Newsletter

Un modello controfattuale per la valutazione delle politiche del lavoro.

SOMMARIO

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Editoriale

Pubblichiamo su questo numero della newsletter un paper dal titolo «*Counterfactual model for labour market evaluation policies*» presentato al 55esimo congresso dell'ERSA (Associazione Europea di Scienze Regionali), nell'ambito della sessione sui metodi controfattuali per la valutazione delle politiche regionali.

Il paper presenta in maniera estesa una metodologia di valutazione dei percorsi individuali di reimpiego (Dote Unica Lavoro in particolare), utilizzando gruppi di controllo estratti dal sistema delle Comunicazioni Obbligatorie (COB).

Il sistema delle comunicazioni obbligatorie ha una ampia copertura settoriale e può essere utilizzato su tutto il territorio nazionale come base dati per l'analisi longitudinale delle carriere e per la valutazione di efficacia dei percorsi di politica del lavoro. Come ogni altra fonte amministrativa le COB richiedono procedure analitiche e di controllo di qualità dei dati per un appropriato uso ai fini statistici; le esperienze maturate in questi anni in ambito accademico ed operativo costituiscono una importante base di partenza per ogni utilizzo e sforzo metodologico futuro.

E' auspicabile che i metodi di valutazione di efficacia delle politiche del lavoro possano trovare diffusione nel paese, all'indomani delle riforme del mercato del lavoro che dovrebbero assicurare un rilancio delle politiche attive.

In particolare la valutazione dovrà cercare la risposta a due categorie di domande:

- le politiche attive aiutano effettivamente a trovare lavoro? Le politiche attive "fanno la differenza" per chi vi partecipa (come il paper presentato dimostra per DUL), oppure supportano persone che avrebbero trovato lavoro comunque?;
- l'organizzazione delle politiche, i ruoli e le responsabilità, il disegno dei percorsi e le risorse destinate sono adeguate? Quali cambiamenti sono necessari per aumentare l'efficacia delle politiche?

Senza rispondere a queste domande, vale a dire senza una continua iterazione fra valutazione, progettazione e riordino delle politiche, non è possibile innescare un processo di miglioramento che porti le politiche attive ad un livello di efficacia tale da rendere diseconomico il sistema dei sussidi passivi e attrarre le risorse necessarie a rendere i modelli di erogazione sostenibili nel medio periodo.

Giampaolo Montaletti
Direttore Vicario Arifl

«Counterfactual model for labour market evaluation policies»

Labour market interventions (policies) consist of all the initiatives and measures shared between public institutions and subjects authorized to promote employment and re-employment. Each region in Italy, in accordance with the Ministero del Lavoro, promote formative programs, orientation and job placement activities collected in policies, targeted to well-defined populations. Since many years, Regione Lombardia has provided different types of interventions, such as ***Youth Guarantee*** for youths between 15 to 29 years, ***Piano Provinciale Disabili*** for employed and unemployed workers with disabilities, ***Dote Lavoro***, ***Dote Lavoro Ricollocazione e Riqualificazione***, ***Dote Comune*** for employed and unemployed workers***,*** afterwards collected in a single policy called Dote Unica Lavoro (DUL). *(Guida alle politiche di Regione Lombardia a sostegno dell'occupazione. Febbraio 2013).*

Dote Unica Lavoro was created in October 2013 as a new model of active policies. It gathers various labour market policy interventions and takes into account the different needs of the active population. Three key points explain the guiding principles of the policy: people centrality, personalized services and high performances. These principles are imparted to authorized operators, through which people can obtain modular services on their profile. The provided activities are composed of four different areas: *basic services* such as beneficiary registration, *acceptance and orientation* such as active job search, *training and skill certification* and *job placement* and they depend on the severity of the situation of each beneficiary.

The evaluation of policies and interventions allows the measurement of efficiency and validity of public institution initiatives, with the aim of improving the planning and implementation of the process, and the efficient allocation of available resources. In Italy, the impact evaluation of labour market policies has been largely treated and discussed (Trivellato, 2011), as we will see in the next section. In this context, this working project proposes an empirical evaluation approach for measuring the Dote Unica Lavoro efficacy; conducted by Crisp (Centre of Research in Public Services) in collaboration with the Agenzia Regionale per l'Istruzione la Formazione e il Lavoro (ARIFL) department of Lombardy Region.

Literature review

Generally, evaluation of labour market policies makes use of the so-called non-experimental approach; it is a collection of methodologies applied when it is impossible to assign beneficiaries randomly to an intervention, making it necessary to collect information about subjects who did not benefit from the intervention. Below we describe some of the most used methods in literature.

Among the most significant methods of non-experimental approach, we can find the **Regression Discontinuity Design method (RDD)**. It works well when the exposure to the treatment depends on overcoming a threshold, for example, a subsidy's graded list. The approach consists in creating situations that are more similar to randomization, keeping the first-treated and non-treated subjects near the threshold. The method allows the avoidance of the selection bias, but depends directly on the sample size. Examples of applications of this method are Garibaldi, Pacelli & Borgarello (2004) and Schivardi & Torrini (2008).

The **Differences in differences (DID)** method consists in a difference of times (pre-post treatment) and in a difference of subject outcomes (treated-non treated). The idea is to correct the selection bias measuring the difference between the two groups (treated-non treated) in a previous period. DID subtracts the distance between the two groups pre- and post-treatment, eliminating the part of distortions related to different characteristics between the two groups that do not change in time.

Regression models are useful, in evaluation policies, for reducing differences between treated and non-treated subjects. They make use of *confounding variables* that are variable with a direct impact on the treatment selection and outcome. The assumption under these models is that the variables that influence the treatment selection and outcome are the only ones included in the model. Consequently, the estimates will be more accurate if more variables will be included.

Statistical matching consists in the selection of a control group *ex-post* similar, on observable variables, to the treated group. The effect of the treatment is measured by the difference between the outcome averages of the treated and non-treated groups. Propensity Score Matching belongs to this methodology; example of applications are Heckman *et al*, 1997; Dehejia and Wahba, 1999; Manski and Garfinkel, 1992; Sianesi, 2004, Barbieri and Sestito (2008), Bison, Rettore and Schizzerotto (2010), Paggiaro, Rettore and Trivellato (2010).

Other significant methods are **Instrumental variables** and **Interrupted Time Series Analysis**.

In Trivellato, 2011 several approaches and methodologies applied to labour market evaluation policies are collected from 2000 to 2010: it mentions significant works on TWA (Temporary Work Agency) employment, apprenticeship contrasted to fixed-term contracts, temporary contracts and employment on a variety of flexible contracts.

Counterfactual approach for DUL evaluation: the PSM choice

The evaluation of "Dote Unica Lavoro" makes use of the Propensity score matching (PSM) method, a non-experimental and counterfactual approach, with no testable assumptions. The propensity score matching is widely applied in the evaluation of labour market policies as we can see in Dehejia and Wahba (1999) or Heckman, Ichimura, and Todd (1997). *(Caliendo and Kopeing, Some Practical Guidance for the Implementation of Propensity Score Matching, 2005).*

Propensity Score Matching relies on the assumption that selection into a treatment can be explained purely in terms of observable characteristics (the "unconfoundedness assumption") and on the property that balancing on the propensity score is equivalent to balancing on the observed covariates. *(Arpino, Mealli, The specification of the propensity score in multilevel observational studies, 2008).*

The PS is a statistical technique, created by Rosenbaum e Rubin (1983), defined as the probability of assignment to a particular treatment given a vector of observed covariates: $e_i = Pr(Z_i = 1|X_i)$ "*The Central Role of the Propensity Score in Observational Studies for Causal Effects*" Rosenbaum & Rubin (1983).

The PS predicts, for each individual, the expected probability of receiving a treatment; it is usually estimated with a logistic model which includes a large number of measured variables (affecting both the outcome and the treatment assignment) and allows all the information included in the observations to be resumed in a unique continuous value (score). Consequently, all variables that are not included in the model cannot be measured. Rosenbaum and Rubin (1983) suggest that groups with nearly identical PS have balanced pre-treatment covariates. The matching technique that selects a non-treated group as similar as possible, in terms of PS, to the treated group, is known as Propensity Score Matching.

The balancing of the two groups (treated and non-treated) allows the restriction of the selection bias problem. Selection bias consists in the existing differences between treated and non-treated groups typically observed in observational studies, where the treated and non-treated are not randomly assigned. Variables with a direct impact on the treatment selection have a direct impact also on the outcome, so it makes it necessary to balance these variable to evaluate the effect of the treatment alone. The selection bias restriction depends on data availability. It will be more accurate if more variables are taken into consideration in the construction of the model. Having a database with a lot of information available becomes an extremely important prerequisite for conducting an analysis that ensures reliable results. Once this is done, differences in the treated and non-treated outcomes can be attributed only to the treatment.

Data Quality

According to Italian Labour Law, every time an employer hires or dismisses an employee, or an employment contract is modified (e.g. from part-time to full-time, or from fixed-term to indefinite term) a *"Mandatory Communication"* is sent to a job registry. As of 1997, the Italian public administration has been using an Information System, the so-called *''CO System"* [1],that aims to store all these communications by creating a geographical administrative archive useful for studying the labour market dynamics over time (see, e.g.[2]). This would help analysts in obtaining insightful information about worker career paths, patterns and trends, and facilitating the decision-making processes of civil servants and policy makers. To this end, the archive is required to have a high-quality level since according to the "*garbage in, garbage out"* principle, dirty data can have unpredictable effects on the information derived from them. For these reasons, data quality and cleansing are considered as key steps of the Knowledge Discovery on Database processes that should be performed carefully *before* the data mining task.

In such a scenario, we first focused on the *consistency* dimension that refers to *"the violation of semantic rules defined over (a set of) data items"*. In our settings, semantic rules have been derived from the Italian labour law and the domain knowledge (e.g., an employee cannot have further contracts if active on a full-time basis; a non-existent contract cannot be closed; an indefinite contract cannot be extended; etc.)

For these reasons, we first developed the *"Robust Data Quality Analysis"* [3,4] (and then its Multidimensional instance) a novel technique that allows one to formalise, automatically verify and visualize the quality of the data before and after a cleansing intervention. We analysed the quality of millions of COs by comparing the initial quality level and the quality reached thanks to the application of a well-known ETL-based approach. This technique allowed a fine-grained evaluation on the effectiveness of the cleansing procedure, providing useful insights to analysts on how to refine it[5]. The work has been awarded at the Human-Computer Interaction & Knowledge Discovery Conference in 2013.

Then, we worked on developing an algorithm able to automatically cleanse all these data according to the consistency rules defined[6,7] expressing it by also using Artificial Intelligence Planning algorithms[8,9]. Specifically, we first formally introduced the concept of *universal cleanser*, a repository of all the feasible actions able to cleanse dirty data. We then defined and implemented an algorithm that synthesizes it. While on the one hand, the Universal Cleanser is domain-dependent, i.e. it can deal only with database data conforming to the model that generated it, on the other, it is *data-independent* since, once computed, it can be used to cleanse any dataset that conforms to the model, and this allowed us to use it for cleansing several CO archives composed of millions of records. As a benefit, the universal cleanser allowed the synthesis and exploration of *all* the feasible corrections that a dataset allows in a

[1] The Italian Ministry of Labour and Welfare. 2012. Annual report about the CO system, available at http://goo.gl/XdALYd last accessed 1st July 2015;

[2] Lovaglio, P. G., & Mezzanzanica, M. (2013). Classification of longitudinal career paths. Quality & Quantity, 47, 989–1008;

[3] Mario Mezzanzanica, Roberto Boselli, Mirko Cesarini, and Fabio Mercorio. A model-based evaluation of data quality activities in KDD. Information Processing & Management, 51(2):144–166, 2015;

[4] Mario Mezzanzanica, Roberto Boselli, Mirko Cesarini, and Fabio Mercorio. Data quality through model checking techniques. In Intelligent Data Analysis (IDA), Lecture Notes in Computer Science vol. 7014, pages 270–281. Springer, 2011;

[5] Roberto Boselli, Mirko Cesarini, Fabio Mercorio, and Mario Mezzanzanica. Inconsistency knowledge discovery for longitudinal data management: A model-based approach. In SouthCHI13 special session on Human-Computer Interaction & Knowledge Discovery, Lecture Notes in Computer Science, vol. 7947 (Best paper awarded). Springer, 2013;

[6] Mario Mezzanzanica, Roberto Boselli, Mirko Cesarini, and Fabio Mercorio. A model-based approach for developing data cleansing solutions. The ACM Journal of Data and Information Quality, 5(4):1–28, March 2015;

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[8] Roberto Boselli, Mario Mezzanzanica, Mirko Cesarini, and Fabio Mercorio. Planning meets data cleansing. In The 24th International Conference on Automated Planning and Scheduling (ICAPS 2014), pages 439–443. AAAI, 2014;

[9] Roberto Boselli, Mario Mezzanzanica, Mirko Cesarini, and Fabio Mercorio. Towards data cleansing via planning. Intelligenza Artificiale, 8(1), 2014;

formal, deterministic and automatic way, with no need to manually specify and implement the business-rules for cleaning the data in a common ETL process.

All these techniques have been implemented using model-checking algorithms, whose aim is to verify the correctness of a developed software or protocol with respect to one or more constraints.

It is worth highlighting that we also investigated the effects that different cleansing modalities can have on some statistical indicators that one would compute on the data (*aka* sensitivity analysis[10,11]) as well as on the accuracy of the cleansed data[12,13]. This latter work has been awarded best paper at the Third International Conference on Data Technologies and Applications in 2014.

We combined our data quality techniques for cleansing an integrated archive composed of the labour market archive, the archive of DUL policies with beneficiaries' information and the archive of CIG[14]. We joined these datasets by considering encrypted tax code.

Model description

Dote Unica Lavoro data pertains to residents in Lombardy who are:

- Unemployed workers
- Employed CIG workers
- People looking for their first job (up to 29 years old);

with reference to the period October 2013 to December 2014.

(Dote Unica Lavoro: "Occupati in Lombardia", http://www.lavoro.regione.lombardia.it).

The evaluation of DUL involves approximately 25 thousand beneficiaries: around twenty thousand belong to the group of unemployed workers, four thousand to the group of people looking for their first job, and nine hundred to Employed CIG workers. All the information extracted is derived from administrative databases of mandatory communications, policies and CIG archives provided by the Lombardy Region.

Since average treatment effects vary across groups that share the same observable characteristics (Trivellato, 2011) we decided to explore outcomes through a stratification of the following variables:

- Sex (male, female)
- Age group (15-24 years, 25-34 years, 35-44 years, 45-54 years, 55+ years)
- Nationality (Italian, non-Italian)
- Province of residence
- Educational level (ISCED groups)
- Working condition (employed, unemployed, seeking first job).

For each strata, we also calculated time-dependent variables:

- Subject employed at instant t;
- Subject employed at instant t weighted by contractual typology;
- Working days between instant t-1 and t;
- Working days between instant t-1 and t weighted by contractual typology.

The observation period occurs every 30 days following the policy reference date, the total period of observation consists of 6 months (t=6) for policies that started from October 2013 to December 2014.

[10] Mario Mezzanzanica, Roberto Boselli, Mirko Cesarini, and Fabio Mercorio. Longitudinal data consistency verification using formal methods. International Journal of Information Quality, 3(3):185–206, 2014;

[11] Mario Mezzanzanica, Roberto Boselli, Mirko Cesarini, and Fabio Mercorio. Data quality sensitivity analysis on aggregate indicators. In Markus Helfert, Chiara Francalanci, and Joaquim Filipe, editors, DATA 2012 - the International Conference on Data Technologies and Applications, pages 97–108. SciTePress, 2012;

[12] Mario Mezzanzanica, Roberto Boselli, Mirko Cesarini, and Fabio Mercorio. Improving data cleansing accuracy: A model-based approach. In DATA 2014 - the International Conference on Data Technologies and Applications (best paper awarded). SciTePress, 2014;

[13] Mario Mezzanzanica, Roberto Boselli, Mirko Cesarini, and Fabio Mercorio. Accurate Data Cleansing through Model Checking and Machine Learning techniques, Communications in Computer and Information Science (CCIS) ISSN: 1865-0929, 2015 (to appear);

[14] The cassa integrazione guadagni (CIG) is an institution under Italian Law consisting in financial support, financed by the INPS, in favour of workers who have been suspended from the obligation of carrying out remunerated work or who work reduced hours.

In addition to the dimensions described, we also considered occupational information such as:

- Type of contract
- Occupation
- Economic sector
- Job modality (part-time, full-time).

The control group (non-treated subjects) has been extracted from the administrative mandatory database through the PSM methodology based on the observed characteristics used for stratifying the treated group. For each treated subject, two non-treated have been associated.

As regards the working conditions of the control group, these are derived from the administrative mandatory database with reference to each individual's (treated) starting month of intervention; in fact, each beneficiary has a different policy starting date that we have collected, to simplify matters, at the corresponding starting month.

In this way, a control (non-treated) subject could be associated with different beneficiaries, but only if a different period of observation subsists between the beneficiaries.

Treated workers on CIG have been associated with CIG workers reported in the CIG administrative database.

Data analysis and results

In this section, we can observe the occupational index expressed through the percentage of occupied on the total amount of treated/non-treated, at t moments. As we can see in Figure 1, the treated group has a higher percentage occupation than the non-treated group. One month later, 48% of the treated group are occupied, and after six months, the index reaches 61%. The non-treated group definitely has lower values. The index at t1 indicates that only 6% of the population are occupied, while at t6 it reaches 22%. DUL seems to have a positive direct effect on their beneficiaries according to the observed variables.

Figure 1 - Occupational percentage of treated and non-treated.

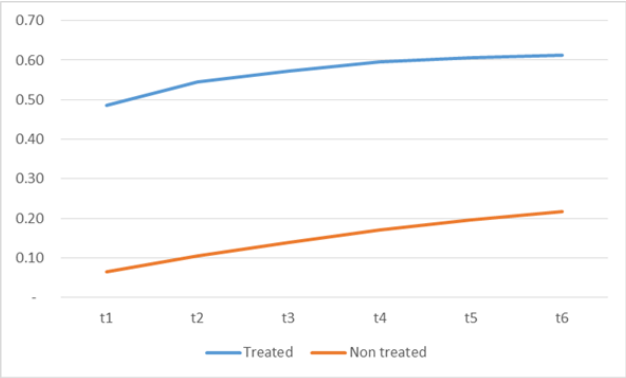
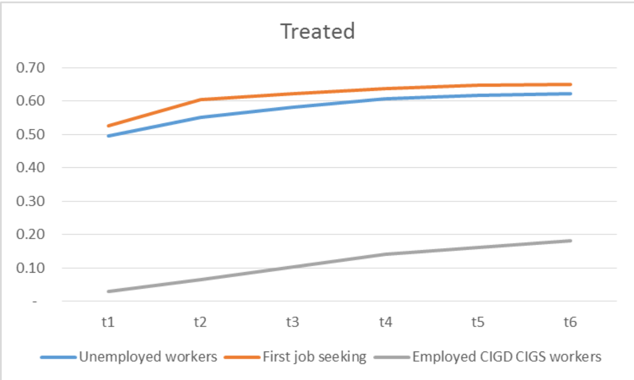


Figure 2 shows differences between the occupational condition of those treated and non-treated. For the treated group "seeking first job" and "unemployed workers", the line graphs are very close and high, while the line graph of Employed CIGS, CIGD workers is lower. For the non-treated group, the three line graphs start close together but with different growth coefficients, at t6 the "seeking first job" graph line has about 0.30 points of distance from the other two.

Figure 2 - Occupational percentage of treated and non-treated per working condition at the starting date of intervention.



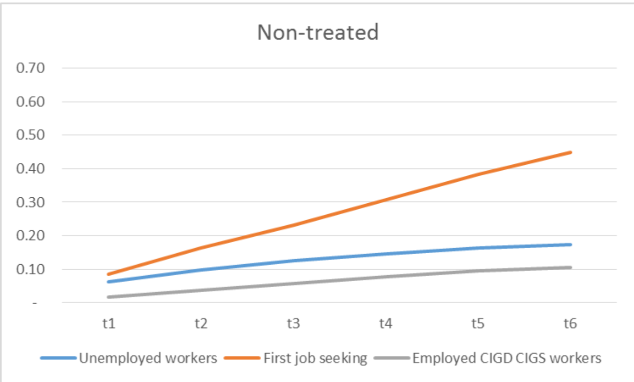
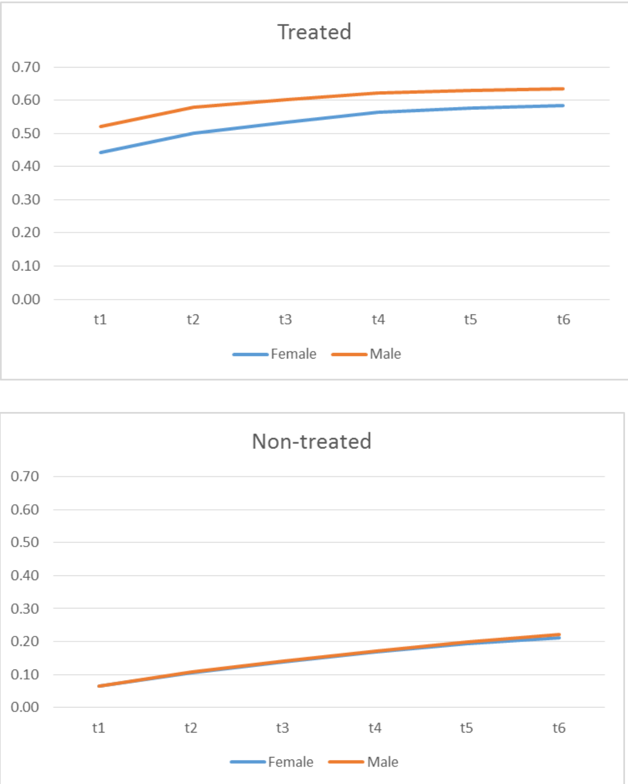


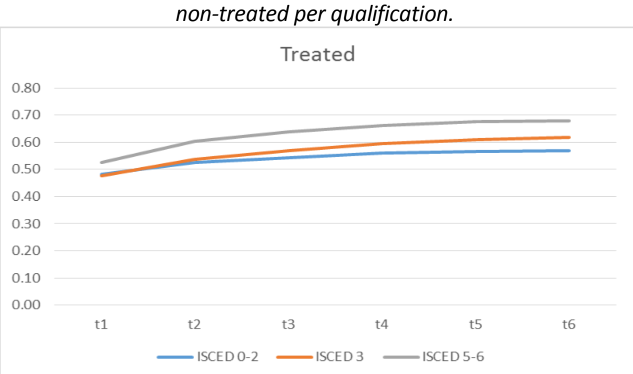
Figure 3 shows differences between males and females for treated and non-treated groups. As we can see, for the beneficiaries, the probability of finding occupation is always better for males than females. No differences are observed for the non-treated group.

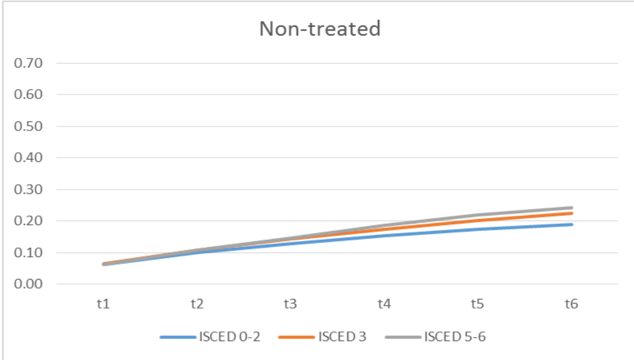
Figure 3 - Occupational percentage of treated and non-treated per gender.



In Figure 4, we can see the percentage of occupation. Beneficiaries with ISCED 5-6 (short-cycle tertiary education and Bachelor's or equivalent level) have a higher occupation percentage than beneficiaries with ISCED 0-2 (early childhood education, primary education, lower secondary education) and ISCED 3 (upper secondary education). No differences are observed for the non-treated group.

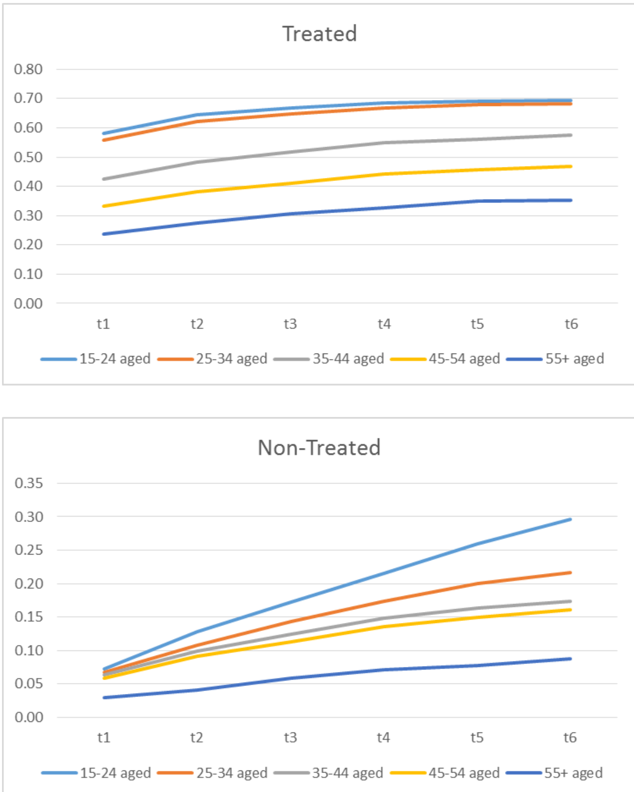
Figure 4 - Occupational percentage of treated and non-treated per qualification.





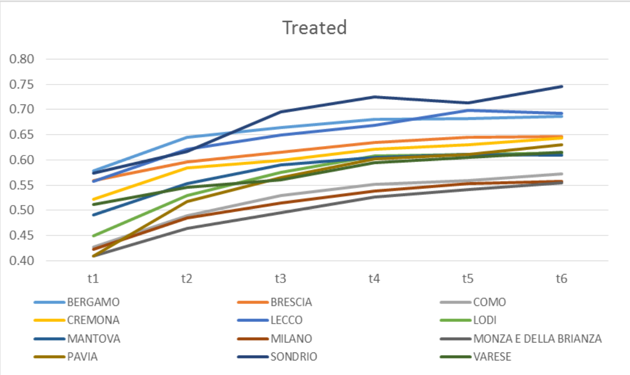
In figure 5, we can observe the occupational percentage for aged groups. Beneficiaries who are less than 34 years old have better employment possibilities than beneficiaries who are older than 35 years old. The non-treated group has a similar occupation percentage at t1, but the growth in the line graphs is different and in t6 subjects who are less than 24 years old, there is a higher percentage of occupation.

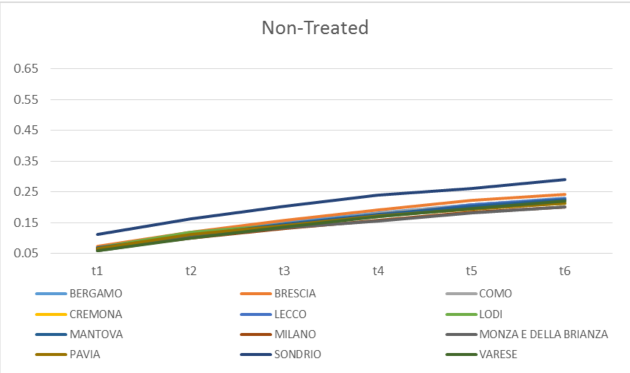
Figure 5 - Occupational percentage for treated and non-treated per age group.



Finally, Figure 6 shows the differences between residence provinces for treated ad non-treated groups. Sondrio is the province with higher values for the two groups. Beneficiaries have different values for provinces, while no differences are resulting in the non-treated group.

Figure 6 - Occupational percentage of treated and non-treated per province





Model limitation and advantages

- Perspective vs retrospective

The evaluation of active policies is normally carried out after the implementation of the policy. Data retrieval for the building of a control sample with the same characteristics of the treated group, therefore, turns out to be a delicate operation and fundamental for a good evaluation result. Being able to intervene in the definition of requisites that are necessary to conduct a good evaluation, before the implementation of the policy, would enable the achievement of better results through a more efficient process.

- Databases from administrative archives

Databases used for the evaluation of DUL, are obtained from administrative archives of mandatory communications. These databases are census-type, with detailed information on workers' careers. However they hold some limitations: they do not cover the entire working population; for example, no data about self-employed workers are available, or data about transfers abroad or, obviously, undeclared work. Data refers to individuals and no household information is reported. On the other hand, administrative archives allow analysts to work with a large sample size, and they do not have the problems usually associated with surveys (non-response, smaller sample size).

- Variables that cannot be measured

Despite the availability of variable and employment demographics of persons who have benefited from the DUL, and through which the non-treated sample has been built, there exist characteristics, such as social, for which it has not been possible to control the selection bias. Sometimes, it may happen that persons participating in the active policy are subject to the risk of social exclusion, because they are ex-inmates, or with difficult family situations. This type of information, with obvious impact on the outcome of the policy itself, cannot be controlled through the use of administrative databases of mandatory communications, creating in fact a distortion in the survey results. Moreover, in order to associate an adequate control group to the group of unemployed beneficiaries, the persons who were unemployed at the time of the study were extracted from the database. However, it is not possible to determine whether, at that point in time, those persons were actively looking for work. For example, they may be persons who are working with a VAT registration number, or have travelled abroad for work or study, or are housewives. In this case, the measurement of the outcome of the non-treated group will definitely have lower values when compared to the outcome of the treated group, since there is less interest on the part of those non-treated to have an employment engagement.

Conclusions and future prospects

The integration of administrative archives has enabled the achievement of positive results in the evaluation of active policies. The availability of detailed data and the presence of high coverage in terms of available population has allowed the building of an accurate evaluation model. Moreover, the process of implementing quality archives has allowed us to deal with highly reliable data with consequent trust in the results obtained in the study.

The proposed counterfactual model (excluding the selection bias problems listed previously) has enabled the obtainment of a positive confirmation on the assessment of the active policy's efficacy. The results achieved demonstrate, in fact, improved performance for DUL beneficiaries. The advantage attributed to policy affiliation, however, tends to subside after some months, approximately five, after which the probability of finding employment is the same between those treated and non-treated.

The experience and knowledge acquired in this study permit, as a future prospect, the improvement of the implementation of policy intervention itself, as well as improving the evaluation of the efficacy by further reducing the presence of selection bias. Moreover, the study and the formulation of additional multi-level models may help to isolate the influence that the attribution of various operators may exert on the evaluation of individual beneficiaries. In this sense, evaluating the performance of such operators may allow, on the one hand, an evaluation of policy efficacy and, on the other, an improvement in the efficacy thereof.

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Lombardia in numeri

	II trim 2014	III trim 2014	IV trim 2014	I trim 2015	II trim 2015
Popolazione*	**9.917**	**9.920**	**9.937**	**9.941**	**9.948**
Maschi	4.848	4.849	4.859	4.861	4.864
Femmine	5.069	5.071	5.078	5.080	5.084
Tasso di attività 15-64*	**70.7**	**70.4**	**71.3**	**70.8**	**70.6**
Maschi	78.4	77.8	78.8	78.5	78.7
Femmine	63.0	62.9	63.8	63.0	62.4
Tasso di occupazione 15-64*	**65.0**	**65.0**	**65.1**	**64.6**	**65.1**
Maschi	72.0	72.3	72.7	72.1	72.9
Femmine	58.0	57.7	57.5	57.1	57.1
Tasso di disoccupazione*	**7.9**	**7.5**	**8.5**	**8.6**	**7.7**
Maschi	7.9	7.0	7.5	7.9	7.2
Femmine	8.0	8.2	9.7	9.5	8.4
Numero occupati*	**4.254**	**4.237**	**4.258**	**4.227**	**4.250**
Maschi	2.387	2.382	2.406	2.394	2.414
Femmine	1.866	1.855	1.852	1.833	1.836
Numero disoccupati*	**366**	**345**	**396**	**398**	**357**
Maschi	205	180	196	206	188
Femmine	161	166	200	192	168

Fonte: ISTAT (Rcfl anno 2014 e II trim 2015). Valori espressi in migliaia (*) e in percentuale (**)

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