)
Demographics		
Average age head of household	0.179**	(0.083)
Educational achievement (years of schooling)	0.142	(0.097)
Household size (no of persons)	-0.076**	(0.036)
Gender head of household (1=male)	-0.045	(0.037)
Main occupation head of household (1=farming)	0.167	(0.131)
Years of farming experience	0.019*	(0.011)
Marital status head of hh (1=married)	0.027	(0.012)
Land ownership		
Average size of owned land (ha)	0.512	(0.321)
Average size land in use (ha)	0.616*	(0.358)
Land productivity (tons/ha)	-0.045*	(0.023)
Number of land plots owned	0.023	(0.016)
Total assets owned (in thousands RWF)	0.014	(0.011)
Association membership and access		
Membership of cooperatives	0.734***	(0.214)
Membership other associations	0.141	(0.109)
Access to rural infrastructure	0.017**	(0.008)
Contact with extension agents	0.936***	(0.156)
Access to credit	0.294**	(0.145)
Previous adoption of innovation	0.714**	(0.342)
Constant	0.579**	(0.264)
LR Chi-square = 23.18;	p-value= 0.06	
Log-likelihood	-177.387	
Number of observations	1343	

* = significant at 10%; **= significant at 5%; *** = significant at 1%

ing methods yield comparable results across the four provinces. In the Western province for example, where the income effect is 0.227 for the NNM, this means that a sericulture adopting household is expected to have an significantly higher income than similar households that do not adopt. Since income is expressed in logarithmic terms, the 0.227 difference translates in an income ratio of 1.25 with respect to his "neighbours" with similar characteristics, or 25% more income.

The results of the IPW estimation based on the same covariates used to estimate propensity scores show an average positive income effect of RWF 684655 per adopting household, which is fairly similar to the corresponding PSM estimate (RWF 693426). The use of probit model for the IPW estimation also yields an average difference of RWF 689354 per household between adopters and non-adopters which remains in the same range. This of income effect of sericulture adoption, although positive and significant, falls short of the anticipated USD 2000, and can only be expected to increase if sericulture diffuses much further to reap the benefits of the economies of scale.

5 Concluding discussion

The adoption of an agricultural technology or new farming methods, such as the case of sericulture in Rwanda, is a rural innovation that may change the output levels from land use or reduce input requirements for a desired level of income. In this paper, we have used the PSM and IPW estimation methods to evaluate the impact of sericulture adoption on income and on poverty, in order to understand whether the slow diffusion could be attributed to lack of profitability. Our results show that for the adopting farmers, the income-enhancing effects of sericulture were positive enough to expect non-adopters to also follow suit. The adoption had also a potential to contribute to poverty reduction as shown by the PSM results.

Potentially profitable technology can however fail to diffuse, even in the presence of government support. The failure of sericulture diffusion in the rural community, where no similar or competing technology existed, necessitates thus a further exam-

Table 5: NNM and KBM matching results for the 4 provinces

	Eastern Province†				Northern Province				Western Province			
	NNM^a		KBM		NNM^a		KBM		NNM^a		KBM	
Variable	Coefficient	(t-value.)	Coefficient	(t-value..)	Coefficient	(t-value..)	Coefficient	(t-value..)	Coefficient	(-value.)	Coefficient	(t-valu
Household income (ln)	0.259***	(2.907)	0.245***	(2.916)	0.274***	3.072	0.282***	(3.512)	0.227***	(3.043)	0.219***	(2.49
Head count poverty ratio	-0.181***	(2.841)	-0.177***	(3.241)	-0.175***	3.051	-0.169***	(3.631)	-0.163***	(3.115)	-0.173**	(2.03
Ratio extreme poverty	-0.123*	(1.913)	-0.114**	(2.157)	-0.091***	2.703	-0.114***	(2.942)	-0.141*	(1.803)	-0.098***	(3.23
Poverty severity	-0.064**	(2.202)	-0.081**	(2.046)	-0.089***	2.812	-0.076***	(3.104)	-0.071**	(2.152)	-0.081***	(3.01
Balancing property	yes		yes		yes		yes		yes		yes	
Common support	yes		yes		yes		yes		yes		yes	
Covariance matrix					Chi-square = 0.57;			p-value = 0.911				
Number of observations						1343						
Log-likelihood						-148.528						

† Southern and Eastern Provinces are Pooled;[a] :bootstrapped, 200 replications

Significance levels : $*$: 10% $**$: 5% $***$: 1%

ination beyond the profitability criterion. We have seen that various hurdles need to be overcome for the adopted technology to diffuse and contribute significantly to the overall growth in the economy. Especially in such a situation where the adopted technology is hardly connected to existing activities, great care needs to be taken to accurately appraise the absorptive capacity needed for the new industry to succeed in an unfamiliar socio-cultural environment.

Like many agricultural technologies, the adoption of sericulture requires much technological knowledge and an intensive level of human skills as shown by Kiyokawa (1984). Despite the identified income benefits of the adoption, however, the implementation process of the sericulture project does not seem to have been adequate to meet the skills requirement for mastering this new technology to the level of embedding it in the local economy. In addition to human skills requirements and market factors, appropriates infrastructure as well as an adequate incentive system to facilitate the technology absorption are necessary in the planning of a successful technology acquisition. Alignment of technology adoption with long-term development objectives, rather than short-term profitability, may provide a way to overcome many of the constraints imposed by these hurdles.

Finally policies to stimulate and support a widespread diffusion are at least as important as those of supporting the initial adoption, as the benefits of many innovations are often predicated on the success of their diffusion. Targeting potential adopters through complex networks can for example be an effective, be it costly, method to increase the adoption rate as suggested by Beaman et al. (2015). Sustained investment in sericulture-related research and university level knowledge in both silkworm rearing and mulberry cultivation will remain necessary to avoid the failures that have plagued other African countries seeking to develop sericulture.

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