Adoption and Impact of Black Pepper Certification in India

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Abstract

This paper analyses the adoption of organic farming under fair trade marketing practices and its impact on household income of black pepper (*piper nigrum*) farmers in India. We use a set of panel data, collected from 300 smallholder farmers who plant black pepper as their main crop in 2010 and 2011.The aim of the paper is to investigate the use of panel data for adoption models using the case of organic and fair trade certified black pepper in Idukki district, Kerala, India. We compare two adoption models: (i) a multinomial cross-section logit applied for both survey years separately and (ii) a panel multinomial random effects logit model. The panel adoption model which allows capturing unobserved heterogeneity in adoption decisions was found to be superior over the cross section models. We find that farm size and market distance are the major factors that influence adoption. To measure the differential gain of adoption, we applied propensity score matching with multiple treatment effects accompanied by sensitivity analysis to test robustness of impact results. Results show that certified organic farmers have a significantly higher income but participation in fair trade regimes does not generate additional monetary benefits.

Keywords: organic agriculture, fair trade, panel multinomial logit using gllamm, propensity score matching, Kerala
JEL: Q1, Q120, Q160, Q180, Q550

1 Introduction

The Indian spices sector is an important part of the agricultural sector and its export value was US$ 2,037.76 million in 2011-2012 (SBI, 2012). Currently in India, 60 out of the 109 spices recognized by the International Organization for Standardization (ISO) are grown. India's share in the international market for spices is 25% and black pepper (*piper nigrum*) amounts to 8% of Indian exports in value terms (PARTHASARATHY et al., 2011).

While until 1999 India was the leading black pepper producer in the world with 76,000 metric tons (MT), by 2010 its production had declined to 51,000 MT (FAO, 2010).

From being a leading exporter of black pepper in the world, India became a net importer (JEROMI, 2007). Productivity of black pepper in India is also low. Hence, it only contributes 25% to global production even though more than 50% of the world´s area of black pepper is in India. The decline in production in India is due to poor farm management, depletion of soil fertility, natural calamity and outbreaks of diseases and pests coupled with increasing input costs (HEMA et al., 2007, and GAFOOR et al., 2007).

The production and profitability of black pepper is highly influenced by its international price. This makes the revenues from black pepper highly volatile (HEMA et al., 2007). The domestic price in India is further influenced by the instabilities in international prices. This has made black pepper a risky crop. As a consequence, many black pepper smallholder farmers in India have shifted to organic farming practices and have adopted fair trade marketing.

While fair trade marketing practices have been introduced in India at least three decades ago, organic farming is more recent and was officially recognized by the Indian Government in 2000 only. The adoption of organic farming practices and the participation in fair trade certification regimes provides access to global markets for smallholder farmers (ADB, 2012). For the black pepper industry in India, organic black pepper marketed under fair trade regimes, provides an opportunity to diversify agricultural export markets. This can contribute to increased and a more stable income from agriculture. While certification improves production standards and labeling generates economic and environmental benefits (WAIBEL and ZILBERMAN, 2007), conversion to organic farming and entering fair trade marketing arrangements is not without costs to farmers. To meet required production and product quality standards can be demanding, especially for resource poor, less educated farmers. Nevertheless, as hypothesized by PARVATHI and WAIBEL (2013) adopting both innovations can be mutually reinforcing. Hence, this paper examines the factors that influence the adoption and impact of such alternative farming systems.

While there are many papers that have analyzed adoption and impact of organic and fair trade certification separately, so far there is no study that has examined the combined effects of both certification schemes. Hence this research studies to what extent black pepper produced organically and marketed under fair trade managements, can improve income of smallholder farmers in India. Moreover, most of the adoption studies do not explicitly examine the counterfactual analysis and the differential gain of adoption. Therefore, we analyze the causal impact of adopting organic and both organic and fair trade certification on smallholder livelihoods and welfare in terms of total household income (JENA et al., 2012, and AMARE et al., 2012). In this context, the objective of the paper is to answer the following questions:

1. What are the drivers that influence the adoption of organic and fair trade certification systems by rural smallholder black pepper farmers?
2. What is the impact of organic and fair trade certified black pepper on household welfare in terms of total income of the household?

Another contribution of this paper is to explore the value of panel analysis in identifying adoption determinates in comparison to cross section analysis which is the common approach followed in literature. The advantage of using panel data with random effects in adoption analysis is that it helps to account for unobserved heterogeneity in adoption decisions. For measuring welfare impact, we employ propensity score matching with multiple treatment effects. Results show that organic farming does have a positive impact on income but fair trade certification does not seem to add additional benefits.

The remainder of this paper is organized as follows. In the next section, the organic and fair trade certification regarding black pepper are described followed by a literature review in section three. Section four details conceptual framework and methodology followed by a description of the data collection procedure and descriptive statistics in section five. The results of the econometric analysis are discussed in section six. Section seven concludes the paper.

2 Organic and Fair Trade Certified Black Pepper

Organic and fair trade standards are a recent phenomenon as far as the black pepper crop is concerned. The problems of soil fertility in conventional black pepper production popularized organic methods of production in India. Under organic standards, certified black pepper farmers have to follow production methods that enhance soil fertility and promote biodiversity. Moreover, organic certification systems are rigorous and require a conversion period of a minimum three years (COULIBALY and LIU, 2006). During this conversion period, the yields are low and smallholders may require additional sources of income to meet their livelihood needs. However, certified organic farmers can sell their black pepper at organic premium prices which are higher than conventional market prices.

The international decline of black pepper prices in 2003-04 (HEMA et al., 2007) prompted the introduction of fair trade standards for black pepper by the Fairtrade Labeling Organization (FLO). Unlike coffee, in which fair trade standards and certification was launched in 1988; it was only introduced for black pepper in 2005 by FLO (FAIRTRADE INTERNATIONAL, 2014). A fair trade certificate offers black pepper farmers certain advantages. In terms of price, it offers a minimum price and a price premium. The minimum price protects farmers against fluctuating market prices by providing a floor price. The price premium is a pro-poor social premium that is given to the cooperative in which the smallholders are members. The cooperative can only use this premium to improve the social conditions of the smallholders like building infrastructure or educational institutions. This premium is not for the smallholder directly and hence does not form a part of their income from black pepper. In addition to this, an organic price differential is offered under fair trade certification systems for organic black pepper farmers. This price differential is added to the minimum price. Hence, organic farmers under fair trade have a higher minimum price as it includes the organic price differential. In effect, an organic farmer under fair trade schemes would get the organic market prices or the minimum fair trade organic price whichever is higher.

The primary difference between the two systems is pricing. Organic certification does not offer any floor pricing. The minimum price offered by fair trade is intended to protect farmers from downside risk. However, this is not the case for conventional black pepper. As per FLO, the minimum fair trade price for conventional pepper does not exist and is equivalent to its commercial price. With regard to organic pepper, 1.13€/kg (approximately INR 75/kg) is set as a floor price in 2005 (FAIRTRADE INTERNATIONAL, 2014a). Therefore, fair trade certification systems for black pepper seem to protect only organic farmers from organic market price shocks. Hence, the benefit of a fair trade certificate becomes significant for organic farmers only when the organic black pepper prices falls below the minimum organic fair trade price for black pepper.

3 Literature Review

Most of the organic adoption studies in literature are based on cross section data and apply a logit or a probit analysis (e.g. BURTON et al., 1999; KHALEDI et al., 2010, and KOESLINGet al., 2008). Some studies like BURTON et al. (2003) use duration analysis to explore the timing of adoption in a dynamic framework. Very few studies explore panel adoption model. For example, PIETOLA and LANDINK (2001) use time series data to identify determinants of organic farming. As they their data set is binary, they apply a switching type probit model and find that decreasing output prices and increasing direct subsidies for organic farming leads to its adoption in Finland. However, hardly any study is available that uses a multinomial panel model.

Most of the organic and fair trade impact studies analyze welfare outcomes like household income or consumption expenditures using propensity score matching (PSM) techniques (e.g. JENA et al., 2012; RUBEN and FORT, 2012, and ARNOULD et al., 2009). JENA et al., 2012, find that although certification increases per capita income, it does not contribute to poverty reduction among Ethiopian organic and fair trade certified coffee farmers. However, in Peru, RUBEN and FORT, 2012, do not find any significant income gains. Similarly only small household welfare impacts were found among fair trade certified farmers in Peru, Nicaragua and Guatemala by ARNOULD et al. (2009).

Few studies like CHIPUTWA et al. (2015) compare three sustainability oriented standards namely; fair trade, organic and UTZ using PSM with multiple treatment effects and find that in general all categories of certified farmers have higher living standards than conventional farmers. Though, in particular fair trade improves household living standards more significantly than organic and UTZ in Uganda. However, most of the fair trade impact studies pertain to coffee and find that certification increases well-being of smallholders (e.g. VALKILA, 2009; VALKILA and NYGREN, 2010; BACON, 2005; BACON, 2010; RAYNOLDS, 2002). Some studies like KLEEMAN and ABUDALAI (2013) analyze welfare outcomes in terms of return on investment (ROI) and find that organic farmers have a higher ROI than conventional pineapple farmers in Ghana.

However, so far little is known on organic and fair trade black pepper adoption and its impact. Hence, we contribute to this literature by applying a panel model to analyze adoption determinants. We also apply propensity score matching with multiple treatment effects drawing from LECHER (2002) to analyze the effect of adoption on household welfare measured in terms of household income.

4 Conceptual Framework and Methodology

4.1 Panel Model for Adoption Studies

Though economists regard technology adoption as a dynamic process, most of the adoption studies use cross-section data. However, studies that are based on cross-section data and compare adopters to non-adopters cannot be used to analyze the characteristics of farmers at the time of adoption. This is because some variables might be endogenous. For example, if in a cross-section adoption study farm size is found to be a significant factor influencing adoption this does not necessarily imply that farmers with larger landholdings are more likely to adopt because larger landholdings might be a consequence of earlier adoption decisions. Also, static adoption models based on cross-section data assume values of time varying variables as constant (BESLEY and CASE, 1993). Using current household, farm and individual characteristics as explanatory variables to describe adoption of an agricultural technology using cross-section data can lead to a misinterpretation of results. While cross-section adoption regressions may provide evidence on correlation, it does not necessarily prove causality. Moreover, it could also be the case that unobserved variables (e.g. farm management skills) influence farm size and certification status leading to spurious correlations.

Hence, adoption studies based on cross-section data can result in biased coefficients with inconsistent estimates.

To overcome the problem of endogeneity due to unobserved heterogeneity, past and recent research (BESLEY and CASE, 1993, and BARHAM et al., 2004) points out the advantage of using panel data for adoption studies. The advantage of a panel model is that it can account for spurious causality in adoption decisions and also establish direction of causality in adoption analysis (BESLEY and CASE, 1993).

Though a perfect experimental design would be ideal, i.e. to follow adopters and non-adopters of a technology before and after introduction with randomized treatments, a second best solution is to have panel data after adoption. As pointed out by DOSS (2006), to understand adoption, farmer's decision needs to be followed over a period of time. Also, panel data allow for controlling heterogeneity across households and thereby accounts for endogenous regressors. Hence, the robustness of adoption models can be improved using panel data, even if no dis-adoption or late adoption is observed in the sample and the variability is only captured by the explanatory variables. The classic adoption model of ROGERS (1995) assumes that adoption follows an *S* shaped diffusion path in which the adoption dynamics depends on the differences across farmer categories. We explore this facet by applying a panel adoption analysis and compare it with a cross section analysis applied to two consecutive years. Hence, on the basis of this foundation, we draw our first hypothesis that (a) panel model is more precise to identify adoption determinants as compared to a cross section model. Also based on the literature review in section 3, we hypothesize (b) adoption increases household welfare measured in terms of household income.

4.2 Adoption Decision

In the literature numerous approaches to model farm technology adoption behavior of farmers and to identify the key factors that facilitate such a decision have been proposed. From an economic perspective final adoption of an agricultural innovation is defined at the farm level as "the degree of use of a new technology in long-run equilibrium when the farmer has full information about the new technology and its potential" (FEDER et al., 1985: 256). The theoretical foundation of adoption is utility theory, i.e. farmers make decisions in order to maximize their utility under uncertainty (FEDER, 1980). Farmers choose an agricultural technology that maximizes their expected utility of profits (DORFMAN, 1996).

In this paper, the farmer is faced with two agricultural innovations, organic agriculture (A_1) and both organic and fair trade certified farming (A_2). Farmers may also choose not to adopt either of the innovations and remain conventional farmers. This is represented as A_0. Therefore drawing from GREENE (2003), a farmer will adopt an innovation only if:

$$V(q^{(i,j)}, X) \geq V(q^0, X); \varepsilon \text{, where } i = 1 \text{ and } j = 2 \tag{1}$$

where, $V(q^2, X, \varepsilon_2)$, $V(q^1, X, \varepsilon_1)$ and $V(q^0, X, \varepsilon_0)$ are utility functions with each technology adoption and no adoption respectively and ε_2, ε_1 and ε_0 are assumed to be independent and identically distributed with zero mean.

Based on PICKLES et al. (2006), we decompose the utilities presented in Equation (1) for the three alternatives:

$$V_0 = X_0 + \varepsilon_0 \tag{2}$$

$$V_1 = X_1 + \varepsilon_1 \tag{3}$$

$$V_2 = X_2 + \varepsilon_2 \tag{4}$$

Assuming $(\varepsilon_{1} - \varepsilon_0)$ and $(\varepsilon_{2} - \varepsilon_0)$ follow independent logistic distributions, a multinomial logit model (MNL) can be presented as:

$$\Pr(choice = i) = \int\delta1\int\delta2 \frac{exp\,(\beta iX)}{1+\exp(\beta iX)+\exp(\beta jX)} \text{, where } i = 1 \text{ and } j = 2 \tag{5}$$

However, the assumption that the errors are independent gives rise to the independence of irrelevant alternatives (IIA) property, which is seen as a limitation (MCFADDEN et al., 1977). To overcome this limitation, we use generalized linear latent and mixed models (gllamm) following RABE-HESKETH et al. (2004). The gllamm model allows for the correlation between random components by introducing shared random effects, u:

$$V_0 = X_0 + u_0 + \varepsilon_0 \tag{6}$$

$$V_1 = X_1 + u_1 + \varepsilon_1 \tag{7}$$

$$V_2 = X_2 + u_2 + \varepsilon_2 \tag{8}$$

But there could also be latent variables like farming skills that affect adoption decisions. These latent variables are specified as $\delta 1 = (u_1 - u_0)$ and $\delta 2 = (u_2 - u_0)$ and are assumed to follow a bivariate normal distribution. The correlations between random components capture unobserved heterogeneity and hence lead to unbiased parameter estimates of adoption determinants. Taking the first alternative, conventional farming as the reference category; the two latent variables, δ_j^1 and δ_j^2 are for the other two categories, namely organic certified and both organic and fair trade certified farming respectively. Therefore, MNL gllamm can be defined with the inclusion of latent variables as:

$$\Pr(choice, x = i) = \int\delta1\int\delta2 \frac{exp\ (\beta iX+\delta1)}{1+\exp(\beta iX+\delta1)+\exp(\beta jX+\delta2)}\, d\delta1\delta2\ ,\text{ where } i = 1 \text{ and } j = 2 \qquad (9)$$

Integration is used as the individual values of the latent variable are not known. We only know that they are distributed bivariate normal. Adaptive quadrature and a modified Newton-Raphson procedure as implemented in RABE-HESKETH et al. (2002) are used for the estimation of multinomial logit using gllamm. In this algorithm, the probabilities associated with the possible values of the latent variables are computed. These are then weighted by their likelihood of occurrence given the distributional assumptions for the latent variables. Moreover, we expand the data in gllamm which enables to include alternative specific covariates or random effects.

To sum up, there are specific advantages in using a panel multinomial logit with random effects. First it allows to capture unobserved heterogeneity at the individual level by introducing alternative specific random effects (δ_j^1 and δ_j^2). This helps to account for heterogeneity in adoption decisions as a farmer´s decision to choose a particular certification strategy might be partly related to unobserved farm and individual characteristics. Second, it effectively captures individual choices that may not likely be independent. This is made possible by capturing repeated observations for the same household sharing the same unobserved random effects. Hence, panel multinomial logit analysis using gllamm allows adoption determinates to be identified while accounting for unobserved heterogeneity.

4.3 Differential Gain of Adoption

We use the impact evaluation approach to measure the differential gains of adoption. Impact evaluation includes ex ante and ex post methods. In this paper, we employ an ex post impact evaluation, wherein data is gathered after technology adoption, to measure the actual benefit accrued to the farmers in terms of income from organic and fair trade adoption. Impact assessment requires identifying a valid counterfactual. In an ex post analysis, we cannot observe the outcome of adopters before adoption. Hence we are faced with a potential self-selection bias. To overcome this problem a counterfactual group has to be generated. There are several methods to correct such a self-selection bias. These include propensity score matching (PSM) (ROSENBAUM and RUBIN, 1983; PEARL, 2009), instrumental variable models (HECKMAN, 1997; IMBENS and ANGRIST, 1994), Heckman selection model (HECKMAN, 1979; LEE, 2001) and endogenous switching regression models (LOKSHIN and SAJAIA, 2004). In this study, a stratified sampling technique with random sampling at the Taluk[1] level was applied to have adequate representation of the three farmer groups, namely conventional, organic and both organic and fair trade certified smallholder farmers. This could inherently lead to sample selection bias induced by non-random program enrollment. But PSM helps to generate valid counterfactuals from a non-random sample (MEZZATESTA et al., 2013). Hence, PSM is used to select reliable counterfactuals from a large pool of conventional farmers in an area with similar conditions.

PSM is generally used for bipartite matching, where we have one control and one treatment group. Since, in this paper, there are three categories of black pepper smallholder households, a propensity score matching with multiple treatment groups is employed following LECHER (2002). Here the propensity score is separately modeled for each of the three groups as $\frac{n\,(n-1)}{2}$. Hence, there are 3 pairs of control and treatment groups as depicted in Table 1.

Table 1. PSM with multiple treatment groups

Category	Control group	Treatment group
1	Conventional	Organic certified
2	Conventional	Both organic and fair trade certified
3	Organic certified	Both organic and fair trade certified

Source: own compilation

A binary logit model is used to estimate the propensity scores of the PSM model with multiple treatment effects. Nearest neighbor one-to-one matching and the kernel matching methods are employed to ascertain the Average Treatment Effect on the Treated (ATT). However, the limitation of this method is that we can only measure welfare based on observable characteristics of our sampled households (NANNICINI, 2007). Hence, if there are unobserved variables that affect the outcomes, a hidden bias might arise. To check the sensitivity of the estimated ATT to hidden bias, we apply a bounds test suggested by ROSENBAUM (2002). This helps to check if the impact results may change with respect to unobserved covariates. The sensitivity analysis estimates the upper and lower bounds to test the null hypothesis for different assumed values of unobserved variables.

[1] Taluk is an administrative division of the district. It is like an entity of the local government and has certain fiscal and administrative powers over the villages and municipalities coming under its jurisdiction.

4.4 Choice of Explanatory Variables

In their seminal paper, FEDER et al. (1985) propose a wide range of explanatory variables like household characteristics, socioeconomic and physical factors. These same variables are also used in organic adoption studies both in developed and developing countries (e.g. BURTON et al., 1999; BURTON et al., 2003; GENIUS et al., 2006; BOLWIG et al., 2009). We represent household characteristics by including age, level of education and farm experience of the household head. Availability of family labor, farm size and access to irrigation are included in farm characteristics. Today agricultural extension agencies play a significant role in information dissipation. Thus, support received from extension agencies is also included as one of the independent variables. Farmers may be more motivated to adopt advancement of new products or technologies if market access is easy. Hence, distance to market is included as a variable. In terms of income, farmers having additional sources of income, apart from agriculture, may be better equipped to diversify the risk of adoption. To capture this, access to non-farm income is included. An easy credit access is useful to invest in agricultural advancements like organic and fair trade certified agriculture. This is captured in terms of the variable, access to credit. The wealth effects are represented through owning livestock assets.

5 Data and Descriptive Statistics

Black pepper in India is primarily cultivated in the Malabar Coast, state of Kerala. This state accounts for nearly 97% of the total black pepper production in India (HEMA et al., 2007). It is the major source of income and employment for the rural households in Kerala, wherein two million farm households are involved in black pepper cultivation. Idukki is the largest black pepper producing district in Kerala and, therefore, it is chosen as our study area.

Idukki is situated in the top Western Ghats surrounded by mountains. Around 86% of the population in Idukki is involved in agricultural activities. The major sources of income are from black pepper, cardamom, tea, rubber and coffee production (DISTRICT ADMINISTRATION, 2011). Idukki has 37.92% of the total black pepper area of Kerala and the contribution of black pepper to total agricultural income is around 20% (SBI, 2008, and ESD, 2011).

In Idukki, the taluks of Udumbanchola and Peerumedu were non-randomly selected as they grow majority of black pepper in the district. Udumbanchola is the largest taluk in Idukki and has 23 villages in total. Peerumedu has 10 villages. Both these taluks share the same topography and are covered by rugged mountains and forests. They experience moderate rainfall and minimum seasonal variation.

A list of smallholder conventional black pepper farmers were obtained from the agricultural office of Idukki district for these two taluks. With regard to certified farmers, the details were collected from a local Non-Government Organisation (NGO), called Peermade Development Society (PDS). It is the largest NGO operating in the district and is a promoter of organic cultivation and fair trade marketing practices. Details of smallholder farmers who are organic certified and both organic and fair trade certified were obtained from PDS. Hence, in terms of management regimes, we have three groups of smallholder black pepper farmers namely: (a) conventional (b) organic and (c) both organic and fair trade certified. We do not have an "only fair trade" certified category. This is because in Idukki, farmers with conventional practices but who practice fair trade certified black pepper are usually large scale tea planters who grow some black pepper as an intercrop. Their minimum landholding is 10 hectares. However, this study was focussed on smallholders, i.e. farmers with less than five hectares of farm land.

It was seen from both lists that all the conventional farmers were concentrated in Udumbanchola. But the organic and both organic and fair trade certified farmers were spread out in both of these taluks, though more than 50% were from Peerumedu. There was no village in these taluks that represented all the three categories of farmers in the lists provided. As the NGO is situated in Peerumedu, it is more active in that region and is only in the process of expanding in other areas of Idukki.

From these obtained lists, a sample of 100 farmers was randomly chosen for each category. Hence, a total of 300 farmers were chosen. These 300 farmers come from 9 villages in Udumbanchola and 5 villages in Peerumedu. Thereby, a total of 300 farmers were surveyed in 2011 from 14 villages in Idukki. In 2012, due to attrition of 3 conventional famers, data was collected from a total of 297 farmers. Also, there was no dis-adoption or late-adoption observed in the sample in 2012.

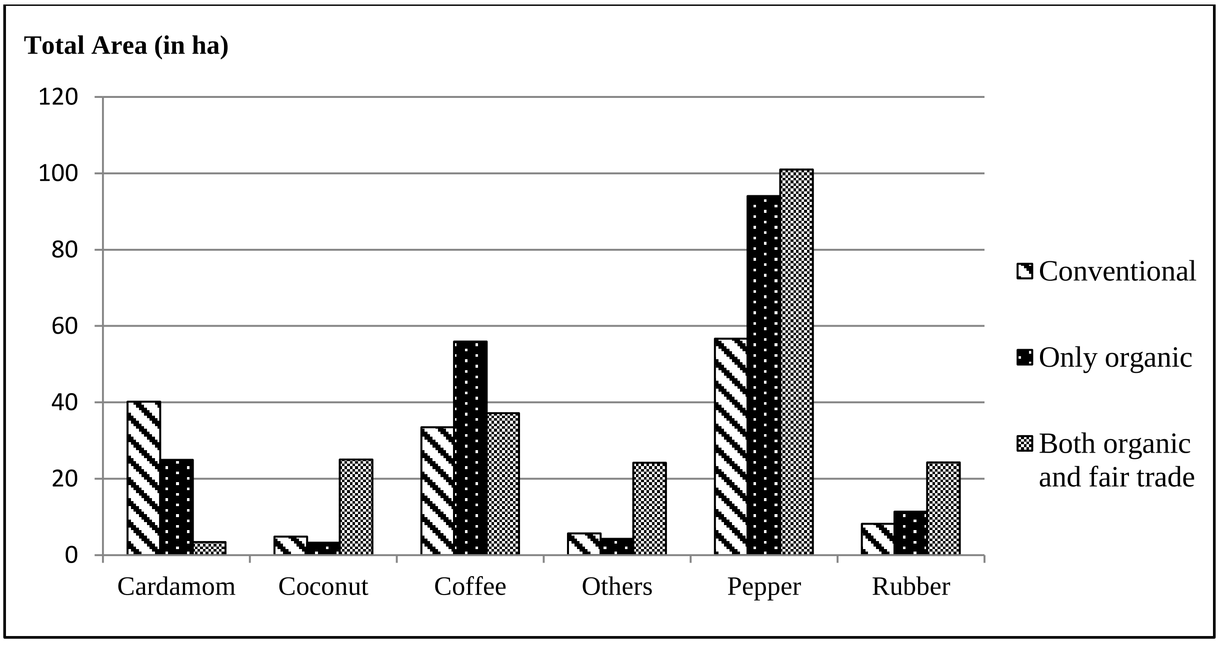
In such a sampling scenario, applying a panel model is better to control for unobserved heterogeneity in the adoption decision regression. Moreover, employing PSM for impact analysis is credible as it helps to select a valid counterfactual from an area where organic and organic fair trade is still not widely introduced. Furthermore, as both the taluks where these 14 villages are located share similar topographical and climatic conditions, they can provide an effective counterfactual group for the PSM analysis.

In the surveys, farmers were asked about prior production year, i.e. 2010 and 2011, respectively. Panel data was collected for two consecutive years in order to measure changes from production decisions that go beyond one year. This also helped to account for endogenous explanatory variables. A household survey questionnaire was used to elicit information about household characteristics, agricultural activities, off-farm employment, asset endowments, credit access and consumption expenditure.

As black pepper is a vine, in the survey area black pepper vines were planted in combination with other crops like areca nut, coconut, silver oak (timber) trees or were tied to teak poles. In the sampled households, for both the groups of certified farmers, the total agricultural land is certified organic not just black pepper. Figure 1 shows some of the major crops grown by the surveyed households. Black pepper is the major crop grown by all the farm households in the sample collected. Cardamom is the second major crop grown by conventional households, followed by coffee. In case of organic certified and both organic and fair trade certified farms, coffee is the second major crop. Some of the other crops cultivated in the surveyed households include coconut, rubber, turmeric, tea, nutmeg, areca nut, ginger, cloves and vanilla. As black pepper is the major crop grown by all the sampled households, it accounts for a large share of their farm income.

The NGO provided the necessary training and technical assistance during conversion phase from conventional to organic production. It also advances the inspection and certification costs for the certification process carried out by international certification agencies for organic farming and fair trade. The condition for the payment of certifications charges is that all certified products (except coconut and rubber) should only be sold to the NGO. To recover the certification costs the NGO reduces the payment for both the categories of certified products.

Figure 1. Major crops grown as per planted area in the surveyed households



Source: own calculation based on household survey 2011 and 2012

Selected input-output parameters of black pepper are shown in Table 2. The organic certified famers perform best among the three groups. They achieve the highest average yield and the lowest average variable costs per hectare. The conventional famers have the lowest yield per hectare. Their average gross income per hectare is less and average variable costs more than the organic certified farmers. Farmers growing both organic and fair trade certified black pepper have the highest farm area. However, their net average income from black pepper is the lowest. Fair trade certification was introduced by the NGO, only around mid-2000s, to its already existing organic certified households. Some households decided to adopt and these households began to sell as organic and fair trade certified producers only in 2009.

Table 2. Farm household level economic benefit from black pepper

Input-Output Parameters	Conventional (Obs.=197)	Organic (Obs.=200)	Both organic and fair trade (Obs.=200)
Area (in ha)	0.30	0.47	0.49
Yield (kg/ha)	574	1240	819
Gross income (in '000 INR/ha)	201	280	185
Variable costs (in '000 INR/ha)	47	34	93
Net income (in '000 INR/ha)	154	246	92
Years practicing certified organic production of black pepper*		6	10

Note: the above are the mean values. *2010 was used as the base year for this calculation and number of observations in each case is 100.

Source: own calculation based on household survey 2011 and 2012

It is also interesting to note that long term organic adopters have ventured into fair trade systems. This indicates that these farmers appear to be early adopters of organic agriculture as well. As the survey data is from 2010 and 2011, it captures only early-adopters of organic and fair trade certified black pepper. Hence, the productivity and economic benefits of this group of households may not yet fully reflect the total potential.

For a better understanding of the factors that drive adoption, respondents, i.e. mainly the head of households were asked what their key purpose of adopting any of the two certification systems were. We find that 22% of the farmers felt deteriorating soil quality and health concerns (21%) were their chief reason to venture into organic methods of production. Other factors like higher output prices (18%), low input costs (15%) and environmental concerns (14%) contributed to taking a decision towards converting to organic cultivation. The possibility of an assurance of a minimum price (65%) was one of the chief drivers that made organic certified farmers also enter fair trade marketing practices.

Variables used in the analysis are described in Table 3. The household specific characteristics like age, education and farm experience are measured for the household head assuming him/her to be the decision-making authority of the smallholder household. Income is significantly higher for organic farmers in comparison to the other two groups.

On an average, certified farmers are more experienced farmers. Off-farm income is not significant for any of the groups. Both the categories of certified farmers have significantly higher access to credit and shorter distance to market. Also, both the categories of certified farmers have significantly higher farm size than their conventional counterparts, though they have a significantly higher proportion of irrigated land. Moreover, organic farmers earn significantly higher income than the other two categories.

The variability in the independent variables captured by the two years of panel is presented in Table 4. Irrigation access significantly changes for all the three groups. It decreases for conventional and organic farmers but both organic and fair trade certified farmers are able to increase their access to irrigation in 2011. The distance from farm to market also significantly reduces for both the categories of the certified farmers as compared to 2010. With respect to market distance for the certified farmers, they have to sell all their output to the NGO. The NGO would inform them prior the place and time they would come to the nearby town to collect black pepper. The households had to travel to that place to sell their black pepper to the NGO. The distance from the farm to the place of sales was calculated as market distance. This could change from year to year based on the convenience of the NGO. Access to credit facilities and owning livestock significantly increases for the organic farmers. Thus, Table 4 indicates the possibility of endogenous regressors in the multinomial regressions and strengthens the usage of an adoption model based on panel data in this study. It also shows that certain important factors that could affect farmer decisions like irrigation and livestock are not static even in the short run. Hence, at least two years of panel data is better than one year data to study adoption decisions.

Table 3. Description and summary statistics of variables

Variable	Description	Mean	Con Mean	Org Mean	T test Mean Diff (Con - Org)		OFT Mean	T test Mean Diff (Con - OFT)		T test Mean Diff (Org - OFT)	
Age	Age of the household head in years	52.26	50.85	51.97	-1.12		53.93	-3.08	**	-1.96	*
Years of schooling	Education of the household head in years	9.03	9.37	9.79	-0.41		7.94	1.44	***	1.85	***
Farm experience	The farming experience of the household head in years	31.94	29.17	33.06	-3.88	**	33.56	-4.38	***	-0.50	
Household size	Total number of members in the household	4.37	4.46	4.40	0.07		4.26	0.21		0.14	
Dependency ratio	The total household members below 15 and above 65 divided by the rest of the household members	0.41	0.40	0.49	-0.09	*	0.35	0.05		0.14	**
Total Landsize	Total size of the farm in hectares	0.94	0.76	0.97	-0.22	***	1.08	-0.33	***	-0.11	
Have irrigation	If the household has irrigation facility (yes = 1 and no = 0)	0.2	0.37	0.04	0.33	***	0.19	0.18	***	-0.15	***
Extension support	If the household had access to extension support (yes = 1 and no = 0)	0.11	0.17	0.06	0.11	***	0.10	0.07	**	-0.04	
Market distance	The distance from farm to market in kilometers	3.61	5.65	2.91	2.73	**	2.29	3.35	***	0.62	**
Have Off-farm access	If the household has off-farm income (yes = 1 and no = 0)	0.4	0.41	0.36	0.05		0.43	-0.02		-0.07	
Credit access	If the household had access to credit (yes = 1 and no = 0)	0.9	0.82	0.91	-0.09	***	0.98	-0.16	***	-0.07	***
Have livestock	If the household has livestock (yes = 1 and no = 0)	0.57	0.57	0.52	0.06		0.61	-0.04		-0.10	*
Dependent Variable											
Income per capita	Total income of the household divided by the total household size		17741	40542	-22801	***	27461	-9720	**	13081	*
Number of Observations		597	197	200			200				

Note: average exchange rate during the panel survey years was 1US$ = 50 INR. Con: Conventional, Org: Organic and OFT: Organic and Fair Trade

Source: own compilation based on household survey 2011 and 2012

Table 4. Variability between the explanatory variables in two consecutive years of the panel

Explanatory Variables	Conventional			Organic			Organic & Fair Trade		
	Mean		Diff	Mean		Diff	Mean		Diff
	2010	2011		2010	2011		2010	2011	
Age (in years)	50.86	50.84	-0.02	51.63	53.31	1.68	53.65	54.21	0.56
Years of schooling	9.32	9.42	0.10	9.76	9.81	0.05	7.90	7.97	0.07
Farm experience (in years)	29.42	28.92	-0.50	33.38	32.73	-0.65	33.68	33.43	-0.25
Household size	4.52	4.40	-0.12	4.39	4.40	0.01	4.22	4.29	0.07
Dependency ratio	0.42	0.39	-0.03	0.51	0.46	-0.05	0.35	0.36	0.01
Total land size	0.79	0.72	-0.07	1.03	0.91	-0.12	1.05	1.11	0.06
Have irrigation (yes = 1)	0.62	0.10	-0.52***	0.07	0.01	-0.06**	0.03	0.35	0.32***
Have extension support (yes = 1)	0.22	0.11	-0.11*	0.06	0.06	0.00	0.07	0.13	0.06
Market distance (in km)	5.90	5.39	-0.51	3.32	2.50	-0.82*	2.10	2.49	0.39*
Have off-farm income (yes = 1)	0.46	0.36	-0.10	0.40	0.32	-0.08	0.42	0.44	0.02
Credit access (yes = 1)	0.81	0.82	0.01	0.97	0.85	-0.12**	0.99	0.97	-0.02
Have livestock (yes = 1)	0.59	0.55	-0.04	0.45	0.58	0.13*	0.56	0.66	0.10

Note: number of observations is 100 for all the panel years except for conventional category in 2011 which has 97 observations. Mean difference t-test depicts ***significant at 1%, **significant at 5% and *significant at 10% level.

Source: own calculation based on household survey 2011 and 2012

6 Results

This section presents the results of the study in two parts. The first part identifies the main drivers of adoption. The second part shows the differential gains of adopting organic and both organic and fair trade in terms of total household income.

6.1 Adoption Determinants

The multinomial estimations are presented in Table 5. The base category is conventional farming. With reference to organic farming and both organic and fair trade certification systems, the cross-section logit (columns' a' and 'b') gives inconsistent results. Factors represented as significant drivers in 2010 and 2011 are not always the same and the levels of statistical significance also changes between variables for the two years. Hence, cross-section analysis does not give consistent results. This could be due to the variability in variables like irrigation and livestock in the short term. Also, we cannot model random effects in a cross-section multinomial logit due to its econometric limitations of the IIA property wherein the errors of the multinomial logit model are assumed to follow an independent and logistic distribution. Hence, we cannot allow for correlation in the errors to introduce random effects.

We overcome such inconsistencies in the panel model (c) by allowing the two introduced random effects through latent variables $\delta 1$ and $\delta 2$ for organic and both organic and fair trade respectively to correlate. As significant effects are expected in between the two years as shown in Table 5, we include fixed effects at the panel level for the explanatory variables. A higher number of adaptive quadrature points increases the accuracy of analysis of the multinomial model using gllamm (RABE-HESKETH et al., 2004). Though normally 8 points are used, we use 16 adaptive quadrature points to ensure precision of results. The high correlation of 0.883 between the two introduced random effects ($\delta 1$and $\delta 2$) in the panel model (c) indicates presence of unobserved heterogeneity in adoption decision. Hence, by controlling for unobserved heterogeneity, the panel model is more reliable in estimating adoption drivers.

All the variables are significant for organic farming in the panel model (c) except, age and access to credit. More educated farmers with longer years of farm experience are organic adopters as found in studies by AJEWOLE (2010) and WHEELER (2008) respectively. As found by MUSARA et al. (2012) a larger farm size influences agricultural technology adoption. The higher the farm size, the higher is the probability of adoption of organic black pepper production. It is interesting to note that irrigation is significant but has a negative sign. Though further studies are needed, this could be due to the fact that farmers who had access to irrigation facilities preferred to grow other high value crops like conventional cardamom. Extension support is negatively related to organic adoption which can be explained by the fact that in the survey area, in order to increase domestic production, the government through extension agencies awards around 26 Indian Rupees (INR) (less than 1 US$), for every new black pepper seedling planted. Though it is not directly supporting any agricultural innovation, the farmers who avail the services of the extension support have a strong incentive to practice conventional agriculture.

Table 5. MNL cross section (a) and (b) and MNL panel gllamm (c) results

Base Category - Conventional	**(a) 2010**		**(b) 2011**		**(c) Panel**	
Organic						
Variables	**Coef.**		**Coef.**		**Coef.**	
Age (years)	-0.097	***	-0.019		-0.048	
	(0.037)		(0.029)		(0.034)	
Years of schooling	0.040		0.048		0.047	***
	(0.090)		(0.062)		(0.004)	
Farm experience (years)	0.127	***	0.043	*	0.072	**
	(0.032)		(0.023)		(0.034)	
Household size	-0.174		-0.104		-0.127	***
	(0.222)		(0.155)		(0.033)	
Dependency ratio	0.102		0.532		0.410	**
	(0.587)		(0.430)		(0.189)	
Total land size (log)	1.524	***	0.698	***	0.955	***
	(0.399)		(0.215)		(0.342)	
Have irrigation (yes = 1)	-4.492	***	-2.574	**	-3.102	***
	(0.722)		(1.110)		(0.664)	
Have extension support (yes = 1)	-1.131	*	-0.337		-0.820	***
	(0.681)		(0.747)		(0.311)	
Market distance in km (log)	-0.707	***	-1.028	***	-0.649	***
	(0.270)		(0.276)		(0.176)	
Have off-farm income (yes = 1)	-0.060		0.233		0.221	**
	(0.552)		(0.338)		(0.086)	
credit access (yes = 1)	2.070	***	-0.073		0.555	
	(0.700)		(0.454)		(0.800)	
have livestock (yes = 1)	-0.742		-0.295		-0.501	***
	(0.458)		(0.310)		(0.178)	
_Cons	2.334		-1.109		1.406	**
	(2.127)		(1.498)		(0.664)	

Table 5. MNL cross section (a) and (b) and MNL panel gllamm (c) results (cont.)

Base Category - Conventional	(a) 2010		(b) 2011		(c) Panel	
Organic and Fair Trade						
Variables	**Coef.**		**Coef.**		**Coef.**	
Age (years)	-0.087	**	-0.014		-0.028	
	(0.041)		(0.031)		(0.033)	
Years of schooling	-0.204	**	-0.164	**	-0.189	***
	(0.097)		(0.068)		(0.017)	
Farm experience (years)	0.106	***	0.008		0.031	
	(0.036)		(0.024)		(0.041)	
Household size	-0.329		-0.229		-0.297	***
	(0.222)		(0.172)		(0.032)	
Dependency ratio	-0.123		0.356		0.272	
	(0.612)		(0.481)		(0.227)	
Total land size (log)	1.676	***	1.139	***	1.249	***
	(0.424)		(0.261)		(0.176)	
Have irrigation (yes = 1)	-5.350	***	1.363	***	-1.342	
	(0.773)		(0.509)		(2.369)	
Have extension support (yes = 1)	-1.173	*	0.545		-0.521	
	(0.670)		(0.546)		(0.706)	
Market distance in km (log)	-1.183	***	-1.217	***	-0.899	***
	(0.283)		(0.315)		(0.028)	
Have off-farm income (yes = 1)	-0.397		0.424		0.264	
	(0.549)		(0.354)		(0.330)	
credit access (yes = 1)	4.411	***	1.406	**	2.326	**
	(1.365)		(0.681)		(1.118)	
have livestock (yes = 1)	-0.223		0.182		-0.043	
	(0.476)		(0.355)		(0.141)	
_Cons	3.369		2.472		2.654	***
	(2.512)		(1.617)		(0.603)	
Log Likelihood	-204.596		-253.258		-515.158	
Condition number					1263.431	
Correlation of random effects						
Cor ($\delta 1 \delta 2$)					0.883	
Observations	300		297		1791	

Note: robust standard errors in parenthesis. Panel analysis using gllamm is with 16 adaptive quadrature points. ***significant at 1%, **significant at 5% and *significant at 10% level. The number of observations in panel (c) is 1791 as to incorporate random effects the MNL gllamm model expands the dataset so that there is one record for each alternative for each observation (i.e. (300+297)*3).

Source: own calculation based on household survey 2011 and 2012

A shorter distance to market and having access to off-farm income increases organic adoption. Owning livestock is used as an asset indicator in this study. Contrary to other findings (FEDER et al., 1985; SARKER et al., 2009; SHARIFI et al., 2010; OELOFSE et al., 2010), it is noted that it is negatively related to organic adoption. But, since in this study most of the support for adoption including organic manure is provided by the NGO, even farmers who do not own many assets appear to be motivated to adopt organic black pepper. Also, though more studies are required, multi-cropping increases soil fertility as pointed out by DADAL et al. (1991) and perhaps this reduces the need for manure and fertilizers.

The variables education, household and farm size, distance to market and credit access are significant with regard to both organic and fair trade adoption in the panel model. The less educated farmers are adopters of organic fair trade. This could be because of the awareness programs conducted by the NGO in the survey area. The higher the farm size, the more driven the farmers are to adopt organic fair trade. A shorter distance to market proves an impetus to smallholders to explore organic and fair trade agriculture. This could be probably attributed to reduced transportation costs. Having an easy access to credit stimulates its adoption.

The panel adoption model (model c) accounts for endogenous regressors due to unobserved heterogeneity and thereby gives more reliable parameter estimates and determinants of organic and both organic and fair trade certified black pepper. Hence, these results do not reject our first hypothesis that a panel model provides a better identification of adoption determinants. As can be seen from the results, in the presence of unobserved heterogeneity, the panel model is more robust. The determinants for adoption of organic black pepper and for both organic and fair trade are not the same. For example, education is positively related to organic adoption and negatively with both organic and fair trade adoption. This could be specific to black pepper in Idukki because though education helps farmers understand the food safety, environmental and health aspects of organic black pepper farming, the awareness programs conducted by the NGO seems to have played a major role in driving the less educated organic farmers to sell under fair trade marketing schemes. Credit access is observed to be more important for organic farmers to venture into fair trade certifications though it did not play a determining role when adopting organic certification.

Overall, total farm size plays a critical role in adoption. It is highly significant at 1% in all the models (a, b and c) for organic and both organic and fair trade adoption. Having accounted for unobserved heterogeneity in the panel model (c), we find that these innovations are tend to be favored by farmers with a larger farm size. This is consistent with other findings in literature (MUSARA et al., 2012, and CHOUICHOM and YAMAO, 2010). Also, farmers with a larger area have easier access to credit (WEIL, 1970). The variable, distance from farm to market is also highly significant at 1% for both the farming alternatives as found in other studies like DADI et al. (2004).

6.2 Impact Evaluation of Adoption

In this section, we examine the differential gains of organic and both organic and fair trade adoption of black pepper on total household welfare in terms of log income per capita employing PSM with multiple treatment effects as depicted in Table 1. The total household income reflects net revenues from all crops of which black pepper is the major crop (as shown in Figure 1) and other non-farm income. Also, as presented in Table 3, less than 45% of the households had access to off-farm income. Hence, most of the sampled households were dependent on agriculture for their livelihoods and more specifically on black pepper as is the case with Idukki in general.

Table 6. ATT effects of adoption on log total household income per capita

Multiple treatment categories	Estimates	2010 NN one-to-one matching (caliper 0.02)	2010 Kernel matching (caliper 0.01)	2011 NN one-to-one matching (caliper 0.02)	2011 Kernel matching (caliper 0.01)
OO vs. CO	T	10.27	10.28	10.08	10.09
	C	8.93	9.17	9.66	9.46
	Difference	1.34*** (2.77)	1.11*** (5.43)	0.42 (1.14)	0.63*** (3.92)
OF vs. CO	T	9.88	9.89	9.94	10.01
	C	9.07	9.10	9.32	9.51
	Difference	0.81 (1.06)	0.79*** (4.17)	0.61 (1.12)	0.50** (2.52)
OF vs. OO	T	9.89	9.89	10.01	10.01
	C	10.19	10.27	10.25	10.26
	Difference	-0.30 (-0.34)	-0.38*** (-3.39)	-0.24 (-0.31)	-0.25** (-2.07)

Note: ***significant at 1%, **significant at 5% and *significant at 10% level
T-statistics in parentheses, NN = Nearest Neighbour matching, T = Treated group and C = Control group.
CO = conventional, OO = only organic certified and OF = organic and fair trade certified
Source: own calculation based on household survey 2011 and 2012

A logit model is used to predict the propensity scores. The nearest neighbor, one-to-one matching with a caliper of 0.02 and a kernel matching method with a caliper of 0.01 is used to estimate the impact of adoption.[2] The data was sorted randomly before

[2] STATA command psmatch2 (LEUVEN and SIANESI, 2003) is used to estimate PSM.

matching to reduce potential bias. The evaluation is separate for each cross-section year, as we do not have data before and after adoption for the same households to employ the double difference PSM approach. Nonetheless, applying PSM to each year separately enables us to establish consistency of results. All the 200 observations in each category for both the years are retained in kernel matching but only around 75% is retained after one-to-one nearest neighbor matching. The adoption effect on total log income per capita is presented in Table 6 for the year 2010 and 2011, respectively.

The kernel matching shows that adopters of organic black pepper have a significantly higher per capita income in both 2010 and 2011 when compared to non-adopters. Since income per capita is expressed in terms of logarithm, we can interpret the results in percentages. The income effect is quite remarkable in 2010 where organic farmers earn 111% more household income than conventional growers based on the Kernel matching method. A possible reason for this result is that organic pepper farmers perform very well in terms of yield as they have become more professional in pepper farming while conventional might pay less attention to pepper. The change in income per capita is also positive and significant for farmers who adopt both certification schemes with respect to conventional farmers, again based on the kernel matching method. However, the income effect is much lower than for the former group. No positive income effect can be shown for organic black pepper farmers who additionally adopt fair trade regimes. To the contrary, two matching methods yield a significant negative income effect. This is due to additional certification costs. Besides, fair trade will only yield economic benefits if the market price falls below the minimum fair trade price which was not the case in the observation years. Though these PSM results are based on logit models run on each cross-section data, as both years in the kernel matching method show consistently that certified farmers in both categories have significantly higher income than convention growers, our second hypothesis cannot be rejected.

To check the robustness of the PSM results to unobservable factors, the ROSENBAUM (2002) sensitivity analysis is employed and its results are presented in Table 7[3]. Results show that our results from the PSM are insensitive to hidden bias. The kernel based matching method provides the best results that are insensitive with reference to assumed hidden bias (Γ) levels (1, 1.25, 1.50, 1.75 and 2). To overcome the assumption of no hidden bias (Γ = 1), the hidden bias will need to increase by more than a factor of Γ=2 for the kernel matching of log income per capita.

[3] We use STATA command rbounds (GANGL, 2004) to perform the sensitivity analysis.

Table 7. Sensitivity analysis of ATT for log income per capita

Critical level of hidden bias (Γ)	2010			2011		
	OO vs. CO	OF vs. CO	OF vs. OO	OO vs. CO	OF vs. CO	OF vs. OO
NN one-to-one matching (Caliper 0.02)						
Γ = 1	<0.000	<0.000	0.001	0.000	0.001	0.032
Γ = 1.25	<0.000	<0.000	0.000	0.009	0.017	0.002
Γ = 1.50	<0.000	0.000	<0.000	0.053	0.074	0.000
Γ = 1.75	<0.000	0.000	<0.000	0.157	0.190	<0.000
Γ = 2	0.000	0.003	<0.000	0.314	0.349	<0.000
Kernel matching (Caliper 0.01)						
Γ = 1	0.000	0.000	<0.000	<0.000	<0.000	0.000
Γ = 1.25	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000
Γ = 1.50	<0.000	<0.000	0.000	<0.000	<0.000	<0.000
Γ = 1.75	<0.000	<0.000	0.000	<0.000	0.000	<0.000
Γ = 2	<0.000	<0.000	0.000	<0.000	0.000	<0.000

Note: T = Treated group and C = Control group. CO = conventional, OO = only organic certified and OF = organic and fair trade certified
NN = Nearest Neighbour matching
Source: own calculation based on household survey 2011 and 2012

We can, therefore, deduce that even large amounts of unobserved variables will not alter the impact effects of organic and both organic and fair trade certification estimated through kernel matching. Thus, based on the Rosenbaum's bounds results we conclude that the ATT estimates of PSM presented in Table 7 for log income per capita are robust indicators of the effect of adoption of organic and both organic and fair trade certified black pepper. This strengthens the finding that although adoption of both these innovations increases total household income in comparison to conventional famers, fair trade does not add additional benefits over organic certification.

7 Conclusions

In this study we analyzed the adoption and impact of organic farming and fair trade regimes for black pepper in India. We used household panel survey data of two consecutive years to overcome the endogeneity limitations inherent in cross-section analyses. Our analysis shows that using a panel model is superior to a cross-section model and in principle will improve the quality of adoption studies. We find that important variables that can affect adoption decision like owning livestock, having irrigation facility and access to credit are not static even between two years. Hence, having a panel data of just two consecutive years are sufficient to control for such short-term variability in identifying adoption determinants. Also, due to omitted variable bias and the IIA limitation, the cross-section analysis applied to both years separately did not give consistent results. However, when random effects are introduced through the panel gllamm model, unobserved heterogeneity is accounted for and robust adoption determinants are identified.

The main drivers to adopt organic black pepper are business motives rather than health or environmental concerns of decision makers. This is in line with other adoption studies in conventional agriculture in developing countries (e.g. ASFAW et al., 2009; EVENSON and GOLLIN, 2003). Also, larger farmers and those better connected to markets tend to adopt fair trade certified black pepper in addition to organic production. On the other hand the study suggests that non-adopters can also shift to other high value crops such as cardamom provided they have adequate irrigation.

To estimate the differential gains of organic and both organic and fair trade adoption, the effect on the per capita income of the farm household was estimated. The causal impact analysis using three Propensity Score Matching methods (PSM) with multiple treatment effects reveals that farmers who adopted organic as well as organic and fair trade certification schemes achieve higher income than conventional black pepper growers. However, a critical finding of this study is that in the case of black pepper in India fair trade does not add any additional benefit over organic certification. This can be due to the fact that for both organic and fair trade farmers, the additional costs of certification are high which are not sufficiently rewarded by higher market prices in the observed year. Moreover, for a smallholder black pepper farmer in both regimes the advantage of fair trade prices only comes into play if market prices fall below the minimum organic black pepper price. Hence, the major benefit of fair trade is reducing price risk in markets which is less so for organic black pepper. The fair trade price premium above the organic market prices is also a social premium aimed to develop the socio economic conditions of a farming community, for example, in terms of education and infrastructure and has other benefits than farm household income. Since fair trade regimes were only recently implemented in the study region, additional adoption of fair trade certified black pepper is likely to generate benefits the longer farmers are engaged in the fair trade regime as found by BECCHETTI et al. (2011) in the case of Thai Jasmine rice.

More studies are needed to better understand social-based and environmentally-friendly innovations in agriculture in developing countries. As pointed out by JENA et al. (2012), one remaining question is the integration of the different institutions and players involved in fair trade and organic systems.

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