A flexible approach to efficiency analysis with multiple treatments: Using multiple imputation and quantile regression to estimate the impact of quality on the efficiency of cooperatives*

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Abstract

The impact of multiple treatments on firm efficiency can be estimated within the potential outcomes framework theorized by Donald B. Rubin. This paper develops a flexible two-step approach using multiple imputation algorithms to recover unobserved outcomes, and an ordinary regression method on the balanced sample for the estimation of causality. This method is applied to a study of the impact of quality and brand policies on efficiency of French small agricultural cooperatives. A quantile regression approach to frontier analysis and a zero-and-one-inflated beta regression for the export intensity are used on the second step.

Keywords: Agricultural Cooperatives, Causal Inference, Efficiency Analysis, Multiple Imputation, Missing Outcomes, Quantile Regression.
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> For over three decades, I have believed that all problems of causal inference should be viewed as problems of missing data: the potential outcomes under the not-received treatment are the missing data. A straightforward and valid way to think about missing data is to think about how to multiply impute them.
>
> D.B. Rubin
> *Direct and Indirect Causal Effects via Potential Outcomes*

1 Introduction

This paper aims to take Rubin's proposition (2004, p. 167), recently developed in Gutman and Rubin (2013), *seriously.* This proposition can be used as a starting point for an answer to the controversy surrounding the causal inference methodology. In effect, there is an ongoing debate on the theory of matching and randomization for causal inference, dating back to the 1990s (see for example (Heckman and Smith, 1995)). Quasi-experimentation using propensity score matching appear as an a-theoretical alternative to a structural econometric approach which is viewed by some authors as not suitable for "a cautious and risk-averse investigator [who] may care primarily about being right"(Sobel, 2005, p. 128). My approach is built on this controversy. The idea is to design the experiment *explicitly* : we have to show clearly the quantities subject to change due to the various different treatments. We have to open the black box on our assumptions as Leamer (1983, 1985) noted. Furthermore, because of the Bayesian background, my approach is reflexive: we can assess the impact of various informative or uninformative priors on the results. This thought experiment approach can be therefore of interest to any pragmatist, institutionalist or reflexive economic methodology (Davis and Klaes, 2003). My proposition is that this method can better handle the controversy on the various models for causal inference, some making stronger assumptions than others, than the frequentist method (see a recent paper of Heckman et al. (2014) for an argumentation). This proposition clearly fits into Heckman's causality econometric framework (see table 1) and it is also more natural for doing the necessary sensitivity analysis as proposed by Heckman (2005).

In its spirit this proposition is close to those of Imai and Van Dyk (2004); Ho et al. (2007, 2011) : matching as a first step preprocessing data and ordinary parametric method as a second step. The theoretical foundation of this procedure came from the seminal work of Rosenbaum and Rubin (1983). After matching, the sample is balanced on observed variables and therefore the postmatching analysis can be estimated as is done in randomized experiments[1]. For example Bravo-Ureta et al. (2012) estimated a sample selection stochastic

[1]see Guo and Fraser (2010, p. 154) for a general presentation.

Table 1: Three Distinct Tasks Arising in the Analysis of Causal Models from Heckman (2008, p.2)

Task	Description	Requirements
1	Defining the set of hypotheticals or counterfactuals	A scientific theory
2	Identifying causal parameters from hypothetical population data	Mathematical Analysis of point or set identification
3	Identifying parameters from real data	Estimation and testing theory

frontier analysis after matching on participation in an agricultural public policy.

This procedure is applied to the relation of quality and brand policies with the performance of agricultural cooperatives. Various authors have shown that cooperatives can develop successful branding programs as a way to "break out" of the commodity price cycle (Beverland, 2007). Branding and quality signalization can be mixed in agricultural cooperatives (Kontogeorgos, 2012). To my knowledge few papers had been written on this topic, Soboh et al. (2009) didn't mention anything related to brand or quality in their literature review. My contribution will try to fill this gap.

The paper is organized as follows. In the next section, I expose the problem of non-binary treatment and multiple outcomes, the theory of multiple imputation dealing with the problem of potential outcomes and the quantile regression approach to frontier analysis. In the third section, I present a case study based on a French survey on small agricultural cooperatives. I study the impact of quality and brand policies on production and export performance. Finally, the generalization of this method will be discussed in the conclusion.

2 Causal Inference as a Missing Data Problem

Since its apparition in the late 1970s, and its development by D.B Rubin (see (Rubin, 1987, 1996)), multiple imputation has been applied to a variety of areas. In a comprehensive handbook, S. Van Buuren notes that multiple imputation has been extended for dealing with measurement errors [2], comparability of international surveys and "can also be useful to correct for imbalances in observational studies. No such studies seem to have appeared yet"(Van Buuren, 2012, p.255). To our knowledge, few studies can be cited (See(Taylor and Zhou, 2009; Bondarenko and Raghunathan, 2010; Piesse et al., 2010; Gutman and Rubin, 2013)), all based on the works of D.B. Rubin (See (Rubin, 2004, 2005, 2006; Jin and Rubin, 2008). My proposition is a direct extension of these previous works[3].

Gelman (2011) notes three different problems for causal inference: the first is the difficulty of generalizing from experimental to realistic settings; the second is studying questions of

[2]see Blackwell et al. (2014) for a paper on the ability of multiple imputation to handle measurement errors.

[3]Therefore readers may be interested in reading these studies.

forward causation in observational studies or experimental settings with missing data (the traditional focus of causal inference in the statistics and biostatistics literature); and the last is to recall that missingness is inherent in the counterfactual definition of causal effects. Every counterfactual or potential outcome can be conceived in a theoretical missing values framework. A counterfactual is a potential outcome or the state of affairs that would have happened in the absence of the cause (Guo and Fraser, 2010). By definition, it is not observed in real data and referred to a *hypothetical* situation. This "fundamental problem of causal inference" (Holland, 1986) forces the researcher to use all known information (data, beliefs, etc.) to find a suitable value for this hypothetical situation in order to make valid inference. Therefore the classical definition of ACE (Average Causal Effect) by Rubin (1978) which is the average difference between potential outcomes under different treatments can be estimated by multiple imputation.

2.1 Missing Data and Potential Outcomes

Using the notation of Gelman et al. (2014), we can write that an observation is said to be MAR (Missing At Random)[4] if conditional on the observed data the probability of being missing is unrelated to the unobserved data.

$$P(I|y,\phi) = P(I|y_o, y_m, \phi) = P(I|y_o, \phi) \tag{1}$$

with y partitioned between y_m and y_o respectively the missing and the observed part of y, I an inclusion indicator with $I = 1$ if y is observed and $I = 0$ if y is missing, and ϕ the parameters governing the missing data mechanism.

With θ the parameters of the data model, we have

$$P(y_o, I|\phi, \theta) = P(I|y_o, \phi)P(y_o|\theta) \tag{2}$$

we have: $y_o = (y_{o,1}, y_{o,0})$, $y_m = (y_{m,1}, y_{m,0})$ and I can be seen as the indicator choice of the treatment.

Therefore, the potential outcome framework makes it clear that causal inference may be regarded as a missing-data problem, as illustrated below (Piesse et al., 2010).

Table 2: Illustration of missing-data status among potential outcomes with two treatment levels

Treatment status	$Y(0)$	$Y(1)$
$T = 0$	Observed	Not observed
$T = 1$	Not observed	Observed

The standard one binary treatment framework can be easily extended to multiple binary treatments. For example, with two binary treatments T_1 and T_2, we have:

[4]an observation is said to be MCAR (Missing Completely At Random) if the probability of being missing is unrelated to the observed and unobserved data on that unit.

Table 3: Illustration of missing-data status among potential outcomes with two binary treatments

Treatment status	$Y(0,0)$	$Y(1,0)$	$Y(0,1)$	$Y(1,1)$
$(T_1 = 0, T_2 = 0)$	Observed	Not observed	Not observed	Not observed
$(T_1 = 1, T_2 = 0)$	Not observed	Observed	Not observed	Not observed
$(T_1 = 0, T_2 = 1)$	Not observed	Not observed	Observed	Not observed
$(T_1 = 1, T_2 = 1)$	Not observed	Not observed	Not observed	Observed

Here there are four potential states and only one is observed. We just have to impute the three missing states and treat all four states as four observations for one individual on the second step (using methods suitable for clustered data). This problem can be seen as an aggregation problem of N independent surveys in only one survey, as in cross-national survey (Van Buuren, 2012).

In order to tackle the high pattern of missingness, in addition to informative prior, other assumptions can be done (for example exclusion restriction and instrumental variable that are traditional in econometrics (Gelman and Hill, 2006)). In effect we may face a selection problem : the values of y_0 and y_1 that are observed are not necessarily a random sample of the potential y_0 or y_1 distributions. In the generalized Roy model (Heckman and Vytlacil, 2005), the agent choose y_1 (respectively y_0) if the net utility $D^* = y_1 - y_0 - C$ is positive (respectively negative) with C the cost of moving from the benchmark state 0 of no-treatment to the state 1 of treatment. This model is traditional identified by an exclusion restriction (a variable present in the selection process is absent in the outcome equation), although it might simply identified by the correlation of the residuals. As noted by Schafer and Kang (2008, p. 306) (see also (Gelman et al., 2014)), "in causal inference, Multiple Imputation would require us to make assumptions about the inestimable partial correlation between y_1 and y_0 given the covariates. Although this may seem troubling, inferences about ACEs are not concerned with what we assume about this parameter".

2.2 A first preprocessing step using multiple Imputation Estimation

Various algorithms [5] can be used for the imputation of the data. The first is Multivariate Imputation with Chained Equation (MICE) or Fully Conditionally Specified Models (FCS). This algorithm uses a modified version of Gibbs sampler (White et al., 2011). A Bayesian one (Su et al., 2011) is implemented in the R package *MI*. Although theoretical weakness of this approach is that the specified conditional densities can be incompatible, simulations show that it essentially produces unbiased estimates even when that condition is violated (Van Buuren et al., 2006). Furthermore as A. Gelman noted: "One may argue that having a joint distribution in the imputation is less important than incorporating information from other variables and unique features of the dataset (e.g., zero/nonzero features in income

[5] See the relevant papers for the description of the different algorithms.

components, bounds, skip patterns, nonlinearity, interactions)" (Gelman, 2004). Another possibility is to use MCMC (Markov Chain Monte Carlo). A multivariate normal version modified with logical bounds on 0 and taking account the clustering of observations (Honaker and King, 2010) is implemented in the R package *AMELIA* (Honaker et al., 2011). Divide the data matrix D into an observed and a missing part, with $D = \{D^{obs}, D^{mis}\}$. D is assume to be multivariate normal $D \hookrightarrow N(\mu, \Sigma)$ with mean μ and variance Σ. Missing values $\tilde{Y}_{ij}^{mis}$ for the observation i and the variable Y_j are imputed from a linear regression:

$$\tilde{Y}_{ij}^{mis} = Y_{i,-j}.\tilde{\beta} + \tilde{\epsilon}_i \tag{3}$$

with β the regression coefficients calculated deterministically from μ and Σ. The algorithm proposed in *AMELIA* is based on EMB (Expectation-Maximization with Bootstrapping) (see Honaker and King (2010, p. 577)). It generates estimates of the missing elements based on the observed part of D. In the Expectation-step, missing values are estimated with a generalized version of the previous equation based on the *current* estimates of μ and Σ and the observed data. In the Maximization-step, a new estimate of μ and Σ is computed from the current version of the completed data. These steps are repeated until convergence of the iterations.

Various authors evaluate these different procedures. In general, semi-parametric methods like PMM (Predictive Mean Matching) seem to perform well and can be seen as a good work-around (Van Buuren, 2012; Su et al., 2011; Yu et al., 2007) of other procedures. But in presence of high amount of missingness, which is the case of our approach, bias can appear, as these procedures only imputed observations in the range of observed values. Multivariate normal with logical bounds can be more robust as one can use ridge prior (Honaker and King, 2010) (see next section). On the other hand, Multivariate normal with logical bounds may be less robust than PMM against misspecification of imputation model (and presence of skewed distributions) (Marshall et al., 2010; Van Buuren, 2012; Kropko et al., 2014). We can use a ridge prior in order to tackle the problem of high missingness. It helps with numerical stability by smoothing estimated covariances toward zero without changing the means or variances (Honaker and King, 2010). This prior can be regarded as a form of empirical Bayes inference (see (Schafer, 1997), a method in which the prior distribution is estimated from the data [6].

An alternative is a Bayesian conditional multiple imputation with an appropriate prior that can stabilize the estimated potential outcomes. Gelman et al. (2008) propose a weakly informative prior, which is "an attempt to let the data speak while being strong enough to exclude various unphysical possibilities which, if not blocked, can take over a posterior distribution in settings with sparse data" (Gelman, 2009, p. 176). As observed by Rubin (2004), we can place restrictions on the possible values of the potential outcomes using Bayesian prior distributions. The priors used in both multiple imputation algorithms have in common to

[6] In contrast to standard Bayesian methods, for which the prior distribution is fixed by definition prior to the observation of the data (Casella, 1985).

lower the probability of extreme values and handle sparse data.

Our benchmark algorithm will be $AMELIA$ because informative Bayesian priors about individual missing data cells can be included. $AMELIA$ has also an advantage in its flexibility and its efficiency. The incorporation of priors follows basic Bayesian analysis where the imputation turns out to be a weighted average of the model-based imputation and the prior mean, where the weights are functions of the relative strength of the data and prior (Honaker and King, 2010). These informative prior can come from the elicitation of expert belief or from the analysis of previous studies (Garthwaite et al., 2005) and are helpful with sparse data (Lenk and Orme, 2009).

Multiple imputation is subject to the problem of the inclusion of the substantive model and the imputation model (Carpenter and Kenward, 2013). The substantive model and the imputation model are said to be *congenial* (Meng, 1994). This principle implies that the number of predictors should be chosen as large as possible, beyond the variable of interest (used in the econometric models). It reinforces the plausibility of the MAR assumption (Van Buuren and Groothuis-Oudshoorn, 2011). This assumption of MAR is fundamental for most of the multiple imputation approaches. Imai (2013) has proposed that the MAR assumption is analogous to the unconfoundedness hypothesis in matching studies. This assumption is the following:

$$(Y_{0,i}, Y1, i) \perp T_i | X \tag{4}$$

Conditional on covariates X the assignment (or the choice observed) of a treatment T_i is independent of the outcomes of non-treatment and treatment (respectively $Y_{0,i}$ and $Y1, i$. In other words, conditional on observed variables, the observation of the outcome is independent of the expected outcome values. Therefore the outcome is missing at random. Note that imputation based on MNAR (Mssing Not At Random) assumption, missingness depending on the unobserved outcome, is currently under development (e.g. pattern-mixture model, selection mode... (see Carpenter and Kenward (2013). As noted by Molenberghs et al. (2008), the fundamental problems that are implied by these models are that tests of sensitivity to unverifiable modeling assumptions are needed. Fortunately the overimputation procedure (described in the next section) can be used as a way to graphically inspect the plausibility of the MAR assumption.

Another important assumption, the SUTVA (Stable Unit Treatment Value Assumption) imposes an exclusive restriction of no social interactions. In effect, this assumption imposes the fact that the value of the outcome for a unit exposed to a treatment will be the same no matter what treatments the other units receive. Procedures allowing for the relaxation of this assumption are currently under development (Heckman and Vytlacil, 2005).

2.3 Semi-parametric and mixture approaches to efficiency analysis

Various possible approaches to frontier analysis with parametric (such as stochastic frontier analysis) or non-parametric (such as data envelopment analysis) methods are traditionally used. An alternative is the semi-parametric approach of quantile frontier analysis. This approach has been applied to the analysis of bank efficiency (Behr, 2010; Koutsomanoli-Filippaki et al., 2013), health system performance (Liu et al., 2008), hotel industry efficiency (Bernini et al., 2004) or the impact of information and communication technology within manufacturing enterprises (Brasini and Freo, 2012).

Quantile regression models the quantiles of the conditional distribution of the outcome as a function of observed covariates. For a quantile $\tau \in (0, 1)$ and a vector X of covariables, we have (Kleiber and Zeilis, 2008):

$$Q_y(\tau|X) = X_i^T \beta \tag{5}$$

with $i = 1, ..., N$ observations and β a vector of parameters to estimate, which are obtained by the minimization of $\sum_i \gamma_\tau(y_i - X_i^T \beta)$. γ_τ denotes the piecewise linear function with $\gamma_\tau(u) = u\tau - I(u < 0)$ for I being the indicator function.

The quantile regression estimates for the top-quantile τ_b choosen as a benchmark describe the production process of firms representing the efficient production frontier or benchmark enterprises.

A byproduct of this approach is to define the usual Debreu-Ferrel technical output efficiency as the ratio of the observed output to the output predicted by the production frontier . For the quantile approach to frontier analysis, $\hat{y}_i^b$ is the output predicted for a firm i using the parameters estimated for the benchmark quantile, and y_i the observed outcome. So we have:

$$TE_i = \frac{y_i}{\hat{y}_i^b} \tag{6}$$

with TE_i the technical efficiency of the firm i. By construction, $TE_i = 1$ for the firm belonging to the benchmark quantile [7].

In order to control for industrial composition, Brasini and Freo (2012) define E_i the efficiency outcome as

[7] Note that quantile approach, contrary to stochastic frontier analysis, has the capacity to estimate negative technical efficiency that can appear when one estimate a profit function. In effect, firms can throw away more than 100% of their potential profits (Berger and Mester, 1997). By construct, TE_i is bounded at 0 in the case of stochastic frontier analysis.

$$E_i = -(\ln TE_i - \ln \bar{T}E_i) \tag{7}$$

with $\ln \bar{T}E_i$ the mean of the log-transformed technical efficiency over industry.

In contrast to stochastic frontier analysis, the quantile frontier analysis is flexible as it doesn't require structural parameters . There is a ongoing debate on the inclusion of qualitative variables in the stochastic frontier analysis as an traditional input or additional environmental variable .Behr (2010) also shows that a quantile approach is a robust alternative to stochastic frontier analysis: it is robust to outlier and measurement errors and can deal with heteroscedasticity. One problem mentioned in the literature is that the choice of an appropriate quantile to represent the frontier is relatively arbitrary (Saastamoinen, 2014). Behr (2010) proposes to use the 95th quantile as a benchmark. What seems to be arbitrary for some authors can easily be handled in a Bayesian approach. It simply means an assumption on the share of the population which is efficient? This assumption logically depends on the problem at hand (and prior information available) and on the size of the sample [8]. Choosing the 95th quantile as starting point, I conduct sensitivity analysis using other quantiles (90 or 99th).

I extend the previous studies by taking account one of the main features of our imputed database: we have repeated measures for the same individuals. For example Koutsomanoli-Filippaki et al. (2013) or Brasini and Freo (2012) conduct pooled analysis using a standard quantile regression estimator. Various extension of this estimator (Koenker and Bassett, 1978) address the clustered aspect of data induced by repeated measures or longitudinal design. Linear quantile mixed model algorithm (Geraci, 2014; Geraci and Bottai, 2014) can handle multilevel data. As we have small cluster (with only 4 observations), we choose as a benchmark procedure the algorithm proposed by Parente and Santos Silva (2013) which is a quantile regression with clustered data. This algorithm is implemented in Stata with the procedure *qreg*2 (see (Machado et al., 2013)). For the pooling approach, we can also use the bayesian censored quantile regression estimator, estimated by MCMC. One advantage of this estimator is that no information is lost from the first to the second step as we perform the second step estimation procedure on each of the imputed sample and use all the distribution to assess the confidence interval [9].

Export performance can be measured with the proportion of gross sales made abroad. This is the *export intensity*. This outcome is a share and bounded at 0 and 1. Bottai et al. (2010) propose a logistic quantile regression model. An important assumption is that positive proportion, one and zero come from the same process. An alternative will be to estimate a zero and one inflated beta regression (Ospina and Ferrari, 2012). This model assumes that the response variable has a mixed continuous–discrete distribution with probability mass at zero or one. It will estimate the probabilities of having the value 0 and/or 1 as separate

[8] The benchmark population needs to be sufficiently large for obtaining robust estimations.

[9] As proposed by S. Van Buuren.

processes (using logistic regressions). The continuous component of the model (i.e. $]0,1[$) is estimated by a beta regression:

$$f(y,\mu,\phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1} \tag{8}$$

with $y \in (0,1)$, Γ the gamma function, and μ and ϕ the parameters of the beta distribution $B(\mu,\phi)$.

In order to have unbiased estimates, the second-step regression has to be estimated on each of the Mimputed samples. For a parameter θ, the complete-data-estimation is a combination of the M estimation:

$$\bar{\theta}_M = \frac{1}{M}\sum_{m=1}^{M} \dot{\theta}_m \tag{9}$$

The total variance associated with $\bar{\theta}_M$ is

$$T_M = \frac{1}{M}\sum_{m=1}^{M} \hat{W}_m + \frac{M+1}{M}\frac{1}{M-1}\sum_{m=1}(\hat{\theta}_m - \bar{\theta}_m) \tag{10}$$

with $\hat{W}_m$ the within-imputation variance.

3 The impact of quality on the efficiency of cooperatives

3.1 Presentation of the problem and the sample design

The main problem of using administrative sources for research (Desrosieres, 2000) is that sampling process, questions, collection of data... are designed for the specific needs of the official statistician but not for the needs of the researcher. I describe the design of agricultural cooperatives survey in which different problems appear. There are three different kinds of cooperatives: standard agricultural cooperatives, 2nd order cooperatives (cooperatives of cooperatives) and multistakeholder cooperatives[10]. Due to the particularity of second-order cooperatives and multistakeholder cooperatives, we retain only the small standard agricultural cooperatives in the sample. This exhaustive database of small cooperatives, with less than 10 employees, had been only studied by Magrini et al. (2011). Our contribution is original, because the authors didn't correct for the endogeneity between quality and efficiency.

The treatments are the two variables related to the quality policy ($QUALITY$, $BRAND$). Based on a literature review concerning cooperative efficiency, it is reasonable that the following variables can vary under different treatment states. Two are related to the outcome : the

[10]this is the SICA: société d'intérêt collectif agricole - Society of Agricultural Collective Interest.

gross sales of the cooperative GS and the gross sales made abroad ($EXPORT$). We use the export intensity ($SHARE-EXPORT$). Three are related to the inputs : the labor ($RCH13$), the investment ($INV11$) and the number of members ($MEMBERS$). The control variables are supposed to not vary under the treatment states : the control variables: the relation to the other enterprises ($SUBSIDIARY$, $PARTICIPATION$), the industries (variables beginning with *ape*), and the previous certifications ($NATCERTIF$, $INTERCERTIF$) (see appendix 1).

3.2 Results

Honaker et al. (2011, p.25) states that "the violation of the logical bounds represents part of the true uncertainty of imputation". Gelman et al. (2014) highlight the danger of not using strong external information especially when the data is sparse [11]. In our case, because we have a high amount of missingness, every prior information is useful. Therefore I choose to set the lower boundary at 0 because all the variables are non-negative by nature. Amelia implements these bounds by rejection sampling [12]. I choose a reasonable value for the ridge prior with $r = 0.05$. The other estimation based on various priors are available in appendix 1.

In order to graphically inspect the plausibility of MAR assumption, I use the overimputation procedure developed by Honaker et al. (2011). Overimputing involves sequentially treating each of the observed values as if they had actually been missing. For each observed value a large number of imputations allows us to construct a confidence interval of what the imputed value would have been, had any of the observed data been missing. We can then graphically inspect whether the observed data tend to fall within the region where it would have been imputed had it been missing (see appendix 1).

On the second step, the model estimated for GS is

$$Q_{GS}(\tau|X) = \beta_1.MEMBERS+\beta_2.MEMBERS^2+\beta_3.RCH13+\beta_4.RCH13^2+\beta_5.INV11+\beta_6.INV11^2 \\ + \beta_7.QUALITY + \beta_8.BRAND + \beta_9.QUALITY.BRAND + \alpha + \sum_j \gamma_j.CONTROL_j \quad (11)$$

with j control variables.

As it is standard in quantile regression, I choose $\tau = \{0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 090, 0.95, 0.99\}$. Only results from clustered quantile regression are reported here, as there is only a slight difference with other estimations [13]. The coefficients and the margins estimated are reported in the appendix 2. The impact of a marginal member increases with the quantile: from $1,098$ euros at the 10th quantile to $4,481$ euros at the median, $9,511$ at the 90th quantile and even $22,879$ euros at the 99th quantile.

[11] see also http://andrewgelman.com/2013/11/21/hidden-dangers-noninformative-priors/

[12] When drawing from their posterior, resampling is done repeatedly until a draw that satisfies all the logical constraints is found. In our case, if after all the resampling, the imputations are still negatives, Amelia would simply impute 0. SeeHonaker et al. (2011, p. 23).

[13] all results are available upon request.

Quality has a net effect on gross sales from the 5th quantile to the 50th quantile. The net effect is $255,000$ euros at the 50th quantile. This effect is to be compared with the result observed without balancing the sample, which is only $188,000$ euros (see table 4). Not accounting for endogeneity of the "treatment" lead to an underestimation of the impact of quality on gross sales. Furthermore it leads to avoid a counter-intuitive negative impact at the 99th sample. The effect of brand policy is not significant for any quantile for the corrected sample.

Table 4: Effects of Quality and Brand on the Gross Sales

	effect of $Quality = 1$	effect of $Brand = 1$
Q(0.01)		
corrected sample	5.6451 (5.9987)	4.9581 (9.8595)
uncorrected sample	110.8465*** (39.5305)	4.9575 (45.7099)
Q(0.05)		
corrected sample	62.6032** (24.7788)	34.0446 (35.5738)
uncorrected sample	142.2878*** (30.7940)	-25.2286 (35.6076)
Q(0.10)		
corrected sample	139.1950*** (39.8334)	55.3562 (55.8294)
uncorrected sample	103.1928** (43.1928)	33.5798 (49.9446)
Q(0.25)		
corrected sample	233.3617*** (57.3309)	79.7918 (79.5024)
uncorrected sample	88.1465 (62.6370)	35.1626 (72.4383)
Q(0.50)		
corrected sample	255.4063*** (91.2456)	-62.3444 (122.0424)
uncorrected sample	188.6687** (90.2264)	-92.5838 (104.2204)
Q(0.75)		
corrected sample	199.6906 (149.2327)	-299.9367 (203.6520)
uncorrected sample	348.315 (247.3799)	-280.6546 (286.0500)
Q(0.90)		
corrected sample	108.0132 (236.8795)	-559.2106 (346.3007)
uncorrected sample	218.0097 (498.0654)	-518.0847 (575.9923)
Q(0.95)		
corrected sample	156.1768 (374.7895)	-645.6450 (544.5567)
uncorrected sample	-22.4547 (710.6499)	-483.8087 (821.7377)
Q(0.99)		
corrected sample	1,016.2588 (1,050.6128)	892.6492 (1,671.2809)
uncorrected sample	-525.1768** (253.9465)	-981.0368*** (292.6639)

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

As usual, investment and labor have a positive impact on gross sales. As one can see in the table 5, the efficiency of the cooperatives increases with a quality label and a brand.

The same variables are used for the beta regression with $SHARE - EXPORT$ as a dependent variable (see appendix 3). Conditionally on exporting, brand has a marginal effect of 0.0149 (see table 6). For cooperatives that already export, having a brand policy increase

Table 5: Efficiency by level of treatment

	TE	E
$Quality = 0$ and $Brand = 0$	0.2925***	0.9307***
	(0.0133)	(0.0721)
$Quality = 1$ and $Brand = 0$	0.3279***	0.5652***
	(0.0113)	(0.0566)
$Quality = 0$ and $Brand = 1$	0.3382***	0.6668***
	(0.0149)	(0.0742)
$Quality = 1$ and $Brand = 1$	0.3745***	0.4513***
	(0.0135)	(0.0643)

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the export intensity by 1.5%. The impact of quality is not statistically different from 0. But what is interesting is that the net effect of brand policy is greater for quality labeled cooperatives: in effect cooperative with a brand and a quality label have *ceteribus paribus* an 3.45% increase in their export intensity in comparison with a cooperative with no brand and no quality label.

Table 6: impact of quality and brand on exporting proportion

	SHARE-EXPORT
$Quality = 0$	0.0751***
	(0.0054)
$Quality = 1$	0.0785***
	(0.0055)
$Brand = 0$	0.0746***
	(0.0053)
$Brand = 1$	0.0895***
	(0.0068)
$Quality = 0$ and $Brand = 0$	0.0744***
	(0.0055)
$Quality = 0$ and $Brand = 1$	0.0807***
	(0.0075)
$Quality = 1$ and $Brand = 0$	0.0750***
	(0.0056)
$Quality = 1$ and $Brand = 1$	0.1089***
	(0.0086)

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4 Conclusion

Potential outcomes seem to be a successful approach to causal inference. The novel two-step method proposed in this paper is a simple and flexible approach to a productivity analysis. The EMB algorithm developed by Honaker and King (2010) allows for informative Bayesian priors placed on missing individual cell values. The overimputation procedure is precious to inspect the hypothesis of MAR. I apply this method to a French agricultural cooperatives sample. Quality has a positive and significant effect on gross sales but only for the small to median cooperatives. It also has a significant effect on exportation but only in conjounction with a brand policy.

Various robustness checks can be made in order to improve our reflexive approach: using Bayesian conditional imputation instead of multivariate normal imputation, using single non-parametric imputation using various informative priors, and using other parametric analysis in the second step. For the pooled model, we can use the Bayesian algorithm with adaptive lasso variable selection in order to estimate a parsimonious model (Alhamzawi et al., 2012). Uninformative or informative priors can be placed on the various parameters. For example, in the frontier analysis framework, one can expect that the parameter estimated for labor will be strictly positive.

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5 Appendix

5.1 Appendix 1: Multiple imputation robustness checks

5.2 Appendix 2: Results of the quantile regression

Table 7: Quantile(0.01)

VARIABLES	coef.	dy/dx
11.ape3	-2.0143	-2.0143
	(31.4139)	(31.4139)
12.ape3	-34.3351	-34.3351
	(37.0484)	(37.0484)
13.ape3	3.3013	3.3013
	(24.7601)	(24.7601)
14.ape3	0.2823	0.2823
	(24.2744)	(24.2744)
15.ape3	-3.4977	-3.4977
	(48.8083)	(48.8083)
16.ape3	12.6631	12.6631
	(25.7353)	(25.7353)
17.ape3	6.1523	6.1523
	(24.6090)	(24.6090)
18.ape3	-1.5305	-1.5305
	(29.5114)	(29.5114)
ADHA	0.0365	0.0517
	(0.0424)	(0.0387)
c.ADHA#c.ADHA	0.0001**	
	(0.0000)	
filiale	-1.0632	-1.0632
	(10.6161)	(10.6161)
participation	10.3679	10.3679
	(17.3232)	(17.3232)
1.qualite	4.4243	5.6451
	(6.3926)	(5.9987)
1.marqueoui	1.2344	4.9581
	(12.2524)	(9.8595)
1.qualite#1.marqueoui	11.9066	
	(18.9291)	
certinational	4.7617	4.7617
	(7.2086)	(7.2086)
certifinter	-1.5069	-1.5069
	(8.3396)	(8.3396)
affiliation	0.6670	0.6670
	(5.9905)	(5.9905)
INV11_	-0.1152*	-0.0278
	(0.0637)	(0.0571)
c.INV11_#c.INV11_	0.0008***	
	(0.0002)	
RCH13_	0.0140	0.0439
	(0.0686)	(0.0360)
c.RCH13_#c.RCH13_	0.0001	
	(0.0003)	
Constant	-5.9818	
	(24.3604)	

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Quantile(0.05)

VARIABLES	coef.	dy/dx
11.ape3	-20.5669	-20.5669
	(113.0448)	(113.0448)
12.ape3	-242.3959*	-242.3959*
	(124.4309)	(124.4309)
13.ape3	11.7285	11.7285
	(92.2732)	(92.2732)
14.ape3	-29.9048	-29.9048
	(90.4970)	(90.4970)
15.ape3	-45.3807	-45.3807
	(168.2631)	(168.2631)
16.ape3	54.1429	54.1429
	(94.0250)	(94.0250)
17.ape3	16.2667	16.2667
	(90.4756)	(90.4756)
18.ape3	-42.0895	-42.0895
	(104.0323)	(104.0323)
ADHA	0.5476***	0.5318***
	(0.1779)	(0.1649)
c.ADHA#c.ADHA	-0.0001	
	(0.0001)	
filiale	-18.1783	-18.1783
	(39.0735)	(39.0735)
participation	54.6222	54.6222
	(54.5856)	(54.5856)
1.qualite	52.4271**	62.6032**
	(26.4979)	(24.7788)
1.marqueoui	3.0054	34.0446
	(45.4346)	(35.5738)
1.qualite#1.marqueoui	99.2469	
	(69.3167)	
certinational	24.6483	24.6483
	(27.8654)	(27.8654)
certifinter	-6.2750	-6.2750
	(33.0245)	(33.0245)
affiliation	20.2036	20.2036
	(22.7327)	(22.7327)
INV11_	0.3277	0.3853*
	(0.2433)	(0.2282)
c.INV11_#c.INV11_	0.0005***	
	(0.0002)	
RCH13_	0.2994	0.4205***
	(0.2403)	(0.1584)
c.RCH13_#c.RCH13_	0.0005	
	(0.0007)	
Constant	-35.5568	
	(89.6439)	

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Quantile(0.10)

VARIABLES	coef.	dy/dx
11.ape3	-30.6604	-30.6604
	(170.4270)	(170.4270)
12.ape3	-475.8254**	-475.8254**
	(193.2421)	(193.2421)
13.ape3	45.7634	45.7634
	(138.7500)	(138.7500)
14.ape3	-52.2312	-52.2312
	(136.3826)	(136.3826)
15.ape3	-107.8801	-107.8801
	(258.1062)	(258.1062)
16.ape3	150.7539	150.7539
	(143.8554)	(143.8554)
17.ape3	53.7422	53.7422
	(136.4330)	(136.4330)
18.ape3	-74.5904	-74.5904
	(156.5037)	(156.5037)
ADHA	1.1505***	1.0982***
	(0.3065)	(0.2869)
c.ADHA#c.ADHA	-0.0003**	
	(0.0001)	
filiale	-43.5338	-43.5338
	(62.0725)	(62.0725)
participation	89.5067	89.5067
	(81.2538)	(81.2538)
1.qualite	121.7136***	139.1950***
	(42.5658)	(39.8334)
1.marqueoui	2.0344	55.3562
	(71.1238)	(55.8294)
1.qualite#1.marqueoui	170.4946	
	(104.2638)	
certinational	43.7500	43.7500
	(44.8154)	(44.8154)
certifinter	-15.5168	-15.5168
	(53.6534)	(53.6534)
affiliation	47.3736	47.3736
	(36.4516)	(36.4516)
INV11_	0.9074**	0.9235***
	(0.3554)	(0.3310)
c.INV11_#c.INV11_	0.0001	
	(0.0003)	
RCH13_	0.9361**	0.9891***
	(0.3635)	(0.2556)
c.RCH13_#c.RCH13_	0.0002	
	(0.0008)	
Constant	-72.2775	
	(134.3483)	

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10: Quantile(0.25)

VARIABLES	coef.	dy/dx
11.ape3	-105.8047	-105.8047
	(250.8017)	(250.8017)
12.ape3	-991.8529***	-991.8529***
	(277.1888)	(277.1888)
13.ape3	119.7240	119.7240
	(220.3790)	(220.3790)
14.ape3	-127.3774	-127.3774
	(210.8553)	(210.8553)
15.ape3	-300.1694	-300.1694
	(358.2758)	(358.2758)
16.ape3	383.0768	383.0768
	(238.0316)	(238.0316)
17.ape3	174.7480	174.7480
	(215.0924)	(215.0924)
18.ape3	-237.2784	-237.2784
	(234.3162)	(234.3162)
ADHA	2.7931***	2.6449***
	(0.5008)	(0.4728)
c.ADHA#c.ADHA	-0.0007***	
	(0.0002)	
filiale	-60.3653	-60.3653
	(97.8742)	(97.8742)
participation	163.9929	163.9929
	(114.7464)	(114.7464)
1.qualite	216.9355***	233.3617***
	(60.3694)	(57.3309)
1.marqueoui	29.6888	79.7918
	(101.1304)	(79.5024)
1.qualite#1.marqueoui	160.2029	
	(141.9453)	
certinational	103.5970	103.5970
	(70.2828)	(70.2828)
certifinter	-6.6246	-6.6246
	(80.6136)	(80.6136)
affiliation	136.1776***	136.1776***
	(51.6951)	(51.6951)
INV11_	1.6259***	1.6144***
	(0.4974)	(0.4572)
c.INV11_#c.INV11_	-0.0001	
	(0.0004)	
RCH13_	2.2699***	2.0930***
	(0.5517)	(0.4018)
c.RCH13_#c.RCH13_	-0.0008	
	(0.0011)	
Constant	-15.9423	
	(208.7686)	

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: Quantile(0.50)

VARIABLES	coef.	dy/dx
11.ape3	-361.7660	-361.7660
	(401.9578)	(401.9578)
12.ape3	-1,574.0226***	-1,574.0226***
	(434.0917)	(434.0917)
13.ape3	96.0130	96.0130
	(360.4771)	(360.4771)
14.ape3	-297.5288	-297.5288
	(348.8342)	(348.8342)
15.ape3	-557.8527	-557.8527
	(576.1407)	(576.1407)
16.ape3	747.6819*	747.6819*
	(410.7790)	(410.7790)
17.ape3	406.6818	406.6818
	(361.9591)	(361.9591)
18.ape3	-562.4764	-562.4764
	(375.5747)	(375.5747)
ADHA	4.7139***	4.4813***
	(0.7563)	(0.7160)
c.ADHA#c.ADHA	-0.0012***	
	(0.0003)	
filiale	-80.3329	-80.3329
	(137.8129)	(137.8129)
participation	285.5171*	285.5171*
	(166.2360)	(166.2360)
1.qualite	274.2600***	255.4063***
	(95.7943)	(91.2456)
1.marqueoui	-4.8370	-62.3444
	(156.5606)	(122.0424)
1.qualite#1.marqueoui	-183.8781	
	(210.7621)	
certinational	200.3740*	200.3740*
	(107.8244)	(107.8244)
certifinter	-39.4779	-39.4779
	(129.4545)	(129.4545)
affiliation	218.4560***	218.4560***
	(81.6624)	(81.6624)
INV11_	2.7453***	2.6522***
	(0.8632)	(0.7972)
c.INV11_#c.INV11_	-0.0008	
	(0.0006)	
RCH13_	3.7988***	3.3798***
	(0.8040)	(0.5871)
c.RCH13_#c.RCH13_	-0.0018	
	(0.0014)	
Constant	373.1871	
	(346.7267)	

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Quantile(0.75)

VARIABLES	coef.	dy/dx
11.ape3	-801.3212	-801.3212
	(642.4603)	(642.4603)
12.ape3	-2,291.6444***	-2,291.6444***
	(637.3920)	(637.3920)
13.ape3	-11.3603	-11.3603
	(550.9807)	(550.9807)
14.ape3	-518.6481	-518.6481
	(540.5959)	(540.5959)
15.ape3	-1,115.9975	-1,115.9975
	(911.6407)	(911.6407)
16.ape3	1,321.1933**	1,321.1933**
	(635.8230)	(635.8230)
17.ape3	780.8898	780.8898
	(549.4097)	(549.4097)
18.ape3	-1,129.4532*	-1,129.4532*
	(594.4040)	(594.4040)
ADHA	7.0604***	6.7306***
	(1.1916)	(1.1302)
c.ADHA#c.ADHA	-0.0017***	
	(0.0004)	
filiale	-132.7892	-132.7892
	(214.8936)	(214.8936)
participation	345.8495	345.8495
	(280.3523)	(280.3523)
1.qualite	260.7706*	199.6906
	(155.7395)	(149.2327)
1.marqueoui	-113.6311	-299.9367
	(261.9896)	(203.6520)
1.qualite#1.marqueoui	-595.7063*	
	(346.0529)	
certinational	256.9491	256.9491
	(173.4108)	(173.4108)
certifinter	-30.7214	-30.7214
	(216.5507)	(216.5507)
affiliation	282.5122**	282.5122**
	(129.7145)	(129.7145)
INV11_	2.9718***	3.1261***
	(1.1113)	(1.0710)
c.INV11_#c.INV11_	0.0014***	
	(0.0005)	
RCH13_	4.3880***	4.1218***
	(1.1995)	(0.9484)
c.RCH13_#c.RCH13_	-0.0011	
	(0.0016)	
Constant	1,291.5100**	
	(525.5694)	

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13: Quantile(0.90)

VARIABLES	coef.	dy/dx
11.ape3	-1,136.2543	-1,136.2543
	(1,145.5290)	(1,145.5290)
12.ape3	-3,254.1153***	-3,254.1153***
	(1,134.0651)	(1,134.0651)
13.ape3	-143.2386	-143.2386
	(1,006.7866)	(1,006.7866)
14.ape3	-830.7298	-830.7298
	(991.0058)	(991.0058)
15.ape3	-1,623.9764	-1,623.9764
	(1,670.3246)	(1,670.3246)
16.ape3	1,973.9536*	1,973.9536*
	(1,083.3856)	(1,083.3856)
17.ape3	1,198.5159	1,198.5159
	(1,003.0217)	(1,003.0217)
18.ape3	-1,524.9937	-1,524.9937
	(1,083.3395)	(1,083.3395)
ADHA	9.9666***	9.5114***
	(2.0201)	(1.9037)
c.ADHA#c.ADHA	-0.0023***	
	(0.0007)	
filiale	-365.1874	-365.1874
	(339.1010)	(339.1010)
participation	477.2196	477.2196
	(462.4288)	(462.4288)
1.qualite	225.7312	108.0132
	(249.5024)	(236.8795)
1.marqueoui	-200.1483	-559.2106
	(439.4765)	(346.3007)
1.qualite#1.marqueoui	-1,148.0905*	
	(601.1708)	
certinational	317.9016	317.9016
	(271.2892)	(271.2892)
certifinter	-124.4133	-124.4133
	(341.0100)	(341.0100)
affiliation	389.0855*	389.0855*
	(220.1842)	(220.1842)
INV11_	3.7703**	3.8641**
	(1.7253)	(1.6552)
c.INV11_#c.INV11_	0.0009	
	(0.0009)	
RCH13_	4.9274**	4.6588***
	(1.9665)	(1.4662)
c.RCH13_#c.RCH13_	-0.0011	
	(0.0030)	
Constant	2,532.3928***	
	(969.6269)	

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 14: Quantile(0.95)

VARIABLES	coef.	dy/dx
11.ape3	-1,378.8775	-1,378.8775
	(1,772.5719)	(1,772.5719)
12.ape3	-4,052.0292**	-4,052.0292**
	(1,749.1682)	(1,749.1682)
13.ape3	-228.7885	-228.7885
	(1,500.6260)	(1,500.6260)
14.ape3	-1,132.4230	-1,132.4230
	(1,466.9791)	(1,466.9791)
15.ape3	-2,203.3841	-2,203.3841
	(2,633.9803)	(2,633.9803)
16.ape3	2,742.3202*	2,742.3202*
	(1,615.8428)	(1,615.8428)
17.ape3	1,626.6835	1,626.6835
	(1,513.9307)	(1,513.9307)
18.ape3	-1,808.8445	-1,808.8445
	(1,644.3651)	(1,644.3651)
ADHA	13.6883***	13.0022***
	(2.8368)	(2.6650)
c.ADHA#c.ADHA	-0.0035***	
	(0.0010)	
filiale	-553.3856	-553.3856
	(581.4166)	(581.4166)
participation	541.6300	541.6300
	(720.8459)	(720.8459)
1.qualite	271.4119	156.1768
	(395.4469)	(374.7895)
1.marqueoui	-294.1558	-645.6450
	(688.2055)	(544.5567)
1.qualite#1.marqueoui	-1,123.8756	
	(993.2536)	
certinational	222.1629	222.1629
	(432.7460)	(432.7460)
certifinter	-162.4805	-162.4805
	(517.8156)	(517.8156)
affiliation	405.5697	405.5697
	(348.0632)	(348.0632)
INV11_	4.0265	4.1011
	(2.7500)	(2.6348)
c.INV11_#c.INV11_	0.0007	
	(0.0017)	
RCH13_	4.7461	4.7147**
	(2.9733)	(2.1149)
c.RCH13_#c.RCH13_	-0.0001	
	(0.0051)	
Constant	3,482.6255**	
	(1,469.9157)	

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 15: Quantile(0.99)

VARIABLES	coef.	dy/dx
11.ape3	-932.6402	-932.6402
	(5,287.6199)	(5,287.6199)
12.ape3	-5,139.0685	-5,139.0685
	(5,062.1133)	(5,062.1133)
13.ape3	207.5839	207.5839
	(4,267.3976)	(4,267.3976)
14.ape3	-1,066.1879	-1,066.1879
	(4,136.1191)	(4,136.1191)
15.ape3	-2,897.0680	-2,897.0680
	(7,376.7458)	(7,376.7458)
16.ape3	10,205.2172**	10,205.2172**
	(4,871.5048)	(4,871.5048)
17.ape3	3,573.8931	3,573.8931
	(4,178.0085)	(4,178.0085)
18.ape3	-1,843.3505	-1,843.3505
	(4,647.3402)	(4,647.3402)
ADHA	24.2102***	22.8798***
	(6.2620)	(5.8448)
c.ADHA#c.ADHA	-0.0067***	
	(0.0025)	
filiale	-1,497.3409	-1,497.3409
	(1,595.1984)	(1,595.1984)
participation	1,194.5513	1,194.5513
	(1,939.0487)	(1,939.0487)
1.qualite	517.2975	1,016.2588
	(1,083.2949)	(1,050.6128)
1.marqueoui	-629.2789	892.6492
	(1,904.3725)	(1,671.2809)
1.qualite#1.marqueoui	4,866.3167	
	(3,670.0709)	
certinational	116.7999	116.7999
	(1,202.9851)	(1,202.9851)
certifinter	-128.6415	-128.6415
	(1,485.7026)	(1,485.7026)
affiliation	285.5788	285.5788
	(1,004.6479)	(1,004.6479)
INV11_	1.7462	1.9650
	(6.8239)	(6.4248)
c.INV11_#c.INV11_	0.0020	
	(0.0050)	
RCH13_	3.9909	5.3029
	(8.6167)	(5.7175)
c.RCH13_#c.RCH13_	0.0057	
	(0.0171)	
Constant	5,088.4126	
	(4,097.1099)	

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.3 Appendix 3: Results of the zero-one-inflated beta regression

Table 16: Results of the zero-one-inflated beta regression

	(1)	(2)	(3)	(4)
VARIABLES	proportion	oneinflate	zeroinflate	ln_phi
11.ape3	-0.0910	0.0298	-0.0359	
	(0.2699)	(1.9620)	(0.2898)	
12.ape3	0.2075	1.5744	-0.4860	
	(0.2625)	(1.9059)	(0.3444)	
13.ape3	-0.2394	-0.3537	-0.0864	
	(0.2229)	(1.8275)	(0.2508)	
14.ape3	-0.0969	0.0783	-0.3259	
	(0.2230)	(1.7920)	(0.2527)	
15.ape3	0.0324	-2.9000	0.5050	
	(0.3919)	(6.7322)	(0.3415)	
16.ape3	-0.0991	-0.6917	0.0359	
	(0.2284)	(1.8800)	(0.2611)	
17.ape3	-0.1105	-0.3241	-0.3174	
	(0.2244)	(1.8214)	(0.2527)	
18.ape3	-0.0187	0.4135	0.4654*	
	(0.2445)	(1.8628)	(0.2689)	
ADHA	**-0.0007*** **	-0.0052**	0.0005	
	(0.0002)	(0.0023)	(0.0004)	
c.ADHA#c.ADHA	**0.0000** **	0.0000	-0.0000	
	(0.0000)	(0.0000)	(0.0000)	
filiale	0.0245	0.1136	0.0164	
	(0.0699)	(0.4524)	(0.1117)	
participation	-0.0547	-0.4749	-0.1802	
	(0.0824)	(0.6856)	(0.1308)	
1.qualite	0.0088	**-0.4884***	**1.6155*** **	
	(0.0442)	(0.2936)	(0.0633)	
1.marqueoui	0.0869	-0.0525	**0.6188*** **	
	(0.0790)	(0.4772)	(0.1566)	
1.qualite#1.marqueoui	**0.3247*** **	**-14.0623*** **	**0.4549***	
	(0.1035)	(1.7195)	(0.2370)	
certinational	0.0911	-0.1122	-0.3511***	
	(0.0573)	(0.2942)	(0.0755)	
certifinter	-0.0154	0.0429	0.0404	
	(0.0659)	(0.3556)	(0.0835)	
affiliation	-0.0242	-0.1840	-0.0044	
	(0.0419)	(0.2500)	(0.0601)	
INV11_	-0.0005	-0.0014	-0.0071***	
	(0.0004)	(0.0034)	(0.0014)	
c.INV11_#c.INV11_	0.0000***	-0.0000	0.0000***	
	(0.0000)	(0.0000)	(0.0000)	
RCH13_	-0.0004	-0.0033	-0.0046***	
	(0.0003)	(0.0025)	(0.0009)	
c.RCH13_#c.RCH13_	0.0000	0.0000	0.0000**	
	(0.0000)	(0.0000)	(0.0000)	
Constant	-2.3282***	-2.0078	-1.2065***	1.4936***
	(0.2383)	(1.7978)	(0.2511)	(0.0853)

Clustered standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$