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Assessing the Causal Effect of Decoupled Payments on farm labour in Tuscany Using Propensity Score Methods

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Abstract:

We analyze the impact on employment of the 2003/2005 CAP reform (decoupled payments) in Tuscany farms. We use data coming from census (2000 and 2010) and administrative archives, and apply propensity score-based methods to evaluate the average treatment effect of payments on employment-related outcomes, taking into account that the assignment mechanism of payments was non-random. We further investigate impact heterogeneity using a generalized propensity-score matching methodology focussing on a subgroup of farms. Results show that there exists some effect of the payments on employment and that the impact is heterogeneous over the different amounts of payments.

Keywords: Policy evaluation, Labour, Common agricultural policy, Propensity score, Dose-response function

JEL codes: Q18, Q12, J43

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1 Introduction

Since the Treaty of Rome, the Common Agricultural Policy (CAP) represents the main EU policy instrument aimed at supporting agricultural income and rural areas sustainability. The CAP has undergone significant changes in time due to the changing role of Agriculture in societies, to various types of pressure on budget allocation and to the citizens changing preferences about food and environment. Agricultural economics literature has focussed on assessing the CAP impact on the use of productive factors, notably of labour. Overall, empirical results suggest a positive effect of the CAP on the maintenance of farm labour (Nordin, 2014) and a negative effect on the creation of off-farm labour allocation (Ahern et al., 2006). Other studies, at the opposite, find that the more stable stream of income due to decoupling leads to the substitution of household labour with external labour (Benjamin and Kimhi, 2003). In this paper, we study the causal effect of decoupled payments on farm labour in Tuscany farms. The objective is to assess if, and to what extent, decoupled payments may affect the level of on-farm labour as well as its allocation among household and non-household workers.

In order to evaluate the effectiveness of agricultural policies in terms of expected impacts, both ex-ante and ex-post impact evaluations are needed. Ex ante evaluation techniques allow policy makers to predict the likely impact of a change in policy prior to their implementation, while evaluating ex post the actual impact of policies and measuring the difference with ex ante predictions may help in improving their performances. Microsimulation models have been increasingly applied in ex ante evaluation of public policies, allowing to assess the potential impact of a policy, changing the assumptions of the policy itself as well as costs/prices parameters. Mathematical programming techniques ground on linear/non linear, static/dynamic models or more sophisticated agent-based models (Viaggi et al. 2011; Basil et al., 2013).

A different approach uses econometric models for policy (ex ante and ex post) evaluation. Ex-ante analyses are often performed using stated behaviour, measuring farmers'copying strategies and assuming alternative policy scenarios (Zimmerman et al. 2009 for a review). A pseudo-counterfactual is derived assuming alternative hypotheses of policy and prices (see for example Douarin, et al., 2007; Bartolini and Viaggi 2013), and impact is quantified through a scenario comparison.

Ex-post analysis often exploits regression or selection models for identifying the set of variables able to explain a specific farms behaviour (i.e. Goodwin and Mishra, 2003). Despite their large application, those methods reveal some weakness in evaluating the effectiveness of a policy, because they do not lead to the estimation of a properly defined causal effect, unless some behavioural strong assumptions are made. A growing literature tries to overcome these shortcomings by applying causal inference methods, based on the potential outcome approach (Rubin, 1974). Here, we follow this stream of research.

In the paper, we first estimate average treatment effects of payments on employment-related outcomes to Tuscany farms, using the treatment (payment) as a binary variable and implementing a propensity score-based matching method. Further we focus on estimating the effects of different payment levels on a subgroup of Tuscany farms, i.e., arable farms with utilized agricultural area greater than the median value, and apply the Generalized Propensity Score (GPS) approach introduced by Hirano and Imbens (2004). More specifically, we first estimate the GPS using a generalized linear model, and then we estimate the dose response function using a flexible parametric form for the regression function of the outcome on the treatment and the GPS. We use an integrated dataset, which results from the linkage of Agricultural Census data (2000 and 2010) and administrative archives with information on decoupled payments from 2000 to 2010.

The rest of the paper is organized as follows. Section 2 provides a brief background on the policy environment in Italy, i.e. the decoupling of payments following the 2003/05 CAP reform. Section 3 introduces the economic theory background. In section 4 details on the used data set are reported together with a descriptive analysis of variables of interest. Section 5 contains the details of the econometric approach and reports our empirical results. Some concluding remarks follow in section 6.

2 The decoupled payments and the effects on labour

The implementation of decoupling policy in Italy follows the historical process, so that since 2005 farmers receive an amount of payment calculated as the sum of payments received during the reference period (2001-2003). Beside this mechanism, the 2003/05 reform ties the financial support to compliance with standards of environmental practices (cross-compliance). Cross-compliance mainly covers directives and regulations contained in the Statutory Management Requirement, that represents the constrains imposed by EU directives at farm levels, and a set of Good Agricultural and Environmental Conditions decided by each regional Authority.

Tuscany region implemented several prescriptions, concerning agronomic, phytosanitary norms and chemical controls. Large part of literature has emphasised the effects of agricultural policy in changing the demand of productive factors.

Since preliminary works of Harrington et al., (1995), the economic literature has emphasised the effect of agricultural policy (such as decoupling) as one of driver of structural changes (Ahearn 2005; Zimmermann et al, 2009), where, among the productive factors, land, labour, capital and investment are the most frequently studied in simulation analysis. While policy debate is dominated by arguments in favour of the maintenance of agricultural payments to preserve employment in agriculture, there is no consensus among scientists about CAP impacts on labour uses. Key and Roberts (2009) show that overall payments increase the profitability of agricultural sectors more than alternative jobs, with the effect to preserve labour in agriculture or even increase it. Hennessy and Renhman (2008), using Irish National Farm Survey, investigate the decoupling influences on the decision to allocate farm household labour between off-farm and on-farm activities. Their main findings show that the decoupling is likely to increase the probability of participating in the off-farm employment market and that the amount of time allocated to off-farm work will increase. With a similar approach, Ahearn et al. (2002; 2006) nd that, where farmers received decoupled payments, those payments resulted in farmers increasing their supply of off-farm labour. Petriks and Zier (2011), by applying a difference in difference method for all CAP measure (first and second pillar) in three regions of East Germany, find diversified impacts across measures. Authors get no marginal effects of the investment-aid measures and payment in less favoured areas, while, at the opposite, agri-envrionmental payments show positive effects. Dupraz and Latruffe (2015) estimate a three-equation system considering different types of labour, using the French Farm Accountancy Data Network database. They point out different patterns across labour conditions relating to CAP reform. Authors find that direct payments reduce farm labour, while second pillar payments have increased it. Bartolini and Viaggi (2011), by simulating counterfactual abolishment of CAP in 9 EU countries, find that, under complete CAP abolishment, most of farmers (about 80%) will be not affected by changes in labour demand. Concerning those remaining farmers, the 10% will reduce expansionistic behaviour assumed under business as usual scenarios and the last 10% will shift from no change to a reduction of labour demand. The authors, using an econometric approach, also find that farmers and farm characteristics play a determinant role in this reduction.

3 Economic theory backgroung

According to the economic theory the optimal allocation of labour plays a key role to explain the effect of decoupled payments on labour-related outcomes.

Farmers' decisions on agricultural production and on labour allocation can be usefully represented by the Farm-Household model (Tailor and Adelman, 2003). A generic farm household, with endowment of household labour $\bar{L}$, wishes to maximise the utility function of the time allocated to the leisure (l_l) and of consumption (C_c)

$$\max U(C_c, l_l), \quad \text{subject to :} \tag{1}$$

$$\bar{L} - l_o - l_a - l_l = 0 \tag{2}$$

$$p_x Q_x + SFP - cc - I_{lab}^{ex}[(L - l_a)w_a] + I_{lab}^{off}[(\bar{L} - l_a - l_l)w_{off}] - p_c C_c = 0 \tag{3}$$

$$Q_x = Q_x(\alpha, L, A, K) \tag{4}$$

$$L = l_a + l_e \tag{5}$$

where α corresponds to the generic technology, L represents the labour use on farm activity, A the amount of land operated, K the capital use on farm. SFP represents the amount of payment received, cc the cost of cross compliance, and $\bar{L}$ is the sum of household time allocated among off-farm labour (l_o), on-farm labour (l_a) and leisure time (l_l).

Following Deninger et al. (2008), $Q(\alpha, L, A, K)$ is a simplified well-behaved production function with generic technology α, with the amount of farm labour L ($L = l_a + l_e$), both on-farm household (l_a) labour plus external labour (l_e), paid at wage w_a, the area operated (A) and the capital (K). I^{ex}_{lab} and I^{off}_{lab} are two indicators which represent the acquisition of the external labour and the activation of off-farm household labour. These indicators are equal to zero in the absence of external labour and off-farm household labour, respectively, and equal to one otherwise (e.g. when the farm household use external labour). The decision variables are the amount of agricultural labour and the amount of household labour used. By substituting equations (2), (4) and (5) into equation (3) the household full income function, i, can be derived. The full income fuction i equals the sum of the household expenditure for agricultural activities and the expenditure for household consumption:

$$i = p_x Q_x(\alpha, L, A) + SFP + I^{off}_{lab}[(\bar{L} - l_l - L - L_e)w_{off}] = p_c C_c + cc + I^{ex}_{lab}[(L - l_a)w_a] \tag{6}$$

The optimal labour amount L (on farm household labour and external labour purchased) can be obtained maximizing equation (1) subject to equations (2) and (4):

$$i = U(C_c, l_l) + \lambda\{p_x Q_x(\alpha, L, A, K) + SFP + I^{off}_{lab}[(\bar{L} - l_l - L - L_e)w_{off}] + \tag{7}$$

$$-p_c C_c + cc + I^{ex}_{lab}[(L - l_a)w_a]\} + \gamma(\bar{L} - l_o - l_a - l_l),$$

where λ and γ represent the two Lagrange multipliers associated with the constraints. Studies on comparative static analysis suggest that decoupled policy seems not to affect the labour allocation (Key and Roberts, 2009). However, simple static models result do not encounter for uncertainty and risk aversion. Despite it, the less uncertainty of SFP compared against other farm incomes determines high propensity to invest and to adopt new technology for risk adverse farmers. As a result, increasing in SFP positively affects the technology adoption with shifting of technology towards, for example, adoption of labour saving innovations (Moro and Sckokai, 2011).

In what follows we advocate the use of a statistical approach to investigate if farm labour (household and external labour) has been affected by the 2003/2005 CAP reform. Adopting the framework of the potential outcome approach to causal inference, we use flexible/non parametric methods to establish reasonable comparisons, without relying on strong economic/behavioural assumptions.

4 Data description

In order to recover all the information needed for our analysis, we run a two-step record linkage procedure. First, we linked the 2000 and 2010 censuses units, then we merged the matched data with the Regional Agency for Payments in Agriculture (ARTEA) database containing data on decoupled payments. In both cases, we applied a deterministic record linkage procedure, using the farm code (i.e. a numeric code uniquely identifying the farm) as identifier. Given the high quality of the identifier, the percentage of false unmatched and false matched pairs is negligible (Copas and Hilton, 1990). The resulting sample is composed by 35,943 farms representing 29.6% of 2000 census units and 49.6% of 2010 census units. The units which do not find a link may be: i) farms born in the 2001- 2010 period; ii) farms born in 2000 or before and died in the 2000-2010 period iii) farms whose code was recorded with errors in the 2000 and/or in the 2010 censuses (false unmatched cases), iv) farms whose farm manager changed over the period 2001-2010. The ARTEA administrative archive records all the decoupled payments received by the Tuscany farms over the period 2008-2010. Each and every farm from the census data source is expected to find a link in the ARTEA archive, provided it received at least one payment in the selected period. Hence matched units identify farms which received payments whereas unmatched units correspond to farms which did not receive any payments over the period 2008-2010. In this paper, we refer to the former as treated farms and to the latter as untreated farms. Finally, we recovered contextual variables at the municipality level from Istat official statistics.

The statistical methods applied in the paper (propensity score matching and generalized propensity score approach) rely on the use of a selected set of covariates and outcome variables described in Table 1. We include independent variables related to the farm, to the farm owner's characteristics, and local macroeconomic indicators. Outcome variables instead are related to on farm labour, specifically to the change in the number of labor units working in the farm from 2000 to 2010, considering household and external labor units separately.

Farms not receiving decoupled payments (untreated farms) are about 38% of the sample. The empirical distribution of average annual payments, classified in eight categories, shows a positive skewness (Figure 1). Annual payments over 20000 euros are excluded from the impact evaluation analysis (about 2% of the sample).

Table 2 presents some descriptive statistics by treatment group (treated and untreated). We note that most independent variables show quite similar mean value (or proportion for qualitative variables), so that the two groups may be reasonable compared. The outcome variables show some dissimilarities which suggest the presence of some effect of treatment, even if not properly conditioned on confounders. Analyzing just treated farms, which represent 62% of the selected sample, we note that farms receiving lower amount of decoupled payments per year increase the number of labor units working in the farm, instead farms receiving higher amount of decoupled payments show negative effects on farm labor. Actually, Table 3 shows that change in total, household and external farm labor decreases in the amount of decoupled payments received. This suggests the opportunity to investigate the possible heterogeneity of the impact by different level of payments.

5 Methodological framework and empirical results

5.1 Propensity score methods

Receiving or not the decoupled payment or a different level of payment is not exogenous to farms' characteristics, implying that farms exposed to different levels of the treatment variable can systematically differ in important ways other than the observed treatment. In the context of the potential outcome approach to causal inference, propensity score methods are often used in observational studies to adjust for differences in pre-treatment variables, and to draw inferences about the effects of binary treatments (Rosenbaum and Rubin 1983).

In the case of a binary treatment (receiving or not the payment) the treatment indicator t_i equals one if unit i receives treatment and zero otherwise. The potential outcomes are then defined as $Y_i(t_i)$

for each unit i, where $i = 1 \cdots, N$ and N denotes the total population. The individual treatment effect for an unit i can be written as $Y_i(1) - Y_i(0)$. Two parameters, which summarize the distribution of the unobservable individual-level treatment effect, are most frequently estimated in the literature. The first one is the (population) average treatment effect (ATE), $ATE = E(Y(1) - Y(0))$. This parameter might not be of relevance to policy makers because it may include the effect on units for whom the programme was never intended. The second one is the so called average treatment effect on the treated (ATT), $ATT = E(Y(1)|t = 1) - E(Y(0)|t = 1)$, which focusses explicitly on the effects on those for whom the programme is actually intended.

In order to adjust for systematic differences in background characteristics, a key identifying assumption assumes that there are no unobservable variable affecting both treatment assignment and the potential outcomes (unconfoundedness or selection on observables). So that, after conditioning on a set of covariates, the potential outcomes can be assumed conditionally independent of the treatment. Rosenbaum and Rubin (1983) suggest the use of a balancing score, i.e. a function of the relevant observed covariates such that the conditional distribution of these covariates given the balancing score is independent of assignment into treatment. One possible balancing score is the propensity score, i.e. the probability of receiving the treatment given observed characteristics.

Other assumptions that will be maintained in the paper are the stable unit treatment value assumption (SUTVA, Rubin, 1978) that there is neither interference between units nor different versions of the treatment, and the the overlap assumption, requiring that each individual have a positive probability of receiving each treatment level. Note that the assumptions required to estimate the ATT are less restrictive than the assumptions required to estimate the ATE. Estimating the ATT requires a weaker form of the unconfoundedness assumption and a weaker version of the overlap assumption.

Matching methods provide simple and intuitive tools for adjusting the distribution of covariates among samples from different populations.

5.2 Empirical evidence: binary treatment

We estimate ATE and ATT effects using propensity score-based matching estimators (for a review, see Stuart, 2010). We use a logit model for the estimation of the propensity score and the set of covariates includes pre-treatment (census 2000) variables decribing farms'characteristics (such as utilized agricultural area, farming specialization, livestock, number of family workers in the farm, network connections) and variables describing the economic context at local level (local activity rate). Due to balancing requirements, we also included some holders' characteristics (gender, age, education), which are presumed to affect both treatment and outcome as individual characteristics may determine different entrepreneurial strategies.

ATE and ATT estimates are reported in Table 4 for the three employment variables. We use a difference-in-difference specification of the outcome in order to remove other potential bias coming from possible unobserved factors correlated to the outcome and to the treatment variable. Looking at the ATE estimates, we found a significative positive effect for all the three outcome variables, while ATT effect becomes null for the third variable.

5.3 Generalized propensity score methods

Recent work has extended propensity-score methods in settings with continuous treatments, where the focus is on assessing the heterogeneity of treatment effects arising from different treatment levels (Hirano and Imbens 2004). Following this stream of literature, we aim to estimate a dose-response function of payments to provide more insight on the heterogeneity of the impact of different level of payments on employment. We briefly describe the continuous treatment framework and the estimation approach. For each i there is a set of potential outcomes $\{Y(t)_i\}$ $t \in \Gamma$ referred to as the individual level dose-response function. Here the parameter of interest is the entire average dose-response function, $\mu(t) = E[Y_i(t)]$, which represents the function of the average potential employment-related outcomes over all possible treatment levels. The observed variables for each unit i are a vector of covariates, the level of the treatment received, and the potential outcome corresponding to the level of the treatment received, $Y_i = Y_i(T_i)$. Note that the focus here is on average dose-response and marginal treatment functions for farms who received the payment, so untreated farms are excluded from the analysis. Starting from some preliminary analysis, we argue that small and medium-big farms behave differently, also depending on farming specialization, so that we prefer starting the analysis focussing on a specific subgroups of farms, i.e., arable farms (FS=1) with UAA greater than the median value. We decoded to focus on these farms, because they are the main target of the decoupling and received higher payments.

Under unconfoundedness, the average dose-response function can be obtained by estimating average outcomes in subpopulations defined by covariates and different levels of treatment. Let define the Generalized Propensity Score (GPS) as the conditional density of the treatment given the covariates. Hirano and Imbens (2004) showed that the GPS is a balancing score and demonstrated that if the treatment assignment mechanism is weakly unconfounded given the covariates, then it is also weakly unconfounded given the GPS. Therefore, GPS can be used to remove biases associated with differences in the observed covariates. The approach can be implemented trough the following steps (Mattei and Bia, 2008, 2012):

1. Specifying a distribution to model the received level of treatment, T_i, given the set of covariates, X_i, and estimating its parameters by maximum likelihood. Here we use a log-normal distribution to model the level of average annual payment given the covariates: $\ln(T_i)|X_i \sim N(\beta_0 + \beta_1' X_i, \sigma^2)$. The GPS is then estimated as

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma^2}}} exp\left(-\frac{1}{2\hat{\sigma^2}}(\ln(T_i) - \hat{\beta}_0 - \hat{\beta}_1 X_i)^2\right) \tag{8}$$

   Let remind that GPS estimation aims to assure that the covariates are balanced across treatment categories. In our case, balancing results satisfied at 5% level.

2. Estimating the conditional expectation of the outcome variable as a function of observed treatment (T_i) and estimated GPS ($\hat{R}_i$). Following Hirano and Imbens (2004), we estimate the conditional expectation of the (continuous) outcome using a flexible function of treatment level and estimated GPS, including an interaction term:

$$\beta_{t,r} = (E[Y_i|T_i, \hat{R}_i] = \alpha_0 + \alpha_1 \cdot T_i + \alpha_2 \cdot \hat{R}_i + \alpha_3 \cdot T_i^2 + \alpha_4 \cdot \hat{R}_i^2 + \alpha_5 \cdot T_i \cdot \hat{R}_i \tag{9}$$

3. Estimating the average dose-response function at a particular value of the treatment t, averaging the (estimated) conditional expectation $\beta(t, r)$ over the GPS at that level of the treatment:

$$\mu(t) = E\left(\hat{Y}_t(i)\right) = \frac{1}{N}\sum_{i=1}^{N} g^{-1}(\hat{\alpha}_0 + \hat{\alpha}_1 \cdot T_i + \hat{\alpha}_2 \cdot \hat{R}_i + \hat{\alpha}_3 \cdot T_i^2 + \hat{\alpha}_4 \cdot \hat{R}_i^2 + \hat{\alpha}_5 \cdot T_i \cdot \hat{R}_i) \quad (10)$$

where $\hat{\alpha}$ is the vector of parameters estimated in the second stage and $\hat{r}(t, X_i)$ is the predicted value of $r(t, X_i)$ at level t of the treatment.

5.4 Enpirical evidence: continuous treatment

Tables 5 and 6 report the outputs of GPS and dose-response function (for the average change in total full time equivalent labour units) estimation, respectively. Results are statistically weak and the treatment level does not significantly affect the dose-response function, while parameters related to the estimated GPS are statistically significant, so the dose-response function depends on the probability to receive a given treatment level rather than on the payment itself. Figure 6 shows the average dose-response functions and the marginal treatment effect functions (defined as derivative of the corresponding dose-response functions) for the three outcomes. The average change in total full time equivalent labour units appears to be positive and to increase as the amount of payment increases, even if the 95% confidence bands cover the null effect. The right panel of the same figure suggests that the marginal effect increases in low payment levels, while decreases or increases less faster in high payments levels. The global effect is mainly due to the behaviour of the household farm labour (see second left panel), while the impact of payments on the external farm labour results negligible.

6 Concluding remarks

Given the high rate of unemployment all over the Europe, understanding the impact of CAP on farm labor is a key issue to enhance the agricultural policy. According to the existing literature, the magnitude of the CAP reform effect, even if on different target outcomes and stemming from first and second pillar, is quite low (Olper et al. 2013) and differs according to treatment intensity (Esposti, 2014).

This paper, focussing on the first pillar, aims at assessing the impact of decoupled payments on the change in farm labor units over the period 2000-2010 through a (generalized) propensity score matching. Our work represents a first attempt to better understand CAP impacts on agricultural labour maintenance, investigating SFP under two different perspectives: a) using payment as treatment binary variable (beneficiaries versus not beneficiaries) and b) using different payment levels as different doses of treatment.

Our results suggest that there exists some effect of decoupled payments on employment and that the impact is heterogeneous over the different amounts of payments. We found a significative positive effect of receiving payment (both ATE and ATT estimates) in increasing full time equivalent labour units. We argued that the effect differs between small and medium-large farm. On a specific subgroup of medium-large arable farms we found negligible effects, however we can see that the dose-response function is increasing in amount of payment, while the marginal effect is strongly increasing in low payment levels, and decreasing (or slowly increasing) in high payments levels.

These preliminary results show an uneven contribution of SFP level on labour in the Tuscany Regions. When beneficiaries are compared against not-beneficiaries, our results seem not fully confirm previous literature findings, showing positive effects of the decoupling on labour. There is no consensus in previous literature findings, even if most of the work refers to negative or neglected effects. Further, we are not aware of similar studies for Italy or Tuscany, to be used as a benchmark for comparison. Instead, a puzzling evidence comes from the analysis of the impact of different SFP levels, where lower levels of payments show higher (positive) effects on labour changes. Younger farmers (observed in both census occasions and matched) are included in our sample, so that the analysis mainly focus on more structured farms, which can be considered less vulnerable and more likely to growth and invests. Our results suggest that substitution between household labour and external labour, availability of labour saving technologies and off-farm income opportunities are central issues to fully understand the dynamics of employment in the rural areas. Some Authors have stressed that, due to risk adverse attitude, farmers are more likely to invest (for example, in labour saving technologies) with decoupling, because of the less uncertainty of payments, compared against agricultural production and historical payment systems (Esposti, 2013). Hence, such a risk attitude can determine a substitution effect between labour and technology with reduction of labour.

The analysis specifically concerns the Tuscany Region, which is particularly valued for provision of ecosystem services by agricultural management. Even if we focus on farmers specialised in arable crops, and then mainly in commodities production, the maintenance of rural viability trough the CAP may determine higher second order effects on the rural economies (i.e., agro-tourism, diversification, and cultural identification on the territory) larger than in other Italian Regions.

Further investigations are required, to check the robustness of these results and to enlarge the analysis to other groups of Tuscany farms. Finally, we are planning to consider alternative employment-related outcome variables coming from administrative archives or surveys.

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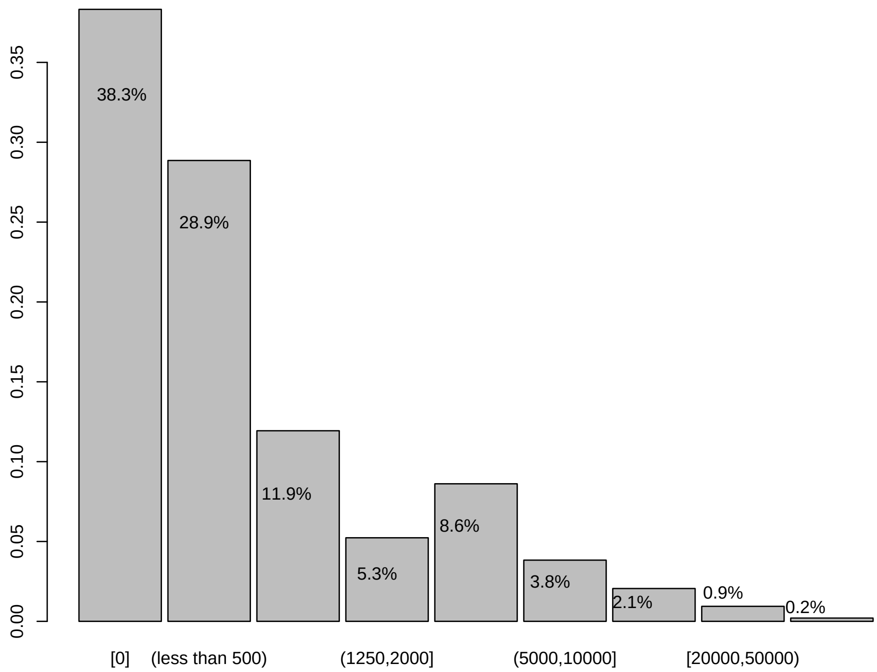

Figure 1: Empirical distribution of farms by levels of decoupled average annual payment.

Name	Description	Categories or measure units
AGE	Age of the owner	years in 2000
EDU	Education level of the owner in 2000	EDU = 1 upper secondary education and more
		EDU=0 till lower secondary education
SEX	Gender of the owner	SEX =1 male
		SEX=0 female
UAA	Utilized agricultural area	Number of hectares in 2000
LSU	Livstock unit	Number of LSU in 2000
Netwrk	Network membership	Netwrk=0, No
		Netwrk=1, Yes
Nfamwrk	Family members working in the farm	Number of members in 2000
FS	Farm specialization	FS = 1 Arable
		FS = 2 Horticultural
		FS = 3 Permanent
		FS = 4 Ruminant
		FS =5 Granivore
		FS = 6 Mixed crops
		FS =7 Mixed livestocks
		FS=8 Mixed livestock crops
		FS=9 Other
PROV	Province of residence	PROV=1, Massa-Carrara
		PROV=2, Lucca
		PROV=3, Pisa
		PROV=4, Firenze
		PROV=5, Livorno
		PROV=6, Pisa
		PROV=7, Arezzo
		PROV=8, Siena
		PROV=9, Grosseto
		PROV=10,Prato
UNMP rate	Unemployment rate	by Municipaliy, in 2000
ACT rate	Activity rate	by Municipaliy, in 2000
Change FTE all	Full time equivalent all labour units	change 2000-2010
Change FTE fam	Full time equivalent household labour units	change 2000-2010
Change FTE ext	Full time equivalent external labour Units	change 2000-2010

Table 1: Description of covariates and outcome variables.

	Untreated		Treated	
	Mean	Standard Deviation	Mean	Standard Deviation
UAA	11.45	43.16	11.45	25.14
LSU	2.32	20.13	3.03	14.53
Netwrk	0.30	0.46	0.47	0.50
Nfamwrk	0.30	0.66	0.31	0.67
FS1	0.13	0.34	0.21	0.41
FS2	0.10	0.30	0.01	0.12
FS3	0.61	0.49	0.56	0.50
FS4	0.04	0.18	0.06	0.23
FS5	0.003	0.05	0.003	0.06
FS6	0.06	0.24	0.10	0.30
FS7	0.002	0.05	0.003	0.06
FS8	0.03	0.16	0.04	0.19
FS9	0.03	0.16	0.02	0.14
Age	55.62	13.33	55.33	13.12
Education	0.45	0.50	0.49	0.50
Gender	0.76	0.43	0.72	0.45
Massa	0.07	0.25	0.02	0.14
Lucca	0.12	0.32	0.05	0.21
Pistoia	0.13	0.34	0.07	0.26
Firenze	0.14	0.35	0.13	0.34
Livorno	0.04	0.20	0.06	0.24
Pisa	0.10	0.30	0.09	0.29
Arezzo	0.16	0.37	0.23	0.42
Siena	0.12	0.32	0.12	0.33
Grosseto	0.11	0.32	0.21	0.41
Prato	0.01	0.12	0.01	0.10
ACT rate	48.72	4.70	48.55	4.48
UNMP rate	6.03	1.79	5.76	1.61
Change FTE all	−0.028	3.123	0.090	1.118
Change FTE household	0.101	0.941	0.118	0.900
Change FTE external	−0.129	2.975	−0.028	0.621

Table 2: Descriptive statistics: treated and untreated farms.

Change in full time equivalent all labour units			
Interval	Observations	Mean	Standard Deviation
$0 < t < 500$	10373	0.187	0.779
$500 \leq t < 1250$	4290	0.137	0.966
$1250 \leq t < 2000$	1881	0.053	1.076
$2000 \leq t < 5000$	3096	-0.038	1.424
$5000 \leq t < 10000$	1378	-0.079	1.485
$10000 \leq t < 20000$	739	-0.183	1.726
$20000 \leq t < 50000$	338	-0.465	2.231
$t \geq 50000$	74	-1.458	4.504
Change in full time equivalent household labour units			
Interval	Observations	Mean	Standard Deviation
$0 < t < 500$	10373	0.190	0.748
$500 \leq t < 1250$	4290	0.152	0.888
$1250 \leq t < 2000$	1881	0.062	0.986
$2000 \leq t < 5000$	3096	0.007	1.026
$5000 \leq t < 10000$	1378	-0.052	1.171
$10000 \leq t < 20000$	739	-0.048	1.199
$20000 \leq t < 50000$	338	-0.080	1.190
$t \geq 50000$	74	-0.101	1.108
Change in full time equivalent external labour units			
Interval	Observations	Mean	Standard Deviation
$0 < t < 500$	10373	-0.003	0.211
$500 \leq t < 1250$	4290	-0.015	0.320
$1250 \leq t < 2000$	1881	-0.009	0.378
$2000 \leq t < 5000$	3096	-0.045	0.952
$5000 \leq t < 10000$	1378	-0.028	0.865
$10000 \leq t < 20000$	739	-0.136	1.126
$20000 \leq t < 50000$	338	-0.385	1.793
$t \geq 50000$	74	-1.358	4.289

Table 3: Descriptive statistics: employment-related outcome variables by levels of decoupled average annual payment.

Outcome variable	ATE	Std. Err.	95% Conf. Interval	
Change in amount of farm labour				
All	0.098	0.024	0.050	0.145
Household	0.039	0.012	0.016	0.061
External	0.059	0.022	0.017	0.102
Outcome variable	ATT	Std. Err.	95% Conf. Interval	
Employment				
All	0.083	0.025	0.034	0.131
Household	0.043	0.013	0.018	0.068
External	0.039	.022	−0.003	0.082

Table 4: ATE and ATT estimation (propensity-score matching - treatment model: logit). Robust standard errors (Abadie and Imbens,2012).

	Coefficient.	Standard Error	*P*-value
Gender	0.059	0.060	0.326
Age	−0.009	0.003	0.001
Education	−0.138	0.066	0.037
Family work	−0.038	0.057	0.509
Livestock unit	0.048	0.091	0.601
Local activity rate	−0.006	0.007	0.398
Network	0.189	0.058	0.001
Constant	6.903	0.335	0.000
Log likelihood = −1825.25		$Prob > chi^2 = 0.0000$	

Table 5: Estimate of the generalized propensity score. The log transformation of the treatment variable is used. The balancing property is satisfied at level 0.05

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	Coefficient	Standard Error	P-value
T	-0.0001	0.00005	0.272
T^2	$4.78e-09$	$3.40e-09$	0.160
GPS	-2.439	1.024	0.017
GPS^2	4.127	1.874	0.028
$T * GPS$	.0001	0.0003	0.860
$Constant$	0.491	0.132	0.000
$F(5, 1303) = 2.70$		$Prob > F = 0.0194$	

Table 6: Estimate of the dose-response function. Outcome variable: change in total full time equivalent labour units

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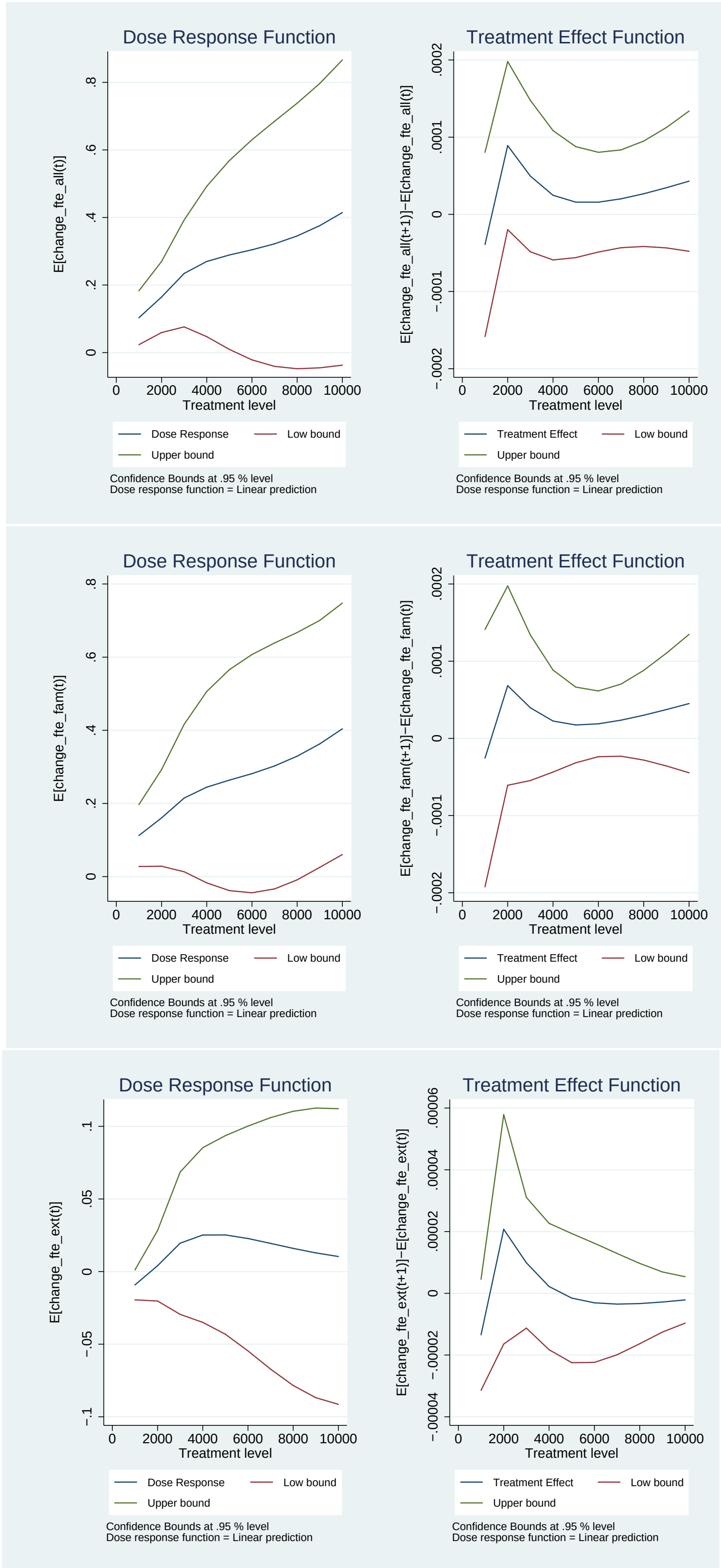

Figure 2: Dose-response and marginal treatment effect functions.