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Application of the Generalized Propensity score. Evaluation of Public Contributions to Piedmont Enterprises♣

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Abstract

In this article, we apply a generalization of the propensity score of Rosenbaum and Rubin (1983b). Techniques based on the propensity score have long been used for causal inference in observational studies for reducing bias caused by non-random treatment assignment. In last years, Joffe and Rosenbaum (1989) and Imbens and Hirano (2000) suggested two possible extensions to standard propensity score for ordinal and categorical treatments respectively. Propensity score techniques, allowing for continuous treatments effect evaluation, were, instead, recently proposed by Van Dick Imai (2003) and Imbens and Hirano (2004). We refer to Imbens' approach for the use of the generalized propensity score, to widen its application for continuous treatment regimes.

Introduction

This paper aims to evaluate economic supports to Piedmont industries, using data source from INPS, ISTAT and ASIA. Regional and national development policies are an important feature for setting up and supporting local industries. On the one hand, reference is made to active policies in favour of occupation, in order to improve employment for particular target groups (youth and women) who have difficulty in entering the labour market; on the other hand interventions aiming at removing barriers (credit rationing for example) that limit productive development, investment, applied research for pre-competitive and environment safeguard development, internationalization and commercial promotion of companies. The analysis of one or more public policies is to be set in a sequence of evaluation processes: the logic that leads to the intervention definition (process analysis), the evaluation of implementation (performance analysis) and its ability to achieve positive effects (impact analysis). In this study attention will be focused on this latter aspect, taking into consideration the whole system of economic measures, relative to grants and loans at special rate, to Piedmont industry (regional, issued by Regions, national, EU co-financed), from 2001 to 2003. Some regional policies have been already analysed in E. Rettore and A. Gavosto (2001), Mealli and Pagni (2002), but also in Chiri and Pellegrini (1995); Bagella and Becchetti (1997); Chiri *et al.*(1998); Bagella, (1999); Pellegrini (1999); Bondonio (2002); Carlucci and Pellegrini (2003). As far as the Italian experience is concerned, the state of art on impact evaluation in this field is not completely satisfying. There is a lack of a wide range evaluation, considering connections among different policy tools and using updated statistical and econometric techniques, whose success strongly depend on the availability and reliability of data, to be obtained by integrating different data sources. Moreover, the role of Regional authorities in the management of economic interventions for industry has amplified over the past few years, thanks to innovations in regional funding (legislative decrees 112 and 123, 1998). In particular, as far as our observational study is concerned, the Piedmont Region needs empirical evidence according to which a correct future evaluation and efficient programmes to support companies must be established. This paper's aim is to provide a useful research with respect this.

In this article, we apply a generalization of the propensity score of Rosenbaum and Rubin (1983b). Techniques based on the propensity score have long been used for causal inference in observational studies for reducing bias caused by non-random treatment assignment. In last years, Joffe and Rosenbaum (1989) and Imbens and Hirano (2000) suggested two possible extensions to standard propensity score for ordinal and categorical treatments respectively. Propensity score techniques, allowing for continuous treatments effect evaluation, were, instead, recently proposed by Van Dick Imai (2003) and Imbens and Hirano (2004). We refer to Imbens' approach for the use of the generalized propensity score, to widen its application for continuous treatment regimes. We implement this methodology to the *public contributions* (*treatment variable*) supplied to Piedmont industries, during years 2001 – 2003, using data source from INPS, ISTAT e ASIA. *Due,* in fact*, to the variety of funds* set by public policies, the *treatment* turns out to be a *continuous variable*. We are interested in the effect of *contribution* on occupational level[1], also distinguishing between the two types of contribution: grants and loans at special rates[2]. Just as in the binary treatment, adjusting for the GPS removes all bias associated with differences in the covariates. This allows us to estimate the *marginal* treatment effect of a specific contribution level on employment, comparing the outcome of units that have received that specific level of contribution with respect to units that have received another one (*counterfactual units*), but both of them similar in characteristics. This methodology refines the intervention effect evaluation on employment, from an economic trend present at the same time as treatment, in order to avoid that in presence of positive or negative economic trends, the contribution effect could be overestimated or underestimated respectively. We employ the method in a parametric setting, although more flexible approach - semi-parametric or non-parametric - are also possible and comparing the results with the regression based methods. It is important to underline that a different approach has been already applied in order to estimate the contribution effect on employment during years 2001 – 2003. Bondonio (2006) developed a specific analysis methodology for this study, a "Difference in Difference" model carried on in three phases:

- First, all pre-treatment variables information (company characteristics measured before treatment - in 2000 - which may influence employment dynamics from 2000-2003) are summarized with a propensity score. The propensity score is estimated

[1]We are going to elaborate a specific algorithm to implement a multinomial logit method checking for balancing property of categorical variables (grants and loans at special rates).
[2] All loans at special rates are converted into the Equivalent Gross Subsidy through a specific formula.

applying a probit model. This was made according to the type of contribution (grant, loan at special rate or both of them), then according to the company size and finally according to the activity field.

- Second, all beneficiary and no-beneficiary companies with “very” different pre-treatment characteristics from the remaining sample enterprises were eliminated, (that is, the formers non comparable were dropped). This was useful in order to estimate the counterfactual employment dynamics – i.e, what would have happened without economic supports – essential for the evaluation of effects.

- Third, a DID model combined with the PRS was implemented in order to remove systematic differences, between treated and untreated companies, constant over time that might influence the employment level during intervention (fixed effects). As a result the outcome variable was specified in terms of employment variation 2000-03, $Y_{2003} - Y_{2000}$. This specification, rather than the logarithm of variation $[ln(Y_{2003} / Y_{2000})]$ or percentage $[(Y_{2003} - Y_{2000}) / Y_{2000})$ allowed to highlight the socio-economic positive effects for the whole community area of the beneficiary companies. In fact, if it is true that a little employment variation is important for micro and small companies but not for the big ones, this would however not be true from a public welfare point of view, that was just what the paper was interested in.

1 Application of the GPS: the economic supports to the Piedmont Enterprises

This study covers all measures - basically grants and loans at special rates - of financial support in favour of enterprises in Piedmont between 2001 and 2003 (regional, given to regions, national and EU co-financed): Here we report some of the most important:

- Productive activities in depressed areas (488/92 Industry)
- Research and development - Applied research (L.297/99 D.M.593/00)
- Economic support to investments for enterprises (DOCUP 2000-06 Ob.2 areas)
- Productive development - Economic support to investments (1329/65)
- Promotion and economic support to new entrepreneurship (R.L. 28/93)
- Promotion of technological innovation for small/medium enterprises. Interventions for quality-systems (R.L 56/86).

The *administrative data* collected by ASIA (1996-2003) supply, for each of the 47.641 *enterprises population*, tax identification number, activity field, province, occupation. Further regional sources (Finpiemonte, Mediocredito

Bank) yield the different types of *funds* assigned to the industries according to the law and the date of provision. As already written, the final database is obtained merging the *ASIA archive administrative data* on contributions (2001-2003) with *Census* (2001) *data*, including the following variables:

- business name;

- municipality and corporate address;

- industrial activity field (Ateco 2002);

- juridical classification;

- employees (mean by year, permanent and temporary, 2001-2003)[3];

- grant concession and payment date (according to each law);

- subsidized financing (based on E.G.S computation for loans);

- company type according to the number of employees and local unit localization (unilocalization and plurilocalization, with corporate domicile inside or outside the region);

[3] The total number of employees refers to the total number of employees who work for all company local units. This implies that for plurilocalized companies, present all over the country, the total number of employees is over the total number of workers actually employed in Piedmont.

- craft or non-craft enterprise.

We combine a DID approach to the GPS based methods by using difference in employment in stead of employment level as outcome variable for the 5.296 *treated units sample*. The difference in fact should remove “fixed effects” constant over time that might influence the employment level during intervention. As a consequence, systematic differences in distribution of these characteristics between companies having received a specific contribution level and companies supported with a different amount of financing could cause a biased treatment effect estimation. Hence, taking into account the variation between 2000 and 2003 employment, instead of the simple occupational level, allows us to correct for this. As a result, all *pre-treatment variables* measured before policy intervention - occupation before 2001 as well as activity field, province…etc - are all included in the model. We will list them in detail, in the next paragraph.

2 The Generalized Propensity Score specification according to the size of the company.

In order to introduce the practical implementation of the Generalized Propensity Score methodology, we assume a flexible parametric approach to model the conditional distribution of the financing (*treatment variable*) given the covariates. We do that by first distinguishing enterprises of different dimension. The probability of receiving a lower or higher economic support is, in fact, supposed to be strictly related to the company size. In addition treatment effects are very likely to be heterogeneous with respect to company size. As a result, we divide the sample in *small*, *medium* and *big* industries, proceeding to estimate the effects inside each group of enterprises, thus highlighting the effects heterogeneity according to the company size.

We assume a normal linear model for the logarithm of the contributions for the small and medium companies. We transform the treatment variable by taking the logarithms, leading to a model specification with much better skewness and kurtosis values. The treatment range taken into consideration excludes the 1st and 99th percentile of the distribution for each dimensional class. The normal distribution assumption of the intervention given covariates is suitable according to the residual analysis of the model specification itself. Here we show the model specification and residuals analysis (residuals graph) for the conditional distribution of the logarithm of financing (Ln_t) given the pre-treatment variables, relative to small (0-49 number of employees) and medium (49-249 number of employees) enterprises:

$$Ln\_t | X_i \approx N(\beta_0 + \beta_1^{'} X_i, \sigma^2)$$

where X_i are represented by the following covariates:

> PROV = 8 binary variables (7 included in the model) denoting the type of province for the sample of Piedmont enterprises in the analysis.

NON_ART = binary variable denoting the non-craft characteristic (NON_ART = 1) or other (NON_ART = 0) for the sample of Piedmont enterprises in the analysis.

UNILOC = binary variable denoting if the corporate domicile of Piedmont enterprises is inside or outside the region.

TOT_ADD2000 = occupational level in 2000 (mean by year, permanent and temporary employees)

SETT = 8 binary variables (7 included in the model) denoting the type of manufacturing activities of Piedmont enterprises in the analysis, according to Ateco2002 classification for ASIA_ISTAT data .

APRE = (control) binary variable denoting if the enterprise began its activity during any year after 2000.

CHIUDE = (control) binary variable denoting if the enterprise closed after any year after 2000[4].

For the big companies we adopt a normal linear model for the contributions (leading, in this case, to a better specification of the regression):

$$t|X_i \approx N(\beta_0 + \beta_1^{'} X_i, \sigma^2)$$

[4] The control variable CHIUDE assumes a negative value if the enterprise closed after any year after 2000, that is it is set to zero.

with 5 binary variables for the activity field (SETT) instead of 8 and without the NON_ART variable (characteristics not present inside this group).

Figure 1: Residuals Graph of Logarithm of the contributions given the covariates (small enterprises)

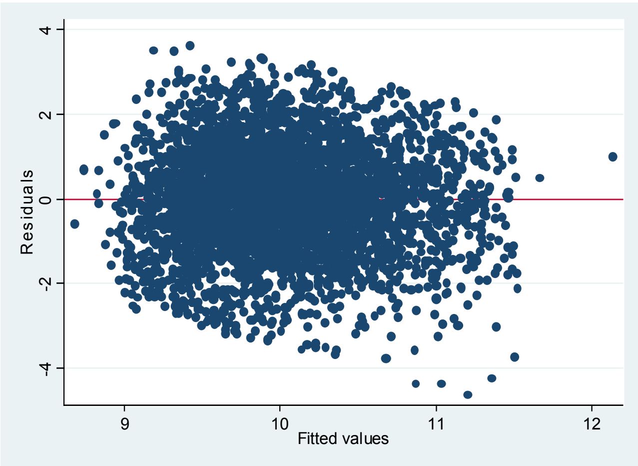
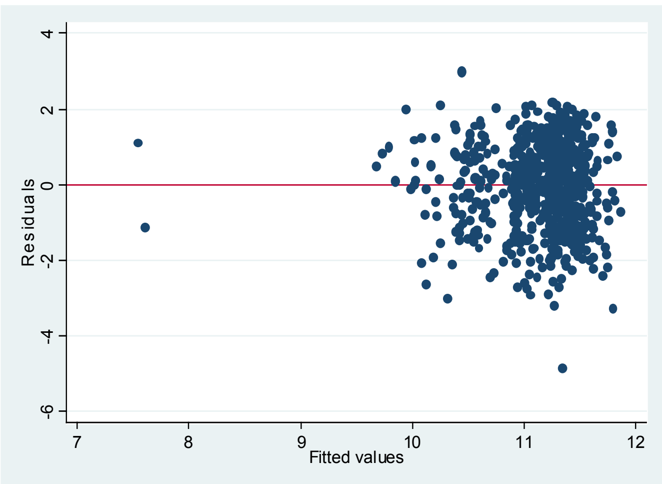
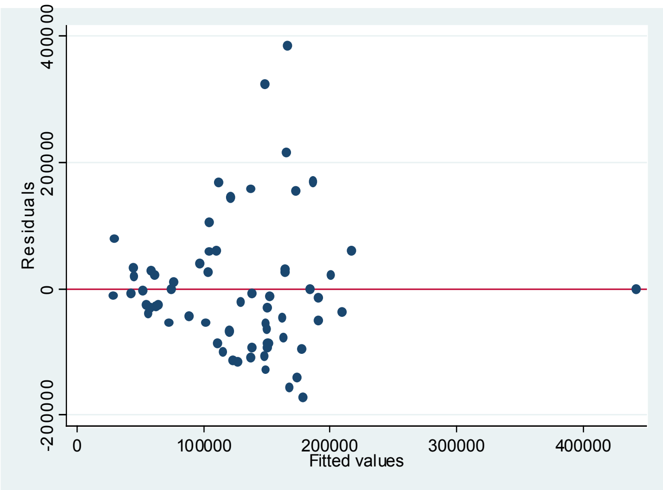


Figure 2: Residuals Graph of Logarithm of the contributions



given the covariates (medium enterprises)

Figure 3: Residuals Graph of the contributions given the covariates (big enterprises)



As already underlined, we may consider more general models such as mixtures of normals or heteroskedastic normal distributions. However, in our application, the Gaussian density function is assumed to be an opportune specification for the Generalized propensity score estimation. In the following section we will explain in more detail the procedure developed to test the balancing property of the GPS with respect to all pre-treatment variables included in the model.

3 Verifying the balancing property

After having estimated the Generalized Propensity Score, through the conditional distribution of the treatment variable given the covariates:

$$\hat{gps} = \phi(T_i; X_i)$$

we need to verify whether this specification is suitable, investigating if the GPS balances the covariates. The procedure is more complex than in the binary case and it is summarized below:

Test the *Balancing Property*:

1. Split the *treatment*'s range in k equally spaced intervals, where k is chosen by the user.

2. Calculate the *mean or a percentile* of the treatment and evaluate the *gps* at that specific level of T. Let $t_{k,p}$ be the chosen value of the treatment.

3. Split the estimated *gps*' range in j equally spaced intervals, where j can be arbitrarily chosen.

4 Within each *j-th* interval of *gps,* for each covariate compute the differences between the mean for units with $t_j > t_{k,p}$ and that for units with $t_j <= t_{k,p}$

5 Combine the differences in means, calculated in previous step, weighted by the number of observations in each group of gps_i interval and then in each treatment interval.

6 If the test *fails*, the Balancing Test is not satisfied and one or more of the following alternatives can be tried:

a) Specify a different propensity score;

b) Specify a different partition of the range of the estimated *gps*;

c) Specify a different sub-classification of the treatment.

The ado command and the syntax will be introduced in the next section, in order to show, in more detail, the specific procedure implemented for the GPS estimation and the balancing property test.

4 The gpscore program: command and application, according to the companies' size.

The gpscore program is a regression-like command. Here the syntax:

gpscore *varlist* [if *exp*] [in *range*] [*fweight iweight pweight*], gpscore(string) predict(string) sd(string) Cutpoints(varname numeric） index(string) nq_gps(numlist) [regression_type(string) DETail level(real 0.01)]

Note:

It's important to clean up the dataset, in particular to delete observations with missing values.

In gpscore, the options gpscore(string) predict(string) sd(string) Cutpoints(varname numeric) index(string) nq_gps(numlist) are compulsory.

In gpscore program user will run gpscore to estimate the generalized propensity score and test the balancing property.

It is possible to assume only a *normal* functional form for the treatment given the covariates, typing the regression command.

Let's describe the options more specifically:

gpscore(string) is a compulsory option and asks users to specify the variable name for the estimated generalized propensity score.

predict(string) is a compulsory option and asks users to specify the variable name for the estimated treatment variable given all covariates.

sd(string) is a compulsory option and asks users to specify the variable name for the corresponding (estimated) standard deviation.

Cutpoints(varname numeric) categorizes exp using the values of varname as category cutpoints. For example, varname might contain percentiles of another variable, generated by centile function. It includes the quantiles according to which divide the treatment's range.

index(string) asks users to specify the mean or the percentile to which referring inside each class of treatment.

nq_gps(numlist) requires, as input, a number between 1 and 100 that is the quantile according to which divide gpscore range conditional to the index string of each class of treatment.

regression_type(string) fits a model of dependent variable on independent variables using linear regression.

detail displays more detailed output concerning the steps performed by the balancing test for each level of treatment *t* and gpscore conditional to that *t*.

level(real #) requires to set the significance level of the tests of the Balancing property. The default is 0.01. As Ichino has showed (2002), this significance level avoids to reject, with a "certain" probability, one of the test of the balancing property although it is actually true.

In our empirical study we implemented this algorithm testing the balancing property for small, medium and big enterprises and computing three different generalized propensity score estimations, one for each dimensional class.

So, for example, the treatment range for the small companies was divided in 4 intervals (according to the 10th, 30th, 60th, and 100th centile of the treatment respectively) and each estimated GPS, conditional on the treatment median for each of the 4 treatment groups, was divided in 3 blocks (according to the 25th, 75th, and 100th centile of the propensity score distribution). Here the corresponding command:

```
xi: gpscore ln_t prov1 prov2 prov3 prov4 prov5 prov6 prov7
non_art2 uniloc2  sett1 sett2 sett3 sett4 sett5 sett6 sett7
tot_add2000 chiude apre, gpscore(pscore) predict(hat_ln_t)
sd(sigma_hat) cutpoints(cut) index(p50) nq_gps(3) level(0.01)
```

In the medium enterprises the treatment range was divided in 5 intervals (according to the 20th, 40th, 60th, 80th and 100th centile of the treatment respectively) and each estimated GPS, conditional on the treatment median for each of the 5 treatment groups, was divided in 4 blocks (according to the 25th, 50th, 75th and 100th centile of the propensity score distribution). Here the corresponding command:

```
xi: gpscore ln_t prov1 prov2 prov3 prov4 prov5 prov6 prov7
non_art2 uniloc2  sett1 sett2 sett3 sett4 sett5 sett6 sett7
tot_add2000 chiude apre, gpscore(pscore) predict(hat_ln_t)
sd(sigma_hat) cutpoints(cut) index(p50) nq_gps(4) level(0.01)
```

Finally, in the big companies, the treatment range was divided in 3 intervals (30th, 60th and 100th centile of the treatment respectively) and each estimated GPS, conditional on the treatment median for each of the 3 treatment groups, was divided in 3 blocks (according to the 25th, 75th and 100th centile of the propensity score distribution). Here the corresponding command:

```
xi: gpscore t prov1 prov2 prov3 prov4 prov5 prov6 prov7
uniloc2 sett2 sett3 sett4 sett5 sett6 tot_add2000 chiude
apre, gpscore(pscore) predict(hat_t) sd(sigma_hat)
cutpoints(cut) index(p50) nq_gps(3) level(0.01)
```

Here the results for the estimated generalized propensity score inside the small, medium and big enterprises, the balancing properties test relative to each dimensional class.

Table 1: Generalized propensity score estimation and balancing properties in small enterprises

```
****************************************************
End of the algorithm to estimate the generalized pscore
****************************************************
```

	Mean Difference	Standard Deviation	t-value	p-value
prov1	.00738	.02229	.33129	.74044
prov2	-.00239	.00863	-.27682	.78193
prov3	-.00296	.01256	-.23544	.81388
prov4	-.00134	.01389	-.09652	.92312
prov5	-.00081	.00963	-.08422	.93289
prov6	.00256	.01294	.19803	.84303
prov7	-.00053	.01033	-.05172	.95875
non_art2	.02287	.01907	1.1992	.23052
uniloc2	-.00727	.01652	-.43967	.6602
sett1	-.00098	.00576	-.17079	.86439
sett2	-.00134	.01081	-.12368	.90158
sett3	.00083	.01686	.04938	.96062
sett4	-.00061	.01563	-.03914	.96878
sett5	-.0063	.02094	-.30079	.76359
sett6	.00039	.01931	.02005	.98401
sett7	.00741	.01158	.63966	.52243
tot_add2000	.69131	.41585	1.6624	.09651
chiude	-4.1e-05	.00831	-.00493	.99606
apre	0	0	.	.

The balancing property is satisfied

```
end

sum pscore

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
      pscore |      3943    .2821614    .1118859   .0003668   .3989423
```

Table 2: Generalized propensity score estimation and balancing properties in medium enterprises

```
****************************************************
End of the algorithm to estimate the generalized pscore
****************************************************
```

	Mean Difference	Standard Deviation	t-value	p-value
prov1	-.10337	.04604	-2.2454	.02508
prov2	-.02224	.02311	-.96235	.33623
prov3	.05924	.03414	1.7352	.08317
prov4	.01056	.0341	.30972	.75687
prov5	-.00191	.01755	-.10887	.91334
prov6	.01471	.02474	.59464	.55229
prov7	.01867	.03426	.54504	.58591
non_art2	-.00162	.01155	-.13997	.88873
uniloc2	-.03366	.05455	-.61699	.53745
sett1	-.00329	.01194	-.27601	.78262
sett2	.00395	.02215	.17821	.85861
sett3	.01952	.04586	.42569	.67047
sett4	-.01082	.03533	-.30636	.75943
sett5	.01555	.04601	.33799	.73548
sett6	-.00513	.04987	-.10287	.91809
sett7	-.02252	.03583	-.62847	.52992
tot_add2000	2.7048	4.6869	.57709	.56408
chiude	.00358	.02069	.17323	.86253
apre	0	0	.	.

The balancing property is satisfied

```
end

. sum pscore

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
      pscore |       676    .2766309    .1058829    .000042   .3989407
```

Table 3: Generalized propensity score estimation and balancing properties in big enterprises

```
****************************************************
End of the algorithm to estimate the generalized pscore
****************************************************
```

	Mean Difference	Standard Deviation	t-value	p-value
prov1	-.01785	.13417	-.13301	.89478
prov2	.03608	.03608	1	.32266
prov3	-.03438	.11467	-.29981	.7657
prov4	.01931	.09489	.20347	.83969
prov5	-.01033	.05705	-.18116	.85705
prov6	.04431	.11143	.39765	.69277
prov7	-.05935	.11585	-.51233	.61092
uniloc2	-.02467	.17186	-.14356	.88649
sett2	.00234	.14141	.01655	.98687
sett3	-.03667	.10395	-.35281	.72588
sett4	.05011	.11501	.43566	.66516
sett5	-.04635	.18067	-.25654	.7987
sett6	-.00983	.14331	-.06859	.94562
tot_add2000	-.8313	125.18	-.00664	.99473
chiude	0	0	.	.
apre	0	0	.	.

```
The balancing property is satisfied

end

. sum pscore

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
      pscore |        63    .3011026    .1109757   .0004503   .3989423
```

5 The causal effect estimation: model specification and marginal effects

As already underlined, in order to estimate the causal for continuous treatment, we first need to compute the conditional expectation of the outcome, $E[Y \mid T = t, R = r]$, that is equal to:

$$\mathrm{E}[Y \mid T = t, R = r]=\mathrm{E}[Y(t) \mid r(t,X) = r]= \beta(t, r)$$

and estimated as a function of a specific level of contribution and of a specific value of GPS $R = r$. As already written, it should be clear that

B(t,r) does not have a causal interpretation. We, in fact, need to average the conditional expectation over the marginal distribution *r(t,X)*:

$$\mu(t) = \mathrm{E}[\mathrm{E}[Y(t) \mid r(t,X)]]$$

to estimate the *causal effect* as a comparison of $\mu(t)$ for different values of t. In our application we specified a quadratic approximation in the model, in order to estimate the variation of the employment 2003-2000. We have:

$$\begin{aligned}\beta(t,r) &= E[\Delta add03\_00 | t,r] = \\ &= b_0 + b_1 t + b_2 \log(pscore) + b_3 t^2 + \\ &+ b_4(\log(pscore))^2 + b_5 \log(pscore)t\end{aligned}$$

Let's describe in more detail the model. First we specify a regression the variation of the employment 2003-2000 - that is $\Delta add03\_00$ - on the contribution T_i and $pscore_i$ for the small, medium and big Piedmont companies. We used the logarithm of the score rather than the level, also including all second order moments of financing and log(pscore):

$$\begin{aligned}\beta(t,r) &= E[\Delta add03\_00 | t,r] = \\ &= b_0 + b_1 T_i + b_2 \log(pscore) + b_3 T_i^2 \\ &+ b_4(\log(pscore))^2 + b_5 \log(pscore)T_i\end{aligned}$$

Second, we estimated these parameters by ordinary least squares using the $\hat{gps} = \phi(T_i; X_i)$, previously obtained applying the *gpscore* program.

Third, given the estimated parameters, we estimated the *outcome* $\hat{\mu}(t)$ at treatment level *t* as follows:

$$\hat{\mu}(t) = E[\Delta add\hat{0}3\_00] =$$

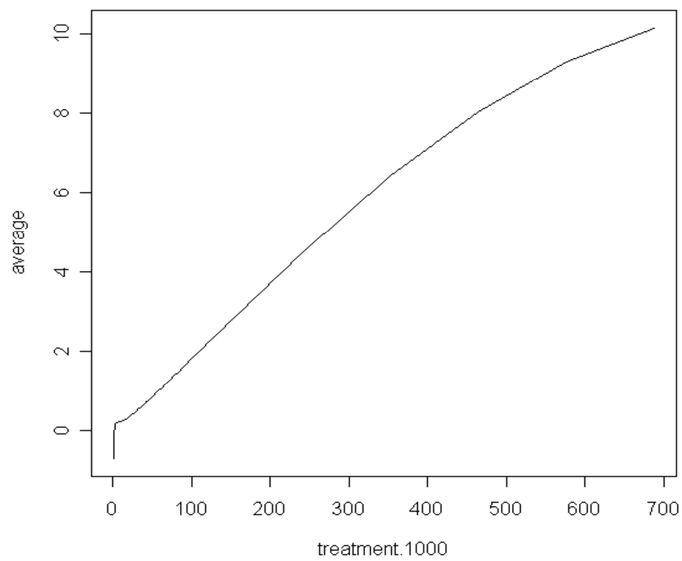
$$= \frac{1}{N}\sum_{i=1}^{N}(\hat{b}_0 + \hat{b}_1\, t + \hat{b}_2\, \log(ps\hat{c}ore) + \hat{b}_3\, t^2 +$$

$$+ \hat{b}_4 (\log(ps\hat{c}ore))^2 + \hat{b}_5 \log(ps\hat{c}ore)t$$

We did this for each level of treatment we are interested in, to get an estimate of the entire dose-response function as a mean weighted by each different $ps\hat{c}ore = \hat{r}(t, X_i)$, estimated in correspondence of that specific level of contribution *t*. Note that, in order to compute standard errors and confidence intervals, we used the *Bootstrap method* taking into account the estimation of the GPS and of the β parameters. As a result, after having averaging the dose-response over the pscore function for each level *t*, we also computed the derivatives of $\hat{\mu}(t)$, that we can define as the *marginal causal effect* of a variation of the contribution, Δt, on the variation of the employment 2003-2000. We reported the $\hat{\mu}(t)$ and the corresponding *t-statistics* values, also computing the confidence bands for the derivatives $\mu(t+\Delta t)-\mu(t)$ and the differences $\mu(t+50000)-\mu(t)$ relative to small, medium and big enterprises (with *t* divided for 1000).

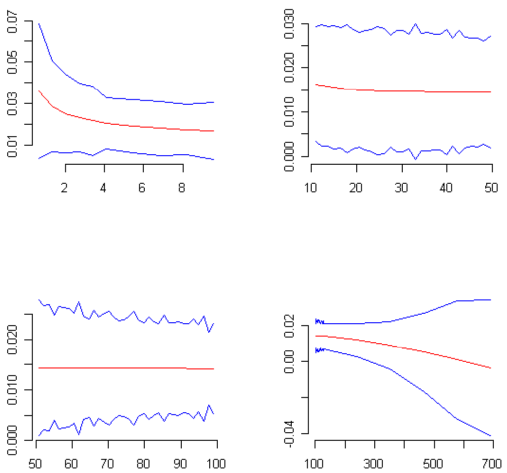
5.1 Small enterprises

Figure 4: $\Delta \hat{add03\_00}$ distribution



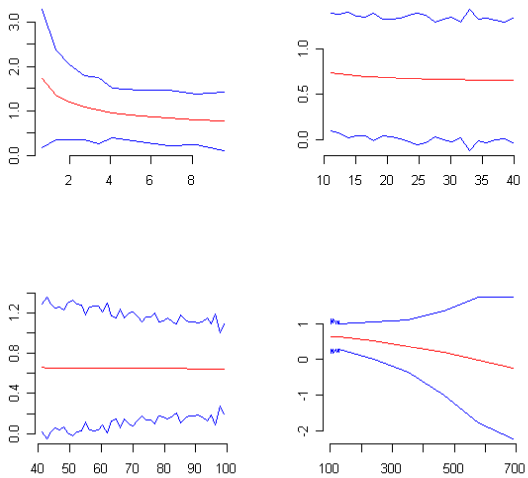
In Figure 4 is showed the distribution of the outcome, $\Delta \hat{add03\_00}$, for small enterprises, for different values of *t*, that increases with respect to *t*. According to the derivatives confidence bands (Figure 5), the marginal effects $\mu(t+\Delta t)-\mu(t)$ relative to the estimated outcome values are significant for levels of the treatment ranging from (about) 1000 euro to (about) 300000 euro. In figure 5bis we reported the dose-response differences[5] distribution $\mu(t+50000)-\mu(t)$ computed relative to each t we are interested in - and the corresponding confidence bands 95%. For instance, if the treatment increased from 1000 euro to 51000 euro (50000+1000), the number of employees would increase of about +1.7. Let' s briefly report another example: if the treatment increased from 30000 euro to 80000 euro (50000+ 30000), the number of employees would increase of about +0.66.

Figure 5: Dose-response derivatives $\mu(t+\Delta t)-\mu(t)$ and confidence bands 95% (*1000) - Small enterprises



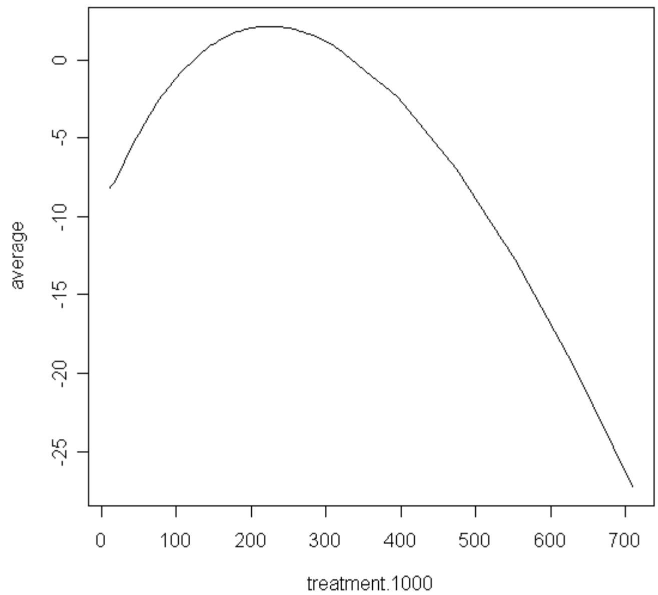
[5] We computed the standard errors for every derivatives and difference distributions applying Bootstrap procedure.

Figure 5bis: Dose-response differences $\mu(t+50000)-\mu(t)$ and confidence bands 95% - Small enterprises



5.2 Medium enterprises

Figure 6: $\Delta add\hat{0}3\_00$ distribution



In Figure 6 is showed the distribution of the outcome, $\Delta add\hat{0}3\_00$, for medium enterprises[6]., for different values of *t*, that increases with respect to *t* until (about) 300000 euro. According to the derivatives confidence bands (Figure 7), the marginal effects relative to the estimated outcome values are significant for levels of the treatment ranging from (about) 40000 euro to

[6] We ignored the dose-response distribution values ranging from about 1000 euro to 10000euro, because of the presence of some outliers in correspondence of that specific values of contribution.

(about) 200000 euro In figure 7bis is reported the dose-response differences distribution – [$u(t$ + 50000)- $u(t)$] computed relative to each t we are interested in - and the corresponding confidence bands 95%. For instance, if the treatment increased from 50000 euro to 100000 euro (50000+50000), the number of employees would increase of about +3.7. Let' s briefly report another example: if the treatment increased from 100000 euro to 150000 euro (50000+ 100000), the number of employees would increase of about +3.8.

Figure 7: Dose-response derivatives $\mu(t+\Delta t)-\mu(t)$ and confidence bands 95% (*1000) - Medium enterprises

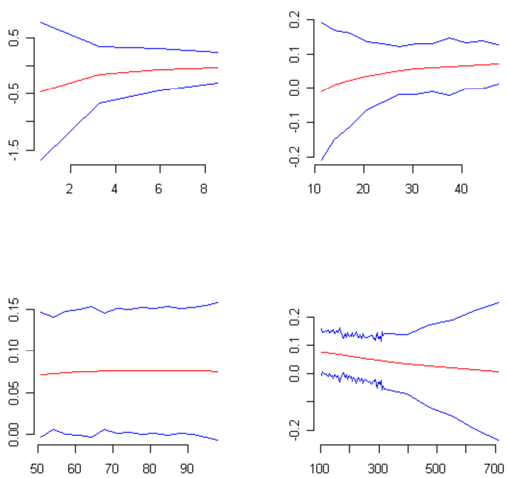
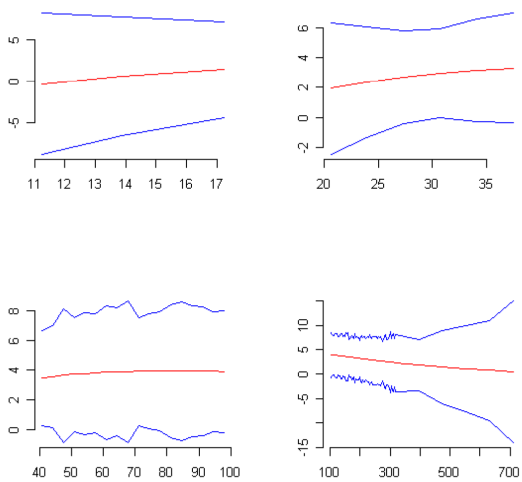
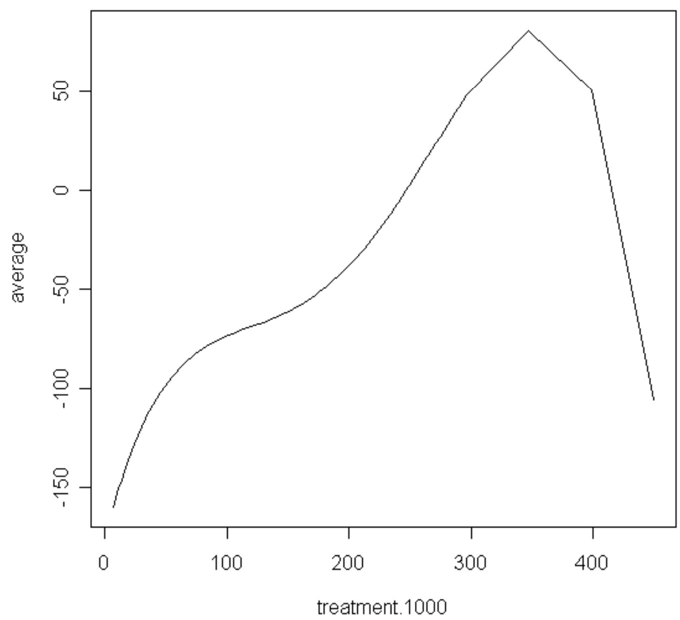


Figure 7bis: Dose-response differences $\mu(t+50000)-\mu(t)$ and confidence bands 95% - Medium enterprises



5.3 Big enterprises

Figure 8: $\Delta add\hat{0}3\_00$ distribution



In Figure 8 is showed the distribution of the outcome, $\Delta add\hat{0}3\_00$, for big enterprises, for different values of *t*, that increases with respect to *t* until (about) 300000 euro. According to the derivatives confidence bands (Figure 9), we never get significant marginal effects relative to the estimated outcome (and this result is also confirmed for the dose-response differences distribution [*u*(*t* + 100000)- *u*(*t*)].

Figure 9: Dose-response derivatives $\mu(t+\Delta t)-\mu(t)$ and confidence bands 95%(*1000) - Big enterprises

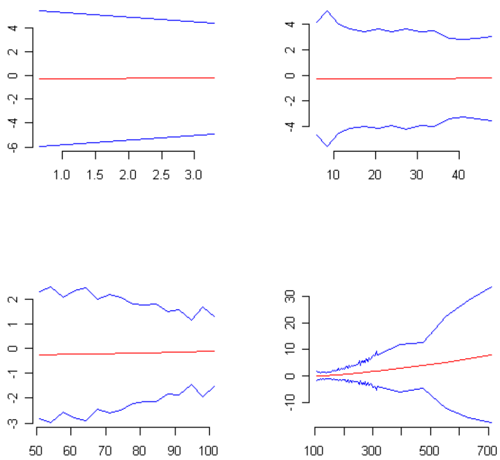
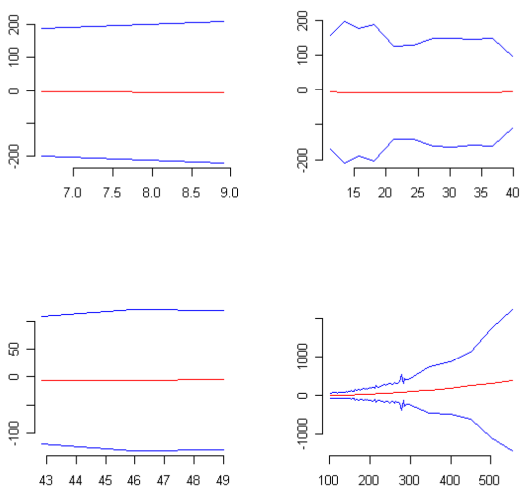


Figure 9bis: Dose-response differences $\mu(t+50000)-\mu(t)$ and confidence bands 95% - Big enterprises



6 A comparison with the regression based methods

In order to compare the contribution effects estimates on the variation employment 2003-2001, obtained trough the GPS implementation, we also applied regression based methods. Hence, we obtained estimates from a simple linear regression and then from a quadratic regression, considering the same covariates and range of treatment defined above with respect to small, medium and big enterprises:

Linear regression

$$\Delta add03\_00 = \alpha_0 + \alpha_1 t + \alpha_2 X_i$$

Quadratic regression

$$\Delta add03\_00 = \gamma_0 + \gamma_1 t + \gamma_2 t^2 + \gamma_3 X_i$$

6.1 Small enterprises

Table 4 Linear regression estimates for small enterprises

Source	SS	df	MS
Model	45181.2087	19	2377.95835
Residual	220421.187	3923	56.1868946
Total	265602.396	3942	67.3775739

Number of obs =	3943
F(19, 3923) =	42.32
Prob > F =	0.0000
R-squared =	0.1701
Adj R-squared =	0.1661
Root MSE =	7.4958

va03_00	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
t_bis	.0174883	.0015611	11.20	0.000	.0144277	.0205489
prov1	-.0651443	.5933619	-0.11	0.913	-1.228471	1.098182
prov2	.4081543	.8377076	0.49	0.626	-1.234229	2.050538
prov3	-.2374253	.7018475	-0.34	0.735	-1.613446	1.138595
prov4	1.150514	.6799047	1.69	0.091	-.1824859	2.483514
prov5	.2907491	.7853076	0.37	0.711	-1.2489	1.830399
prov6	.9047063	.697393	1.30	0.195	-.4625807	2.271993
prov7	-.8378833	.7925099	-1.06	0.290	-2.391654	.715887
sett1	2.630043	1.963127	1.34	0.180	-1.218803	6.47889
sett2	1.708612	1.798733	0.95	0.342	-1.817927	5.235151
sett3	2.299835	1.764111	1.30	0.192	-1.158826	5.758497
sett4	2.977384	1.762247	1.69	0.091	-.477623	6.432391
sett5	2.127821	1.752117	1.21	0.225	-1.307325	5.562968
sett6	2.550171	1.751775	1.46	0.146	-.8843052	5.984647
sett7	2.802141	1.797237	1.56	0.119	-.7214658	6.325749
non_art2	.9845046	.2662816	3.70	0.000	.4624411	1.506568
uniloc2	-.8895861	.335642	-2.65	0.008	-1.547635	-.231537
chiude	-15.91844	.6633787	-24.00	0.000	-17.21904	-14.61784
apre	(dropped)					
tot_add2000	-.1350214	.0115462	-11.69	0.000	-.1576586	-.1123842
_cons	.2793069	1.852418	0.15	0.880	-3.352486	3.911099

In table 4 are showed the corresponding contribution effects estimates on employment variation, applying a *linear* regression method. We can note that the effect of an additional unit on the outcome is estimated to be equal to an increase of about +0.017 number of employees, that would correspond to (about) +1.7 number of employees if the treatment increased of 100000 euro. This value is highly significant - the *t_value* is equal to 11.20 - and it is coherent with respect to the results of the GPS procedure. Note that the specified regression model assumes that the causal effect is constant and specifying a model that includes effects heterogeneity is not so trivial, because one would need to specify precise interactions of the treatment variable with some of the covariates. Moreover, through the regression methodology the overlapping of the covariates distributions among treatment groups is not usually a priori verified. As a result, unlike the GPS procedure, results may strongly depend on the extrapolation.

Table 5: Quadratic regression estimates for small enterprises

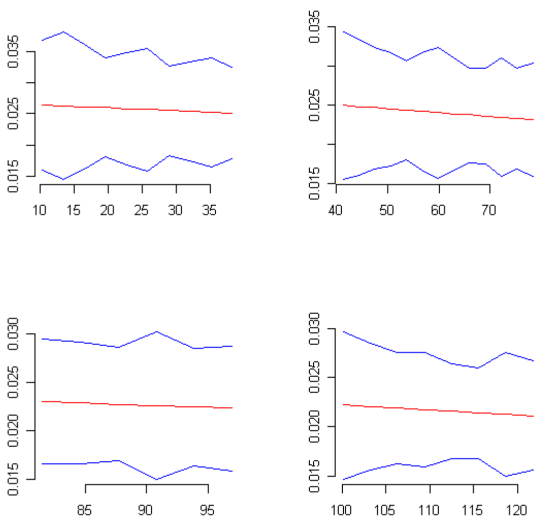
Source	SS	df	MS
Model	45652.7998	20	2282.63999
Residual	219949.596	3922	56.0809782
Total	265602.396	3942	67.3775739

Number of obs =	3943
R-squared =	0.1719
Adj R-squared =	0.1677
Root MSE =	7.488723
Res. dev. =	27046.35

va03_00	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b0	.2020234	1.850863	0.11	0.913	-3.426721	3.830768
/b1	.0269169	.0036061	7.46	0.000	.0198468	.0339869
/b2	-.0000238	8.20e-06	-2.90	0.004	-.0000399	-7.70e-06
/b3	-.102644	.5929434	-0.17	0.863	-1.26515	1.059862
/b4	.3890043	.8369437	0.46	0.642	-1.251882	2.02989
/b5	-.2445077	.7011899	-0.35	0.727	-1.619239	1.130224
/b6	1.11886	.6793513	1.65	0.100	-.2130552	2.450775
/b7	.2698136	.7846003	0.34	0.731	-1.268449	1.808077
/b8	.8747587	.6968119	1.26	0.209	-.4913891	2.240907
/b9	-.8681189	.7918313	-1.10	0.273	-2.420559	.6843209
/b10	2.607491	1.961291	1.33	0.184	-1.237756	6.452738
/b11	1.665431	1.797098	0.93	0.354	-1.857904	5.188766
/b12	2.258517	1.762505	1.28	0.200	-1.196996	5.71403
/b13	2.927748	1.760669	1.66	0.096	-.5241641	6.379661
/b14	2.071879	1.750571	1.18	0.237	-1.360237	5.503995
/b15	2.481498	1.750284	1.42	0.156	-.9500537	5.91305
/b16	2.72652	1.795732	1.52	0.129	-.7941363	6.247176
/b17	.9143649	.2671278	3.42	0.001	.3906425	1.438087
/b18	-.8847611	.3353296	-2.64	0.008	-1.542198	-.2273243
/b19	-15.91179	.6627571	-24.01	0.000	-17.21118	-14.61241
/b20	0	.	.	.	.	.
/b21	-.1390907	.0116204	-11.97	0.000	-.1618733	-.1163081

In table 5 the results of the estimation of a quadratic regression are presented. The contribution effect derived from this regression are shown in Figure 10. We can note that the effect of an additional unit on the outcome is estimated to be equal to an increase of about +0.026 number of employees, that would correspond to (about) +2.6 number of employees if the financing increased of 100000 euro. This estimate is highly significant – the *t_value* is equal to 7.46 – but overestimated with respect to the results of the GPS procedure. The quadratic regression model has the same drawbacks as explained for the linear regression. Here follows the corresponding Dose-response derivatives distribution and the relative confidence bands 95%.

Figure 10: Dose-response derivatives and confidence bands 95% (*1000) for the quadratic regression - Small enterprises



6.2 Medium enterprises

Table 6: Linear regression estimates for medium enterprises

Source	SS	df	MS
Model	117975.626	19	6209.24349
Residual	475993.41	656	725.599711
Total	593969.037	675	879.954129

Number of obs =	676
F(19, 656) =	8.56
Prob > F =	0.0000
R-squared =	0.1986
Adj R-squared =	0.1754
Root MSE =	26.937

va03_00	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
t_bis	.0265167	.0079493	3.34	0.001	.0109075	.0421259
prov1	-11.87511	7.028567	-1.69	0.092	-25.67631	1.926093
prov2	-8.739067	8.467943	-1.03	0.302	-25.36661	7.888476
prov3	-2.43621	7.590814	-0.32	0.748	-17.34143	12.46901
prov4	-7.919047	7.604237	-1.04	0.298	-22.85063	7.012533
prov5	-6.077098	9.441044	-0.64	0.520	-24.61541	12.46121
prov6	-1.870922	8.080505	-0.23	0.817	-17.7377	13.99585
prov7	-9.282515	7.876014	-1.18	0.239	-24.74775	6.182723
sett1	-2.947094	23.90372	-0.12	0.902	-49.88412	43.98993
sett2	5.400102	20.23515	0.27	0.790	-34.33338	45.13358
sett3	-3.170422	19.75527	-0.16	0.873	-41.9616	35.62076
sett4	1.575225	19.71697	0.08	0.936	-37.14075	40.2912
sett5	-1.469376	19.68632	-0.07	0.941	-40.12517	37.18642
sett6	2.273712	19.63797	0.12	0.908	-36.28714	40.83457
sett7	3.940734	19.77982	0.20	0.842	-34.89866	42.78013
non_art2	-.6808461	11.24791	-0.06	0.952	-22.76709	21.4054
uniloc2	-6.160165	2.23017	-2.76	0.006	-10.5393	-1.781032
chiude	-73.32609	6.722198	-10.91	0.000	-86.52571	-60.12647
apre	(dropped)					
tot_add2000	-.0418871	.0258411	-1.62	0.106	-.0926283	.008854
_cons	13.16468	23.82371	0.55	0.581	-33.61525	59.9446

In table 6 are showed the corresponding contribution effects estimates on employment variation, applying a *linear* regression method. We can note that the effect of an additional unit on the outcome is estimated to be equal to an increase of about +0.026 number of employees, that would correspond to about +2.6 number of employees if the treatment increased of 100000 euro. This estimate is highly significant - the *t_value* is equal to 3.34 - and coherent with the results obtained trough the GPS procedure.

Table 7: Quadratic regression estimates for medium enterprises

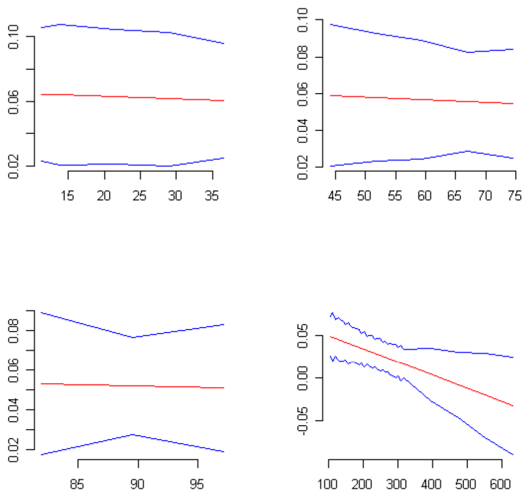
Source	SS	df	MS
Model	120801.338	20	6040.06691
Residual	473167.699	655	722.393433
Total	593969.037	675	879.954129

Number of obs	=	676
R-squared	=	0.2034
Adj R-squared	=	0.1791
Root MSE	=	26.87738
Res. dev.	=	6346.889

va03_00	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b0	13.52238	23.7717	0.57	0.570	-33.15555	60.20032
/b1	.0659945	.0214789	3.07	0.002	.0238188	.1081703
/b2	-.0000777	.0000393	-1.98	0.048	-.0001549	-5.57e-07
/b3	-12.82189	7.029341	-1.82	0.069	-26.62465	.9808667
/b4	-10.03753	8.474682	-1.18	0.237	-26.67835	6.603292
/b5	-2.936836	7.578253	-0.39	0.698	-17.81744	11.94376
/b6	-8.568637	7.594523	-1.13	0.260	-23.48118	6.343911
/b7	-7.571661	9.450423	-0.80	0.423	-26.12844	10.98512
/b8	-2.980785	8.082138	-0.37	0.712	-18.85081	12.88924
/b9	-10.57983	7.885922	-1.34	0.180	-26.06456	4.904909
/b10	-5.212316	23.87833	-0.22	0.827	-52.09962	41.67499
/b11	2.602316	20.23989	0.13	0.898	-37.14058	42.34521
/b12	-5.464852	19.74568	-0.28	0.782	-44.23732	33.30761
/b13	-1.392793	19.73051	-0.07	0.944	-40.13547	37.34988
/b14	-4.288696	19.69443	-0.22	0.828	-42.96053	34.38314
/b15	-.1835753	19.63388	-0.01	0.993	-38.73652	38.36937
/b16	1.417099	19.77727	0.07	0.943	-37.41741	40.2516
/b17	-.1996943	11.22567	-0.02	0.986	-22.24233	21.84294
/b18	-5.853882	2.23062	-2.62	0.009	-10.23391	-1.473854
/b19	-71.4884	6.771383	-10.56	0.000	-84.78464	-58.19217
/b20	0	.	.	.	.	.
/b21	-.0403399	.0257958	-1.56	0.118	-.0909923	.010312

In table 7 are instead showed the corresponding contribution effects estimates on employment variation, applying a regression method *quadratic* in contribution . We can note that the effect of an additional unit on the outcome is estimated to be equal to an increase of about +0.06 number of employees, that would correspond to about +6 number of employees if the financing increased of 100000 euro. This value is significant – the *t_value* equal is to 3.07 – but rather overestimated than the results obtained trough the GPS procedure. Here follows the corresponding Dose-response derivatives distribution and relative confidence bands 95%.

Figure 11: Outcomes derivatives confidence bands 95% (*1000) for the quadratic regression - Medium enterprises



6.3 Big enterprises

Table 8: Linear regression estimates for big enterprises

Source	SS	df	MS
Model	1019866.76	15	67991.1175
Residual	2546478.97	47	54180.4037
Total	3566345.74	62	57521.7054

Number of obs =	63
F(15, 47) =	1.25
Prob > F =	0.2679
R-squared =	0.2860
Adj R-squared =	0.0581
Root MSE =	232.77

va03_00	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
t_bis	.3911861	.2794513	1.40	0.168	-.1709974	.9533697
prov1	136.3105	252.8158	0.54	0.592	-372.2894	644.9103
prov2	170.5799	371.4102	0.46	0.648	-576.601	917.7608
prov3	116.1251	279.7205	0.42	0.680	-446.6	678.8502
prov4	130.6035	280.6037	0.47	0.644	-433.8984	695.1054
prov5	204.265	309.2148	0.66	0.512	-417.7949	826.325
prov6	57.41853	276.6993	0.21	0.837	-499.2287	614.0658
prov7	118.1176	303.5531	0.39	0.699	-492.5523	728.7876
sett1	(dropped)					
sett2	136.6182	275.3368	0.50	0.622	-417.288	690.5243
sett3	370.1611	262.7246	1.41	0.165	-158.3726	898.6947
sett4	195.4573	267.4731	0.73	0.469	-342.6292	733.5437
sett5	127.8275	257.9524	0.50	0.623	-391.1058	646.7607
sett6	153.0745	256.0414	0.60	0.553	-362.0143	668.1633
uniloc2	-88.83941	69.28904	-1.28	0.206	-228.231	50.55215
chiude	(dropped)					
apre	(dropped)					
tot_add2000	-.22297	.0850202	-2.62	0.012	-.3940085	-.0519315
_cons	-203.5351	370.5395	-0.55	0.585	-948.9644	541.8942

Table 9: Quadratic regression estimates for big enterprises

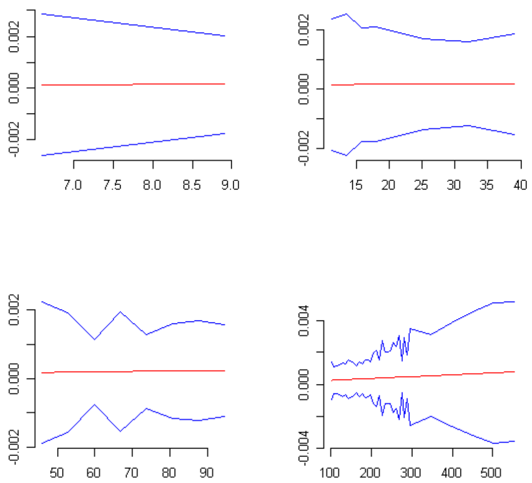
Source	SS	df	MS
Model	1026821.85	16	64176.3654
Residual	2539523.89	46	55207.0411
Total	3566345.74	62	57521.7054

Number of obs	=	63
R-squared	=	0.2879
Adj R-squared	=	0.0402
Root MSE	=	234.9618
Res. dev.	=	846.8605

va03_00	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b0	-189.0868	376.2422	-0.50	0.618	-946.423	568.2494
/b1	.1234242	.8054031	0.15	0.879	-1.497768	1.744617
/b2	.0005993	.0016884	0.35	0.724	-.0027994	.0039979
/b3	123.4575	257.7561	0.48	0.634	-395.3787	642.2938
/b4	148.1987	380.1782	0.39	0.698	-617.0604	913.4578
/b5	97.06527	287.4191	0.34	0.737	-481.4793	675.6099
/b6	116.6577	285.9619	0.41	0.685	-458.9537	692.2691
/b7	189.7986	314.7804	0.60	0.549	-443.8216	823.4187
/b8	47.93302	280.5841	0.17	0.865	-516.8536	612.7196
/b9	92.04938	315.0944	0.29	0.771	-542.2028	726.3016
/b10	0	.	.	.	.	.
/b11	161.1925	286.4269	0.56	0.576	-415.355	737.74
/b12	390.7276	271.4583	1.44	0.157	-155.6896	937.1447
/b13	210.2064	273.1743	0.77	0.446	-339.6649	760.0777
/b14	141.4047	263.1796	0.54	0.594	-388.3483	671.1577
/b15	164.581	260.481	0.63	0.531	-359.74	688.902
/b16	-87.79977	70.00372	-1.25	0.216	-228.71	53.11042
/b17	0	.	.	.	.	.
/b18	0	.	.	.	.	.
/b19	-.223511	.0858354	-2.60	0.012	-.3962888	-.0507333

In table 8 and 9 are showed the corresponding contribution effects estimates on employment variation, applying a *linear* regression and a regression *quadratic* in contribution respectively. It is clear that in both cases we did not get significant estimates of contribution on the outcome and this seems to be coherent with respect to the GPS implementation concerning the treatment effect estimation for the group of the only big enterprises. Here follows the corresponding Dose-response derivatives distribution and relative confidence bands 95%.

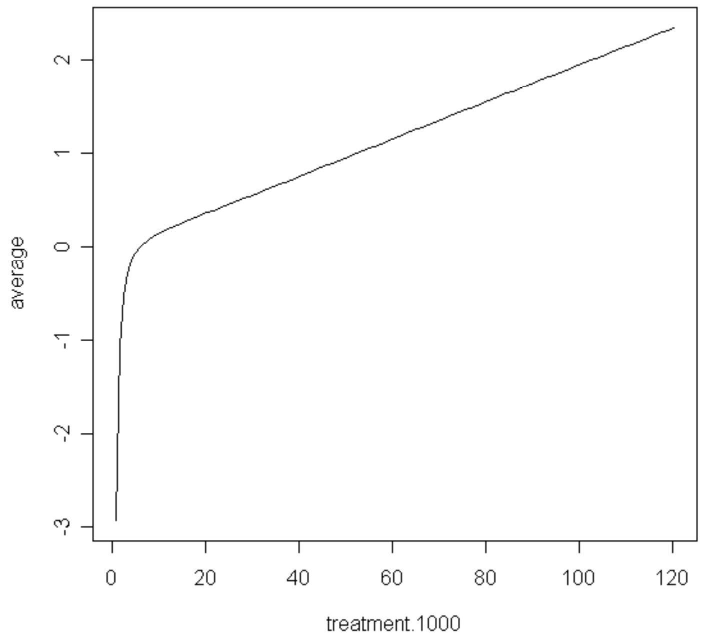
Figure 12: Outcomes derivatives distribution and confidence bands 95% (*1000) for the quadratic regression - Big enterprises



7 The treatment effect estimation according to the grant contribution versus loans at special rates.

We now briefly proceed showing the estimates distinguishing the only grant contributions from the loans at special rates effect on employment, for small, medium and big enterprises. It is important to note that, essentially for loans at special rate effect evaluation on employment for small, medium and big companies, we did not get significant estimates. We will try to explain some reasonable hypotheses about this in the last section.

Figure 13: $\Delta add\hat{0}3\_00$ distribution for small enterprises (grant)



In Figure 13 is showed the distribution of the outcome, $\Delta add\hat{0}3\_00$ for different values of *t*, that increases with respect to *contribution* until (about) 200000 euro. According to the derivatives confidence bands (Figure 14), the marginal effects relative to the estimated outcome values are highly significant for all levels of the treatment ranging from (about) 1000 euro to 200000. In figure 14bis is reported the dose-response differences distribution – [u(t + 50000)- u(t)] computed relative to each t we are interested in - and the corresponding confidence bands 95%. For instance, if the treatment increased from 2000 euro to 52000 euro (2000+50000), the number of employees would increase of about +2 units. Let' s briefly report another example: if the treatment increased from 50000 euro to 100000 euro (50000+ 50000), the number of employees would increase of about +0.8 units. Here follows the corresponding Dose-response derivatives/differences distribution and the relative confidence bands 95%.

Figure 14: Outcome derivatives $\mu(t+\Delta t)-\mu(t)$ and confidence bands 95% (*1000) - Small enterprises (grant)

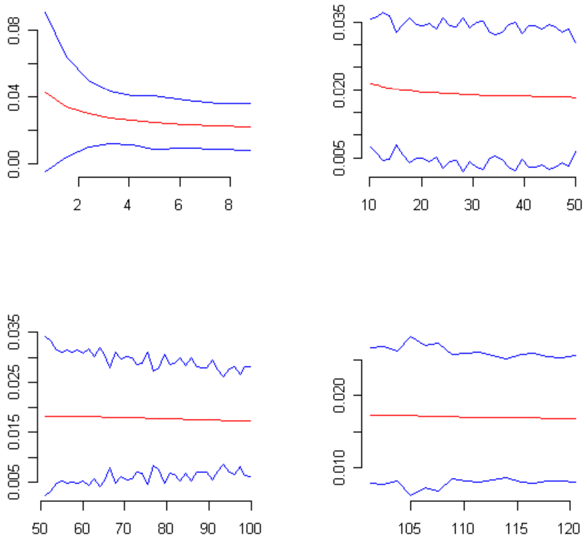


Figure 14bis: Outcome differences $\mu(t+50000)-\mu(t)$ and confidence bands 95% - Small enterprises (grant)

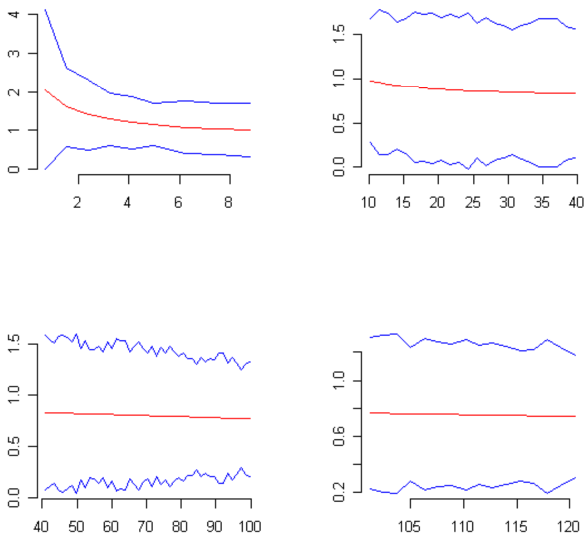
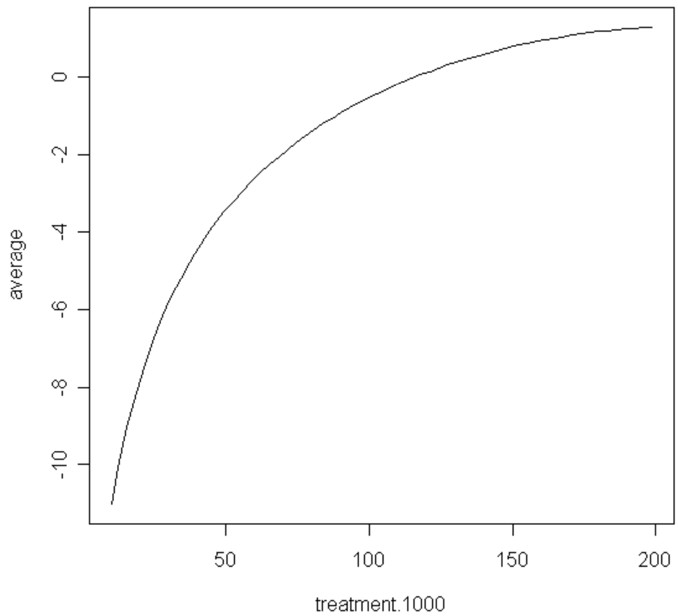


Figure 15: $\Delta add\hat{0}3\_00$ distribution for medium enterprises (grant)



In Figure 15 is showed the distribution of the outcome, $\Delta add\hat{0}3\_00$ for different values of *t*, that increases with respect to the *contributions* until (about) 200000 euro. According to the derivatives confidence bands (Figure 16), the marginal effects relative to the estimated outcome values are significant for levels of the treatment ranging from (about) 40000 euro to (about) 150000. In figure 16bis is reported the dose-response differences distribution – [$u(t + 50000)$- $u(t)$] computed relative to each t we are interested in - and the corresponding confidence bands 95%. For instance, if the treatment increased from 50000 euro to 100000 euro (50000+50000), the number of employees would increase of about +3.7 units. Let' s briefly report another example: if the treatment increased from about 100000 euro to 150000 euro (100000+ 50000), the number of employees would increase of about +3.9 units. Here follows the corresponding Dose-response derivatives/differences distribution and the relative confidence bands 95%.

Figure 16: Outcome derivatives $\mu(t+\Delta t)-\mu(t)$ and confidence bands 95% - Medium enterprises (grant)

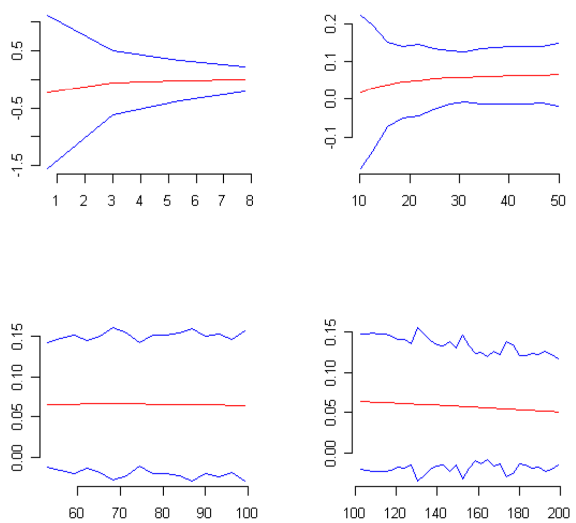
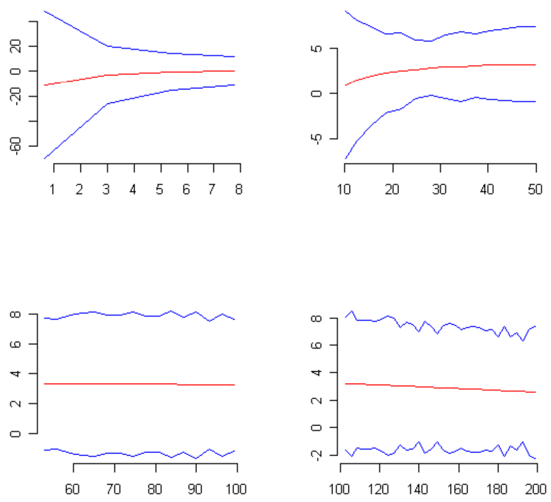


Figure 16bis: Outcome differences $\mu(t+50000)-\mu(t)$ and confidence bands 95% - Medium enterprises (grant)



We now briefly show the all remaining estimates that resulted to have no-significant values (as already underlined, basically for grant to big enterprises and for loans at special rate effect evaluation distinguishing into small, medium and big companies).

Figure 17: Outcome derivatives $\mu(t+\Delta t)-\mu(t)$ and confidence bands 95% (*1000) - small enterprises[7] (loans at special rates)

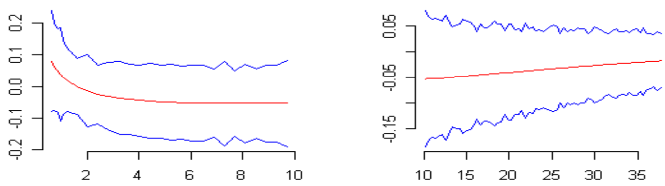
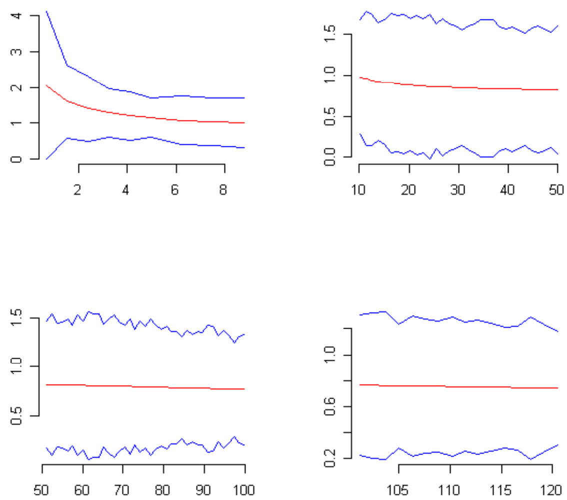


Figure 17bis: Outcome differences $\mu(t+50000)-\mu(t)$ and confidence bands 95% - Small enterprises (loans at special rates)



[7] We did not report the confidence bands for contributions of more than 40000 euro since we did not have a sufficient number of observations.

Figure 18: Outcome derivatives $\mu(t+\Delta t)-\mu(t)$ and confidence bands 95%(*1000) - Medium enterprises (loans at special rates)

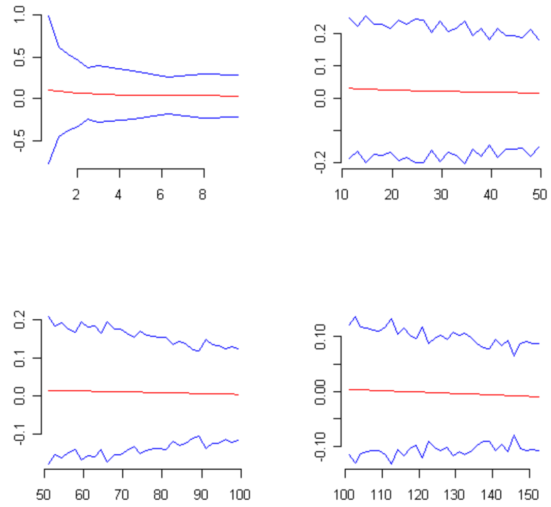


Figure 18bis: Outcome differences $\mu(t+50000)-\mu(t)$ and confidence bands 95% - Medium enterprises (loans at special rates)

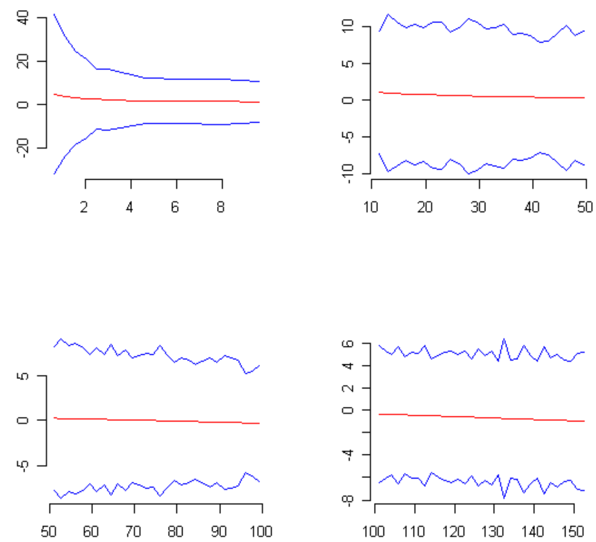


Figure 19: Outcome derivatives $\mu(t+\Delta t)-\mu(t)$ and confidence bands 95% - Big enterprises (loans at special rates)

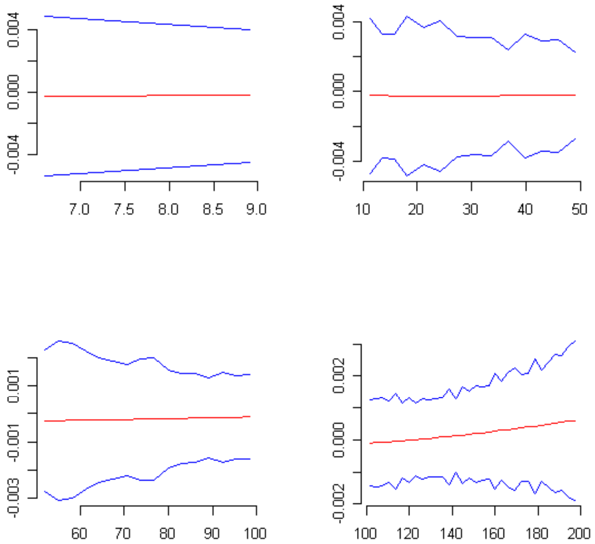
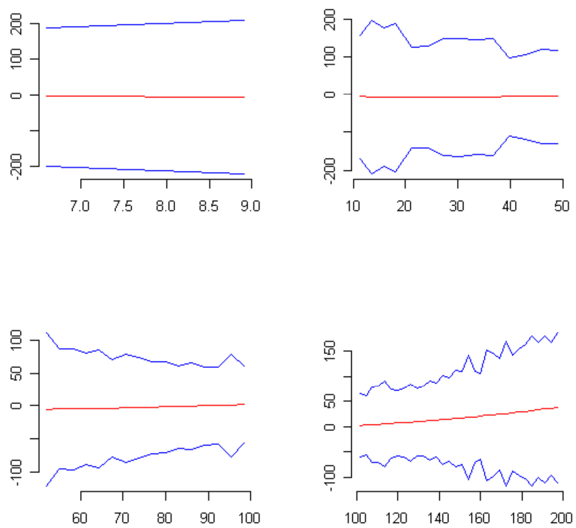


Figure 19bis: Outcome differences $\mu(t+50000)-\mu(t)$ and confidence bands 95% - Big enterprises (loans at special rates)



We did not report the confidence bands for loans at special rates to big enterprises because we did not have a sufficient number of observations.

8 Conclusion and further research

The role of policy maker in management of economic interventions for industry has amplified over the past few years. Empirical evidence is needed in order to establish a correct future evaluation and efficient programmes to support companies. We try to produce an answer for this. Moreover, since the paper aims to estimate the corresponding effect of different levels of contributions on employment for small, medium and big enterprises, we needed to create and implement a software for continuous treatment effects evaluation. In fact, most of research concerning policy evaluation is focused on binary treatment regimes and all available software can be suitably applied, using the standard propensity score method, for the causal effect of binary treatments rather than continuous treatments. As a result, we produced a *stata ado program* generalizing the propensity score such that a correct effect estimation was possible in the continuous treatment case. The main steps are: *i*) estimate the GPS and verify its correct specification by checking the balancing property using the algorithm previously specified; *ii*) estimate the dose-response function and some causal effects of interest from it. Hence, according to the results showed in the previous section, we can say that for small and medium enterprises the effect of an increase of about 50000 euro on contributions - ranging from about 20000 euro to 200000 euro[8] - leads to an employees addition from (about) +1.7 to +0.66 in small

[8] That is the contributions interval according to which significant estimates were found.

companies and from (about) +3.1 to +1.8 in medium companies. For big companies significant results were not found, as well as for the loans at special rates effects for small, medium and big companies. We can try to find some explanations; loans at special rates are usually used in areas of high investment intensity. Hence, the companies mostly involved are the big ones for which an additional contribution of 10000 (50000) euro does not reasonably produce any positive effect in relative terms. This, on the other hand, is not true for small and medium companies, for which receiving an additional contributions of 10000 (50000) euro leads to significant effects on employment (in relative terms). However, it is important to underline that this is a data analysis that needs to be study more in depth, for example the problem of checking the non-observable heterogeneity of treated units with different levels of contributions should be further investigated. In particular, we are also interested in a sensitivity analysis in order to estimate causal effects of interventions, also verifying the robustness of results removing the starting – point assumptions. In addition it would be very useful to include the untreated units in the analysis in order to compare the contributions with the "no intervention" case, as so in absolute terms. With this respect, we are going to elaborate a multilogit normal model (in the gpscore program) in order to evaluate treatments effects for continuous – multivalued treatment variables.

Appendix

```
*gpscore.ado


* VERSION 9
* JULY 06, 2006
* LAST REVISOR: ALESSANDRA & MICHELA

program define gpscore, rclass
syntax varlist [if] [in] [fweight iweight pweight],
gpscore(string) predict(string) sd(string) Cutpoints(varname
numeric)  index(string) nq_gps(numlist) [DETail level(real
0.01)]

/* gpscore nome variabile che contiene i valori adattati del
pscore stimato*/
/* nq(numlist) richiede in input un numero compreso fra 1 e
100 che rappresenta il quantile in cui dividere il range di
trattamento*/
/*index(string) nome dell'indice di posizione (media o
percentile) a cui far riferimento all'interno di ogni classe
d trattamento*/
/*nq_gps(numlist) richiede in input un numero compreso fra 1
e 100 che rappresenta il quantile in cui dividere il range
del gpscore condizionato a index(string) per ogni classe di
trattamento*/

tokenize `varlist'

tempvar touse
g `touse'=0
qui replace `touse'=1 `if' `in'

/* if weights are specified, create local variable */
if "`weight'" != "" {
   tempvar wv
   qui gen double `wv' `exp'
   local w [`weight'=`wv']
   replace `touse'=0 if `wv'==0
}

      gettoken t left: varlist
      gettoken Xvars: left

      loc k: word count `Xvars'
```

```
/*
  if "`in'" ~= "" {
            qui keep `in'
      }
      if "`if'" ~= "" {
            qui keep `if'
      }
*/

/*******/
/* NEW */
/*******/

local T  `t'
confirm new variable `gpscore'
confirm new variable `predict'
confirm new variable `sd'


if `"`detail'"' == `""'  {
 local qui "quietly"
}


di in ye _newline(3)
"***********************************************************"
di in ye                "Algorithm to estimate the
generalized propensity score"
di in ye
"***********************************************************"

di _newline(2) in ye "The treatment is `T'"
sum `t'  if `touse'==1


di _newline(3) "Estimation of the propensity score "

reg `varlist' [`weight'`exp'] if `touse'==1

tempvar hat_treat
qui predict double `hat_treat' if `touse'==1
qui gen double `predict' = `hat_treat'


tempvar res_treat
qui predict double `res_treat' if `touse'==1, resid
qui sum `res_treat'

tempvar sig
```

```
qui gen double `sig' = sqrt((r(sd)^2)*((_N-1)/_N)) if
`touse'==1
qui gen double `sd' = `sig'


tempvar std_treat
qui gen double `std_treat' = `res_treat'/`sig' if `touse'==1


tempvar egpscore
qui gen double `egpscore' = normalden(`std_treat')/`sig' if
`touse'==1
qui gen double `gpscore' = `egpscore'
label var `gpscore' "Estimate of the Generalized propensity
score"
sum `gpscore' if `touse'==1, detail


di in ye _newline(2)
"****************************************************** "
di                   "End of the algorithm to estimate the
generalized pscore "
di
"****************************************************** "

tempvar broken_t
qui xtile `broken_t' = `T' if `touse'==1,
cutpoints(`cutpoin')
tempvar max_broken_t
qui sum `broken_t' if `touse'==1
qui gen `max_broken_t' = r(max)

if("`index'" == "mean"){
local i = 1
while(`i' <= `max_broken_t'){
tempvar mean_T_`i'
qui sum `T' if `broken_t' ==`i' & `touse'==1
qui gen `mean_T_`i'' = r(mean)
tempvar std_mean_T_`i'
qui gen double  `std_mean_T_`i'' = (`mean_T_`i'' -
`hat_treat')/`sig' if `touse'==1
tempvar gpscore_`i'
qui gen double `gpscore_`i'' =
normalden(`std_mean_T_`i'')/sig if `touse'==1
local i = `i' + 1
}
}

foreach x of numlist 1/100{
```

```
if("`index'" == "p`x'"){
local i = 1
while(`i' <= `max_broken_t'){
tempvar p`x'_T_`i'
qui egen `p`x'_T_`i'' = pctile(`T') if `broken_t' ==`i' &
`touse'==1, p(`x')
qui sum `p`x'_T_`i''
qui replace `p`x'_T_`i'' = r(mean)
tempvar std_p`x'_T_`i'
qui gen double  `std_p`x'_T_`i'' = (`p`x'_T_`i'' -
`hat_treat')/`sig' if `touse'==1
tempvar gpscore_`i'
qui gen double `gpscore_`i'' = normalden(`std_p`x'_T_`i'') if
`touse'==1
local i = `i' + 1
}
}
}


local i = 1
while(`i' <= `max_broken_t'){
tempvar broken_gps_`i'
qui xtile `broken_gps_`i'' = `gpscore_`i'' if `touse'==1 &
`broken_t' ==`i', n(`nq_gps')

local j = 1
while(`j' <= `nq_gps'){
tempvar max_`i'`j'
qui sum `gpscore_`i''  if `broken_gps_`i'' == `j'
qui gen `max_`i'`j'' = r(max)
local j = `j' + 1
}
qui replace `broken_gps_`i'' = 1 if
`gpscore_`i''<=`max_`i'1' &  `broken_gps_`i'' ==.
local j = 2
while(`j' <= `nq_gps'){
local k = `j' - 1
qui replace `broken_gps_`i'' = `j' if
`gpscore`i''>`max_`i'`k'' & `gpscore`i''<=`max_`i'`j''  &
`broken_gps_`i'' ==.
local j = `j' + 1
}
qui   sum `broken_gps_`i''
tempvar max_broken_gps_`i'
qui sum `broken_gps_`i'' if `touse'==1
qui gen `max_broken_gps_`i'' = r(max)  if `touse'==1
local i = `i'+1
}
```

```
/************************************************************
****/
/* BEGINNING OF TEST THAT THE PROPENSITY SCORE IS NOT
DIFFERENT */
/************************************************************
****/


if `"`detail'"' != `""'  { /* BEGINDETAIL */

   di _newline(3) "Distribution of gps across treatment
levels"
local i = 1
while(`i' <= `max_broken_t'){
  sum  `gpscore_`i''
local i = `i' + 1
}
   di _newline(3) "Test that the mean propensity score is not
different for treated and controls"

} /* ENDDETAIL */


   if `"`detail'"' != `""'  {
     di _newline(3) in ye "Test given treatment level " `i' "
and gpscore " `j'
      di _newline(1) in ye "Observations in treatment level "
`i' " and gpscore " `j'
   }


local i = 1
while(`i' <= `max_broken_t'){ /*BEGINOFWHILE 1*/
foreach var of local varlist { /* BEGINOFFOREACH */
         if ("`var'" == "`T'" | "`var'" == "`gpscore_`i'") {
/* DO NOTHING */
         }
         else {
        tempvar diff_`var'
       tempvar variance_diff_`var'
       qui gen `diff_`var''  = 0
       qui gen `variance_diff_`var''  = 0
          }
}
local i = `i' + 1
}
```

```
local i = 1
while(`i' <= `max_broken_t'){ /*BEGINOFWHILE 1*/

local j = 1
while(`j' <= `nq_gps'){/*BEGINOFWHILE 2*/

  if `"`detail'"' != `""'  {
      di _newline(3) in ye "Test given treatment level " `i'
" and gpscore " `j'
      di _newline(1) in ye "Observations in treatment level "
`i' " and gpscore " `j'
   }


quietly count if `broken_gps_`i'' == `j'
local nobs_`i'`j'  = r(N)

quietly count if `broken_gps_`i'' == `j' & `broken_t' ==`i'
local nt_`i'`j'  = r(N)

quietly count if `broken_gps_`i'' == `j' & `broken_t' !=`i'
local nc_`i'`j'  = r(N)

   if `"`detail'"' != `""'  { /* BEGINDETAIL */
      di " obs: `nobs_`i'`j'',  control: `nc_`i'`j'',
treated: `nt_`i'`j''"
   } /* ENDDETAIL */

   if `nobs_`i'`j'  ' == 0 | `nc_`i'`j'  ' == 0 | `nt_`i'`j'
' == 0 { /* BEGINOFIF1 */
      if `"`detail'"' != `""'  { /* BEGINDETAIL */
         if `nobs_`i'`j'  ' == 0 {
         local mistyp "observations"
         }
         else if `nc_`i'`j'  ' == 0 {
         local mistyp "controls"
         }
         else if `nt_`i'`j'  ' == 0 {
         local mistyp "treated"
         }

         di _newline (1) "The treatment level `i' does not
have `mistyp'"
         di "Move to next treatment level"
      } /* ENDDETAIL */
   } /* ENDOFIF1 */

   else { /* BEGINOFELSE1 */
```

```
tempvar flag
qui gen     `flag' = 1  if `broken_gps_`i'' == `j' &
`broken_t' ==`i'
qui replace `flag' = 0  if `broken_gps_`i'' == `j' &
`broken_t' !=`i'
tempvar obs_`i'`j' obs_out_`i'`j' obs_in_`i'`j'
qui count if `flag' == 1
qui gen `obs_in_`i'`j'' = r(N)
qui count if `flag' == 0
qui gen `obs_out_`i'`j'' = r(N)
qui gen `obs_`i'`j'' = `obs_out_`i'`j'' + `obs_in_`i'`j''


      foreach var of local varlist { /* BEGINOFFOREACH */
         if "`var'" == "`T'" | "`var'" == "`gpscore_`i''"{ /*
DO NOTHING */
         }
         else { /* BEGINOFELSE2 */

            if `"`detail'"' != `""'  { /* BEGINDETAIL */
               di _newline (3) "Testing the balancing
property for variable `var' in block of gps "   `j' " given
treatment level " `i'
          } /* ENDDETAIL */


            tempvar diff_`var'_`i'`j' sd_diff_`var'_`i'`j'

            tempvar m_in_`var'_`i'`j'
            tempvar  sd_in_`var'_`i'`j'
            qui sum `var'   if `flag'==1
            qui gen `m_in_`var'_`i'`j'' = r(mean)
            qui gen `sd_in_`var'_`i'`j'' = r(sd)

            tempvar m_out_`var'_`i'`j'
            tempvar sd_out_`var'_`i'`j'
            qui sum `var'   if `flag'==0
            qui gen `m_out_`var'_`i'`j'' = r(mean)
            qui gen `sd_out_`var'_`i'`j'' = r(sd)

 qui gen `diff_`var'_`i'`j''  = `m_in_`var'_`i'`j'' -
`m_out_`var'_`i'`j''
 qui gen `sd_diff_`var'_`i'`j''  =
((`sd_in_`var'_`i'`j'')^2/`obs_in_`i'`j'') +
((`sd_out_`var'_`i'`j'')^2/`obs_out_`i'`j'')
 qui replace `sd_diff_`var'_`i'`j''  =
(`sd_diff_`var'_`i'`j'')^0.5
```

```
qui replace `diff_`var''  =  `diff_`var''   + ((`obs_`i'`j''
)/(_N))*`diff_`var'_`i'`j''
qui replace `variance_diff_`var''  = `variance_diff_`var''
+  (((`obs_`i'`j'')/(_N))^2)*((`sd_diff_`var'_`i'`j'')^2)
         } /* ENDOFELSE2 */

      } /* ENDOFFOREACH */
drop `flag'
   } /* ENDOFELSE1 */

local j = `j' + 1

} /* ENDOFWHILE 2*/

local i = `i' + 1
} /* ENDOFWHILE 1*/

local i = 1
while(`i' <= `max_broken_t'){ /*BEGINOFWHILE 1*/
drop `gpscore_`i''
local i = `i' + 1
}

local k: word count `varlist'
foreach var of varlist `varlist' { /* BEGINOFFOREACH */
if ("`var'" == "`T'") {
         }
else{
tempvar t_value_`var'
qui gen `t_value_`var'' =
`diff_`var''/((`variance_diff_`var'')^0.5)
tempvar p_value_`var'
qui gen `p_value_`var''= 2*ttail(_N-`k'-1, `t_value_`var'')
if `t_value_`var''>=0
qui replace `p_value_`var''= 2*(1-ttail(_N-`k'-1,
`t_value_`var'')) if `t_value_`var''<0
}
}

di ""

`quietly' di as text    "              Mean "          "
Standard   "
`quietly' di as text    "              Difference"     "
Deviation   "   "t-value"   "   p-value"
 `quietly' di ""

local problem = 0
```

```
tempname diff sd t_value pvalue

foreach var of varlist `varlist' { /* BEGINOFFOREACH */
if ("`var'" == "`T'") {
         }
else{
qui sum  `diff_`var''
scalar `diff' = r(mean)
qui sum  `variance_diff_`var''
scalar `sd' = r(mean)^0.5
scalar `t_value' = `diff'/`sd'
qui sum  `p_value_`var''
scalar `pvalue' = r(mean)
`quietly' di as text %12s abbrev("`var'            ",12) "  "
as result %7.0g `diff' "      " as result %7.0g `sd'      "
" as result %7.0g `t_value'  "    " as result %7.0g `pvalue'
`quietly' di ""
}
}

foreach var of varlist `varlist' { /* BEGINOFFOREACH */
if ("`var'" == "`T'") {
         }
else{

if `p_value_`var''  < `level' {
             di _newline (1) "Variable `var' is not balanced"
               local problem = 1
            }

}
}


if (`problem' == 0) {

di in gr _newline(2) "The balancing property is satisfied "

}
else {
    `qui' di _newline(1) in red  "The balancing property is
not satisfied "
    `qui' di _newline(1) in red  "Try a different
specification of the propensity score "
    `qui' di _newline(1) in red  "or choose a different
subclassification of the treatment and or the propensity
score range "
}
```

```
disp "end"

end
```

Causal_effect_estimation.do

```
clear
set mem 300m
use
"D:\STATA_Michela\Dati\TUTTE_IMPR_CON_FIN_UL01_ANAG_00_PULITI
.dta", clear

qui egen t=rsum(FP_Dm593- FIN_Docup_4_1b_pho)
destring fg, replace
sort fg
merge fg using  D:\STATA_Michela\Dati\FG2001.dta
drop if _merge==2
drop _merge

gen forma = .
replace forma = 1 if fg ==11
replace forma = 2 if fg ==120
replace forma = 3 if fg ==130
replace forma = 4 if fg ==210
replace forma = 5 if fg ==220
replace forma = 6 if fg ==320
replace forma = 7 if fg <. & forma==.

sort ateco
merge ateco using D:\STATA_Michela\Dati\ateco.dta
drop if _merge==2
drop _merge

sum t, det
drop if t==0

centile t, centile(1 99)
keep if t>=646.3972 & t<= 716036.7

keep if tot_add2000 >0 & tot_add2000 <=49
sum tot_add2000
```

```
gen aux = substr(ateco,1,2)
destring aux, replace

gen str1 sett = "C" if aux>=14 & aux<15
replace sett = "D1" if aux>=15 & aux<16
replace sett = "D2" if aux>=16 & aux<23
*replace sett = "D3" if aux>=18 & aux<=21
*replace sett = "D4" if aux> 21 & aux<24
*replace sett = "D5" if aux>=24 & aux<=25
replace sett = "D6" if aux>=23 & aux<=27
replace sett = "D7" if aux>=27 & aux<=29
replace sett = "D8" if aux>=29 & aux<=33
replace sett = "D9" if aux> 33 & aux<40


replace sett = "E" if aux>=40 & aux<45
replace sett = "F" if aux>=45 & aux<50
replace sett = "G" if aux>=50 & aux<55
replace sett = "H" if aux>=55 & aux<60
replace sett = "I" if aux>=60 & aux<65
replace sett = "J" if aux>=65 & aux<70
replace sett = "K" if aux>=70 & aux<75
replace sett = "L" if aux>=75 & aux<80
replace sett = "M" if aux>=80 & aux<85
replace sett = "N" if aux>=85 & aux<90
replace sett = "O" if aux>=90 & aux<95
replace sett = "P" if aux>=95 & aux<99
replace sett = "Q" if aux>=99


drop aux
*replace sezione = sett if sezione==""
*drop sett



gen ln_t = log(t)

tab sett, gen(sett)
tab prov, gen(prov)
tab non_art, gen(non_art)
tab uniloc, gen(uniloc)


sum t

#delimit ;
xi: reg ln_t i.prov1 i.prov2 i.prov3 i.prov4 i.prov5 i.prov6
i.prov7
```

```
i.non_art2 i.uniloc2  i.sett1 i.sett2 i.sett3 i.sett4 i.sett5
i.sett6 i.sett7 tot_add2000 i.chiude i.apre
;

predict ln_that
predict ln_r, resid
rvfplot, yline(0)




centile t, centile(10 30 60 100)

gen cut = 10 if t<=r(c_1)
replace cut = 30 if t >r(c_1) & t <=r(c_2)
replace cut = 60 if t >r(c_2)& t <=r(c_3)
replace cut = 100 if t >r(c_3)



*drop pscore
#delimit ;
xi: gpscore ln_t prov1 prov2 prov3 prov4 prov5 prov6 prov7
non_art2 uniloc2  sett1 sett2 sett3 sett4 sett5 sett6 sett7
tot_add2000 chiude apre,
gpscore(pscore) predict(hat_ln_t) sd(sigma_hat)
cutpoints(cut) index(p50) nq_gps(3) level(0.01)
;

#delimit cr


sum pscore

centile pscore, centile(0 25 75 100)
qui gen pscore0   = r(c_1)
qui gen pscore25  = r(c_2)
qui gen pscore75  = r(c_3)
qui gen pscore100 = r(c_4)




tabstat pscore if pscore >=pscore0 & pscore <=pscore25,
stats(p50)
tabstat pscore if pscore >pscore25 & pscore <=pscore75,
stats(p50)
```

```
tabstat pscore if pscore >pscore75 & pscore <=pscore100,
stats(p50)
```

```
#delimit ;
nl (va03_00 = {b0} + {b1} *(t/1000) +   {b2} * log(pscore) +
{b3} * t^2/1000000 + {b4} * (log(pscore))^2 +
{b5}*log(pscore) * (t/1000)), variable(t pscore)
;

#delimit cr

matrix B = e(b)
*predict xb

qui gen b0 = B[1,1]
qui gen b1 = B[1,2]
qui gen b2 = B[1,3]
qui gen b3 = B[1,4]
qui gen b4 = B[1,5]
qui gen b5 = B[1,6]


qui sum t, det
qui gen min_t = r(min)
qui gen p10_t = r(p10)
qui gen p90_t = r(p90)
qui gen max_t = r(max)

qui gen treat = min_t
qui sum treat
qui replace treat = r(mean)
qui gen treat_plus = treat + 1

qui gen std_treat= (ln(treat) - hat_ln_t)/sigma_hat
qui gen double r = normalden(std_treat)

qui gen y_hat = b0 + b1*(treat/1000) +  b2*log(r) + b3*
treat^2/1000000 + b4 * (log(r))^2 + b5*log(r) * (treat/1000)
#delimit ;

qui gen y_hat_plus = b0 + b1*(treat_plus/1000) +  b2*log(r) +
b3* treat_plus^2/1000000 +
b4 * (log(r))^2 + b5*log(r) * (treat_plus/1000)
;
```

```
#delimit cr
qui sum y_hat
qui gen mean_value = r(mean)

qui sum y_hat_plus
qui gen mean_value_plus = r(mean)

qui gen mean_diff = mean_value_plus - mean_value
qui gen diff = y_hat_plus - y_hat
qui sum diff
qui replace diff = r(mean)

*Bootstrap

foreach j of numlist 1/100{
qui gen u = uniform()
qui replace u = floor(u*_N+1)
qui gen y_boot = .
qui replace y_boot = tot_add2003[u]

#delimit ;
foreach x of varlist t ln_t
prov1 prov2 prov3 prov4 prov5 prov6 prov7 non_art2 uniloc2
sett1 sett2 sett3 sett4 sett5 sett6 sett7 tot_add2000 chiude
apre
{
;
#delimit cr
qui gen `x'_boot = .
qui replace `x'_boot = `x'[u]
}


#delimit ;
qui xi: reg ln_t_boot prov1_boot prov2_boot prov3_boot
prov4_boot prov5_boot prov6_boot prov7_boot
non_art2_boot uniloc2_boot  sett1_boot sett2_boot sett3_boot
sett4_boot sett5_boot sett6_boot sett7_boot tot_add2000_boot
chiude_boot apre_boot;
#delimit cr

qui predict double hat_ln_t_boot
qui predict double res_t_boot, resid
qui sum res_t_boot
qui gen double sigma_hat_boot = sqrt((r(sd)^2)*((_N-1)/_N))

qui gen double std_t_boot = res_t_boot/sigma_hat_boot
qui gen double pscore_boot= normalden(std_t_boot)
```

```
qui gen std_treat_boot= (ln(treat) -
hat_ln_t_boot)/sigma_hat_boot
qui gen double r_boot = normalden(std_treat_boot)

#delimit ;
qui nl (y_boot = {b0} + {b1} *(t_boot/1000) +   {b2} *
log(pscore_boot) +
{b3} * t_boot^2/1000000 + {b4} * (log(pscore_boot))^2 +
{b5}*log(pscore_boot) * (t_boot/1000)), variable(t_boot
pscore_boot)
;
#delimit cr
qui matrix B_boot = e(b)
qui predict xb_boot

qui gen b0_boot = B_boot[1,1]
qui gen b1_boot = B_boot[1,2]
qui gen b2_boot = B_boot[1,3]
qui gen b3_boot = B_boot[1,4]
qui gen b4_boot = B_boot[1,5]
qui gen b5_boot = B_boot[1,6]

#delimit ;
qui gen y_hat_boot =
b0_boot + b1_boot*(treat/1000) +  b2_boot*log(r_boot) +
b3_boot* treat^2/1000000 +
b4_boot * (log(r_boot))^2 + b5_boot*log(r_boot) *
(treat/1000)
;

#delimit ;
qui gen y_hat_plus_boot = b0_boot + b1_boot*(treat_plus/1000)
+  b2_boot*log(r_boot) +
b3_boot* treat_plus^2/1000000 +
b4_boot * (log(r_boot))^2 + b5_boot*log(r_boot) *
(treat_plus/1000)
;


#delimit cr
qui sum y_hat_boot
qui gen mean_value_boot = r(mean)

qui sum y_hat_plus_boot
qui gen mean_value_plus_boot = r(mean)


qui gen boot_mean_diff_`j' = mean_value_plus_boot -
mean_value_boot
```

```
qui gen boot_diff_`j' = y_hat_plus_boot - y_hat_boot
qui sum boot_diff_`j'
qui replace boot_diff_`j' = r(mean)

drop  *_boot u
}

egen es_mean_diff = rowsd(boot_mean_diff_1-
boot_mean_diff_100)
egen es_diff = rowsd(boot_diff_1- boot_diff_100)


save derivative_newsmall0_49_1_99_var03_00, replace
drop treat treat_plus std_treat  r y_hat y_hat_plus
mean_value mean_value_plus diff mean_diff
drop boot_mean_diff_1- boot_mean_diff_100 boot_diff_1 -
boot_diff_100 es_diff es_mean_diff
save temp, replace


clear
use derivative_newsmall0_49_1_99_var03_00, clear
keep  treat diff es_diff mean_value mean_value_plus
mean_diff es_mean_diff
keep if _n==1
label var  treat "Treatment values"
label var  diff "Derivative dose-response function: E[Y(t+1)
- Y(t)]"
label var  es_diff "Standard Error of the derivative dose-
response function"
label var  mean_value "E[Y(t)]"

label var  mean_value_plus "E[Y(t+1)]"

label var mean_diff "E[Y(t+1)] - E[Y(t)]"
label var es_mean_diff "Standard error of E[Y(t+1)] -
E[Y(t)]"
label var es_diff "Standard Error of the derivative dose-
response function"

save derivative_newsmall0_49_1_99_var03_00, replace
clear

use temp, clear
local i =1
while `i'<=100{
disp `i'
qui gen treat = min_t + `i'*((p10_t-min_t)/5) if `i'<=5
local j = `i' - 5
```

```
qui replace treat = p10_t + `j'*((p90_t - p10_t)/90) if `j'>
0 & `j'<=90
local k = `i' - 95
qui replace treat = p90_t + `k'*((max_t - p90_t)/5) if `k'> 0
& `k'<=5


qui sum treat
qui replace treat = r(mean)
qui gen treat_plus = treat + 1

qui gen std_treat= (ln(treat) - hat_ln_t)/sigma_hat
qui gen double r = normalden(std_treat)

qui gen y_hat = b0 + b1*(treat/1000) +  b2*log(r) + b3*
treat^2/1000000 + b4 * (log(r))^2 + b5*log(r) * (treat/1000)
#delimit ;
qui gen y_hat_plus = b0 + b1*(treat_plus/1000) +  b2*log(r) +
b3* treat_plus^2/1000000 +
b4 * (log(r))^2 + b5*log(r) * (treat_plus/1000)
;
#delimit cr
qui sum y_hat
qui gen mean_value = r(mean)

qui sum y_hat_plus
qui gen mean_value_plus = r(mean)

qui gen mean_diff = mean_value_plus - mean_value

qui gen diff = y_hat_plus - y_hat
qui sum diff
qui replace diff = r(mean)

*Bootstrap

foreach j of numlist 1/100{
qui gen u = uniform()
qui replace u = floor(u*_N+1)
qui gen y_boot = .
qui replace y_boot = tot_add2003[u]

#delimit ;
foreach x of varlist t ln_t
prov1 prov2 prov3 prov4 prov5 prov6 prov7  non_art2 uniloc2
sett1 sett2 sett3 sett4 sett5 sett6 sett7 tot_add2000 chiude
apre
{
;
```

```
#delimit cr
qui gen `x'_boot = .
qui replace `x'_boot = `x'[u]
}


#delimit ;
qui xi: reg ln_t_boot prov1_boot prov2_boot prov3_boot
prov4_boot prov5_boot prov6_boot prov7_boot
non_art2_boot uniloc2_boot
sett1_boot sett2_boot sett3_boot sett4_boot sett5_boot
sett6_boot sett7_boot tot_add2000_boot chiude_boot apre_boot;
#delimit cr

qui predict double hat_ln_t_boot
qui predict double res_t_boot, resid
qui sum res_t_boot
qui gen double sigma_hat_boot = sqrt((r(sd)^2)*((_N-1)/_N))

qui gen double std_t_boot = res_t_boot/sigma_hat_boot
qui gen double pscore_boot= normalden(std_t_boot)

qui gen std_treat_boot= (ln(treat) -
hat_ln_t_boot)/sigma_hat_boot
qui gen double r_boot = normalden(std_treat_boot)

#delimit ;
qui nl (y_boot = {b0} + {b1} *(t_boot/1000) +   {b2} *
log(pscore_boot) +
{b3} * t_boot^2/1000000 + {b4} * (log(pscore_boot))^2 +
{b5}*log(pscore_boot) * (t_boot/1000)), variable(t_boot
pscore_boot)
;
#delimit cr
qui matrix B_boot = e(b)
qui predict xb_boot

qui gen b0_boot = B_boot[1,1]
qui gen b1_boot = B_boot[1,2]
qui gen b2_boot = B_boot[1,3]
qui gen b3_boot = B_boot[1,4]
qui gen b4_boot = B_boot[1,5]
qui gen b5_boot = B_boot[1,6]

#delimit ;
qui gen y_hat_boot =
b0_boot + b1_boot*(treat/1000) +  b2_boot*log(r_boot) +
b3_boot* treat^2/1000000 +
```

```
b4_boot * (log(r_boot))^2 + b5_boot*log(r_boot) *
(treat/1000)
;

#delimit ;
qui gen y_hat_plus_boot = b0_boot + b1_boot*(treat_plus/1000)
+  b2_boot*log(r_boot) +
b3_boot* treat_plus^2/1000000 +
b4_boot * (log(r_boot))^2 + b5_boot*log(r_boot) *
(treat_plus/1000)
;


#delimit cr
qui sum y_hat_boot
qui gen mean_value_boot = r(mean)

qui sum y_hat_plus_boot
qui gen mean_value_plus_boot = r(mean)


qui gen boot_mean_diff_`j' = mean_value_plus_boot -
mean_value_boot
qui gen boot_diff_`j' = y_hat_plus_boot - y_hat_boot
qui sum boot_diff_`j'
qui replace boot_diff_`j' = r(mean)

drop  *_boot u
}

egen es_mean_diff = rowsd(boot_mean_diff_1-
boot_mean_diff_100)
egen es_diff = rowsd(boot_diff_1- boot_diff_100)

save derivative_newsmall0_49_1_99_var03_00_`i', replace

drop treat treat_plus std_treat  r y_hat y_hat_plus
mean_value mean_value_plus diff mean_diff
drop boot_mean_diff_1- boot_mean_diff_100 boot_diff_1 -
boot_diff_100 es_diff es_mean_diff
save temp, replace

clear
use derivative_newsmall0_49_1_99_var03_00_`i', clear
keep  treat diff es_diff mean_value mean_value_plus
mean_diff es_mean_diff
keep if _n==1
qui append using derivative_newsmall0_49_1_99_var03_00
```

```
qui save derivative_newsmall0_49_1_99_var03_00, replace
clear
qui erase derivative_newsmall0_49_1_99_var03_00_`i'.dta
use temp, clear
local i = `i'+1
}

erase temp.dta
```

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