Do business incentives increase employment in declining areas? Mean impacts versus impacts by degrees of economic distress[(*)]

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1. Introduction

Over the past decade, business investment subsidies co-financed through the Structural Funds, and through the European Regional Development Fund (ERDF) in particular, have become popular regional economic development tools for European Union "Objective 2" (Obj.2) areas, regions with declining industrial production. Business incentive packages have been offered in more than 80 Obj.2 areas covering 18% of the EU population. In the 1994-1996 programming cycle alone, approximately five billion Euros, or 11% of the entire EU budget dedicated to the fulfillment of economic and social cohesion objectives, were drawn from the ERDF to finance incentive packages to support small and medium enterprise (SME) investments in Obj.2 areas. Initiatives such as these also have an important role in the current 2000-2006 cycle of EU regional policies and are similar to other spatially targeted programs such as the enterprise zone incentive packages that were first offered in the early 1980s in distressed areas of the United Kingdom, the United States, and other countries.

Despite the wide popularity of these initiatives, no reliable ex-post evidence of their employment impact in the Obj.2 areas is yet available to help EU policy makers refine future geographically-targeted economic development policies. Existing ex-post employment impact results are primarily derived through two evaluation practices: application of standard macroeconomic multipliers to the volume of investments co-financed by the ERDF in the Obj.2 areas (e.g., Ecoter, 2000) and solicitation of entrepreneurs' judgments on the effectiveness of the programs in affecting their investment behavior (e.g., Ernst & Young, 1999). Both types of procedures have serious drawbacks. The multiplier analysis not only cannot measure actual net pre to post intervention employment changes in the target areas, but it also cannot estimate marginal differences in employment impact due to the different program features adopted across EU regions and countries. Thus, this method of evaluation is of limited use for policymakers attempting glean information from previous policy to craft future policy. While surveys may be better suited to capture some of the impacts of policy heterogeneity, the applicability of survey results is limited by response bias: Business respondents have incentives to overestimate the outcomes attributable to the programs in hope of increasing the chances of maintaining the intervention (Bartik, 1991; Boarnet and Bogart, 1996; Dowall, 1996; Lambert and Comes, 2001; Papke, 1993, 1994). For instance, Gabe and Kraybill (2002) documented that economic development incentives tended to have a much greater positive impact on *announced* growth rather than on *actual* growth among expanding business establishments.

Conducting reliable ex-post impact evaluations based on actual pre-post intervention datais difficult, however. Assessing the causal link between the program intervention and observed employment outcomes is challenging because it requires disentangling changes due to the program from changes due to all of the economic and social factors exogenous to the program intervention. This task is particularly demanding for the case of the Obj. 2 area business investment incentives because the targets of the interventions are disadvantaged areas that would likely under perform their respective national economies in the absence of the program intervention. Consequently, impact estimates can be biased if the analysis fails to carefully control for the economic trends and exogenous economic factors that affect employment outcomes concurrently with the program interventions (Bondonio 2000).

Italy presents an ideal opportunity to evaluate the impact of Obj. 2 incentives. While many of the southern regions are impoverished and thus receive the more generous and geographically comprehensive Obj. 1 incentives, the Obj.2 areas are concentrated in center-northern Italy, a region with a great deal of employment in the manufacturing sector and a very diverse industrial base. Italy is also ideal because of the unique availability of data sufficient to perform an outcome evaluation of the business investment incentives offered to SMEs. Such data cover information regarding both the program incentives paid to each assisted SME and the firms' yearly employment changes recorded by the Italian Social Security Agency's (INPS) mandatory worker registration archives.

The econometric models estimated in the paper use INPS employment data sorted by industry and aggregated by geographic areas corresponding to the Obj.2 areas and adjacent non-Obj.2 areas of comparable size. Following an evaluation strategy proven reliable for analyzing US enterprise zone programs (Boarnet and Bogart, 1996; Bondonio, 2002; Bondonio and Engberg, 2000; Greenbaum and Engberg, 2004; Papke, 1993, 1994), the analysis is implemented through a number of parametric difference in difference specifications that allow impact estimates to be retrieved net of the following factors exogenous to the program intervention:

- Local economic trends that may affect Obj.2 areas differently from the non-Obj.2 areas of the EU;

- Cyclical macroeconomic factors that may affect employment growth in both Obj.2 and non-Obj.2 areas during the program intervention period;
- Sector-specific market trends that may affect the performance of firms in the targeted industrial sectors differently than in non-targeted sectors;
- Structural characteristics of Obj.2 areas that may affect firm performance differently than in non-Obj.2 areas.

The econometric specifications utilized also allow the marginal employment impact of the programs' financial generosity to be estimated along with differences in the employment impact due to variations in labor-intensity levels across industrial sectors and different degrees of pre-intervention industrial decline in the treated areas. The analysis finds positive and significant marginal employment impacts in SMEs when the financial generosity of the incentives is increased. The estimated employment impacts, however, are much lower than those offered by the evaluation reports that either apply standard macroeconomics multipliers to the volume of subsidized investments or collect entrepreneurs' judgments on the employment effectiveness of the program. The incentives appeared to be equally effective in areas with labor intensive or capital intensive production processes, and the paper also finds that the incentives were more effective in areas that were less distressed in terms of pre-intervention employment trends. Sensitivity analysis indicates that the significance and magnitude of the impact estimates are robust across various specifications, data, and assumptions regarding the selection process of the target areas and industries. The cost of each new job created, measured in terms of public resources devoted to the incentives, is estimated to be just over 21,400 euros.

The remainder of the paper is organized as follows: The next section discusses the economic rationale for the programs and provides additional information about their history and implementation in the EU and Italy. Section 3 presents the evaluation strategy, and section 4 describes the data. Sections 5 and 6 summarize the empirical model and results, and section 7 offer concluding remarks.

2. EU "Objective 2 area" programs

Large regional disparities in income persist across Europe, and EU expenditures to address these inequalities have grown rapidly to now account for almost a third of the EU budget (Puga, 2002). The European Regional Development Fund was established in 1975 to address these disparities, but the EU did not begin to geographically target its resources until 1989 in response to severe localized declines in industrial production. This geographic targeting of incentives in an attempt to reduce regional inequities has also been justified as a necessary step for the coordination of economies that is necessary for the European Union to succeed (Sweet, 1999). Some have argued, however, that the broader efforts have so far resulted in little regional economic convergence (e.g., Hurst et al., 2000; Rodriguez-Pose and Fratesi, 2004), although the impact of the particular targeted industrial incentives remains under-studied.

The EU's geographically targeted Obj.2 areas are named after one of the *objective propositions* set to regulate and coordinate all of the initiatives co-funded by the EU structural funds. Since 1989, the Obj.2 targeted areas facing severe industrial production declines have been redefined twice, in 1994 and 2000 (Greenbaum and Bondonio, 2004). The three distinct administrative programming rounds cover the periods 1989-1993 (divided into the sub-periods 1989-1991 and 1992-1993); 1994-1999 (divided into the sub-periods 1994-1996 and 1997-1999); and 2000-2006. There were seven different objectives for the 1989-1993 and 1994-1999 programming periods. These were consolidated to three for the 2000-2006 period. While some of the other objectives that focus on the economic adjustment of poor regions are spatially targeted, others that focus on agriculture and the economic integration and training of youth and the long-term unemployed are not. During the 1989-1999 programming periods, the Ob.2 proposition was concerned solely with the promotion of economic revitalization in industrially declining regions. For those programming periods, eligible areas were required to meet three specific distress criteria: an unemployment rate exceeding the EU average for the last three years prior to the beginning of each programming period; the share of industrial unemployment exceeding the EU average in any year after 1975; and an overall decline in industrial employment since 1975. The most recent Ob.2 proposition in the current 2000-2006 period now also embraces boosting development of rural and exclusively urban areas.[1] Eligible areas were extended to include certain rural areas, urban areas with distressed socio-economic conditions and areas with high percentages of jobs in the fishing industry.

[1] Information on the 2000-06 EU Ob.2 programming round can be found at http://europa.eu.int/comm/regional_policy/objective2/areas_en.htm.

Throughout the three programming periods, Obj.2 areas were designated in 56 NUTS_1 regions located in 12 different EU countries covering, on average, more than 16% of their population. For the two earlier programming periods, the designated Obj.2 areas enjoyed a total financing of more than 22.6 billion euros, as shown in Table 1. [2] The percent of each country's population covered by Obj.2 areas during the 1994-1996 sub-period averaged 16.4% and varied from a low of 7.5% in Austria to a high of 34.6% in Luxembourg.

Table 1

The policy features of the Obj.2 area programs vary across the EU. The single regional administrations that have jurisdiction on designated Obj.2 areas each autonomously set their own "program agenda" in which quite different incentives and economic revitalization policy features are adopted following common EU policy guidelines. Business investment incentives targeting small and medium enterprises were a major part of the Obj.2 area regional programs in all countries except Austria, accounting for, on average, almost 60% of the financial value of the incentive packages during the 1994-1996 sub-period, as can be seen in the last column of Table 1.

For the programming period that ended in 1999, Obj.2 areas were designated in 11 regions located in the northern and central parts of Italy: Valle d'Aosta, Piemonte, Liguria, Lombardia, Veneto, Friuli Venezia Giulia, Emilia Romagna, Toscana, Marche, Umbria and Lazio. Obj.2 areas represent approximately 25% of population and 39% of the land area in those north central regions. The percentages of the total contribution devoted to SMEs offered in the Italian Obj.2 areas are similar to those recorded in other EU countries. Because the Obj. 2 areas located in Lombardia cover only a negligible portion of the total population and land area of that region, Lombardia's Obj.2 areas are excluded from the analysis and employment data are excluded for the provinces of Milano and Varese, the only two Obj.2 areas in Lombardia. Further, because Valle d'Aosta's Obj.2 area incentive package does not include any SME investment subsidy, its employment data is included in the analysis only as part of the control group.

[2] Table 1 breaks the 1994-1999 programming period up into the two sub-periods to account for the fact that Austria and Sweden were not members of the EU when the 1994-1996 sub-period began and thus did not receive incentives until the 1997-1999 sub-period. Finland also joined the EU in 1995, although a decision with regard to their Obj.2 incentives was made earlier than for Austria or Sweden.

The specific composition of the Obj.2 area incentive packages set by each Italian region for the 1994-1996 programming period is summarized in Table 2. All regions other than Valle d'Aosta provide SME capital expenditure incentives, human resource training and business technical assistance. Additional business incentives include research and development (R&D) and infrastructure assistance, aid with environmental protection, and tourism incentives.

Table 2

Subsidies to SMEs' investments, which often take different names in the various regional programming documents describing the Obj.2 intervention packages, are the most common type of intervention, typically accounting for more than 65% of the program budgets. In most cases, these subsidies are capital grants that support up to 15 to 30% of the total investment expenditures. They are aimed at expanding production capacity, supporting technological upgrades of the production process, or restructuring plants and equipment. In a few cases, SME capital expenditures incentives take the form of interest rate abatements.

3. The evaluation strategy

This paper focuses on investigating whether there is a direct impact of these Obj.2 area business incentives on the subsequent economic performance of targeted areas. While more global impacts are also likely if the programs are successful, the focus on outcomes measured in the targeted areas is consistent with the main economic rationale supporting geographically targeted policies such as the Obj.2 area business incentives. Such programs are often justified not only on the equity grounds of attempting to reduce regional inequities but also on efficiency grounds as a way to address market failures such as information asymmetries, immobile resources, and externalities that inhibit the efficient spatial distribution of economic activity (Martin, 2000). While imperfect markets for information may prevent people from knowing about economic opportunities in particular locations, market rigidities may preclude them from taking advantage even if aware. Labor is often immobile, and union agreements often restrict the ability of firms from being able to offer lower wages in regions of higher unemployment to take advantage of the underutilized resources (Faini, 1999).

Externalities further distort markets. When based exclusively upon private costs and benefits, firms' location decisions do not properly account for the entire social costs and benefits involved with their decisions. When businesses and people leave urban areas, there is often an increase in urban sprawl and traffic congestion accompanied by environmental and health consequences. Abandoned areas may also be conducive to crime, which only encourages further flight. These increased costs on those who remain behind may justify the use of geographically targeted public incentives (Bartik, 2000; Gyourko, 1998).

There may be economy-wide efficiency gains from moving jobs to places with higher unemployment and lower reservation wages (Bartik, 1991), so Obj.2 area business incentives potentially produce socially desirable outcomes even if the economic growth of the target areas occurs at the expense of the non-target areas. Because the redistribution of jobs is not necessarily zero-sum, it is important to begin the investigation of program effects by looking for impacts in the targeted areas. Successful geographically targeted programs should boost economic growth in the assisted areas by either attracting new firms or helping existing firms to expand their business. While empirical evidence of such increased economic development could be found in increased employment, sales and capital expenditures, this paper uses employment as the outcome measure for two main reasons. First, boosting employment in distressed areas is a top priority for national and regional EU policymakers. Second, firm level employment data are much more reliable and accessible than data on sales and capital expenditures, which are also not readily available for smaller firms.

The Obj.2 area business incentives typically aid the targeted distressed regions by providing a richer program budget that enables a greater number of firms to take advantage of the business incentives than would otherwise be the case. For each assisted firm, however, the value of the Obj.2 incentives is very often comparable to those of other, non-geographically targeted business investment incentives available in each EU country. The fact that individual firms located outside the Obj.2 areas may also gain access to investment incentives comparable to those of the Obj.2 programs suggests the use of empirical models that use outcome data from groups of target and non-target firms aggregated by geography and industrial sector. The empirical method of choice is a longitudinal parametric model that analyzes firm data aggregated by province and 2-digits industrial sector. Aggregated longitudinal data recorded from non-Obj.2 areas is exploited in the model to estimate the counterfactual employment change conditioned on industrial sector and region- specific trends and pre-intervention area-specific characteristics.

This evaluation strategy is preferred to a more basic firm-level comparative analysis of changes in employment between treated and non-treated areas for two main reasons. First, if treated firms were compared to comparison non-Obj.2-area firms that did not receive any other type of public financial aid, there would be concerns about selection bias. The fact that some firms did not succeed in applying for financial incentives for which they were eligible might reflect shortcomings in unobserved managerial abilities, and it is likely that the treated Obj.2-area firms would outperform comparison-group firms even in the absence of the business incentives. Second, if treated firms were compared to non-Obj.2-area firms that received financial incentives from sources other than the Obj.2-area program, the validity of impact estimates would depend critically on precisely observing the quantity and timing of the financial incentives received by the non-Obj.2-area firms. In this case, results from the analysis would be interpreted as estimates of the employment elasticity of firm-specific subsidies rather than as estimates of the employment impact of program interventions targeting selected geographically defined economies.

Threats to the validity of the analysis and control variables

Longitudinal examinations of employment changes in Obj.2 areas relative to non-Obj.2 areas yield reliable impact estimates only if the empirical models successfully control for all factors exogenous to the program intervention that may cause employment changes to be different in the targeted areas than in the excluded areas. With Obj.2 programs, the main factors that may lead to selection and omitted variable biases can be summarized as follows:

A) Business cycles that could similarly affect profitability, investment, and hiring decisions for all firms operating in the same national or regional economy.

B) Economic conditions affecting the costs and revenues of all firms located within the same local economy. Such common local economic conditions may affect investment and hiring decisions for all firms located within the same geographic area regardless of whether or not the firms are eligible to receive public subsidies.

C) Business sector-specific market conditions that could affect costs and revenues for all firms operating in related industrial sectors.

For parametric longitudinal models that compare the pre-post intervention employment outcomes in Obj.2 areas relative to non-Obj.2 areas, the national- or regional-business cycle factors of point A) do not pose any particular threats to the validity of the analysis. Business cycles have the same affects on Obj.2-area and non-Obj.2-area firms and would therefore not bias estimates of employment outcomes. A number of other empirical program evaluation studies have also adopted such approach to control for national- or regional- economic cycle factors (e.g. Batik, 1995; Dowall, 1996; Greenbaum and Engberg, 2004; Boarnet and Bogart, 1996).

Exogenous factors such as the local economic conditions and sector-specific market conditions of points B) and C) potentially pose more significant threats to the validity of the analysis. Concerns regarding the local economic conditions are mitigated because the firms eligible for receiving Obj.2-area incentives predominantly operate in industrial manufacturing sectors. Since their outputs and many of the factor inputs are typically traded in national and international markets, conditions in the local economy play less of a role impacting the costs and benefits of a particular location.[3] Moreover, using a longitudinal approach with simple panel data estimators such as *fixed effects, first-differencing,* or *long-differencing* would allow any residual local economic conditions that may be correlated with the treatment status to be controlled for, provided that such conditions affect the dependent variable in a relatively time-unvarying manner.

Sector-specific market conditions [point C)] pose the greatest threat to analysis of the Obj.2-area incentive program. If firms operating in different industrial sectors are affected by different sector-specific market conditions, they would make different investment and hiring decisions and, therefore, display different employment growth rates even in the absence of the program intervention. If the sector composition of Obj.2-area and non-Obj.2-area economies differ greatly, as is likely to be the case due to the high concentration of declining industrial sectors in the Obj.2 areas, impacts estimated would be biased without adequately controlling for the sector compositions of target and non-target areas. To avoid selection bias, the empirical model must condition to the same

[3] While unemployment rates vary across labor markets, even labor costs are unlikely to vary significantly because of the role unions play in standardizing wages.

industrial sectors the comparison of employment outcomes between Obj.2-areas and non-Obj.2-areas.

One possible drawback of conditioning on industrial sectors is that impact estimates may not be reliable in the event that the Obj.2-area incentives spur investments that allow firms to expand beyond their core businesses into new industrial sectors. This occurrence, however, is likely much rarer for SMEs than for more diversified larger firms. SMEs typically operate in the industrial sector in which their owner or manager is most qualified. Such owner-specific abilities and experience do not vary substantially over time, making it less likely that SME businesses would diversify into other industrial sectors in the short run.

4. Data

The geographically aggregated employment data necessary for the analysis is offered by the “Enterprise Observatory” (EO) of INPS, which is the national social security agency of Italy. INPS tabulates firms’ employment data by province,[4] industrial sector,[5] and firm size.[6] Unlike the case in countries such as the United States, Germany, France, and the United Kingdom, the vast majority of employment in Italy is in smaller firms (Guiso 2003) and the business incentives are thus targeted at SMEs. Therefore, only firms in size classes with fewer than 200 employees are examined.[7] The units of observation for the analysis are cross-sectional province-sector (*p*-*j*) pairs for the years 1984 to 1998:

$Y_{p,j,t}$ = employment level at the end of year *t*, for all SMEs located in province *p* and belonging to the industrial sector *j*.

INPS EO are the most appropriate data available. They offer more reliable employment figures than self-reported employment data obtained from firm interviews or Obj.2 area incentive firm application forms. They include annual employment flows from 1984 to 1998, covering the 1995-1998 intervention period. They allow employment changes to be

[4] There are 102 provinces in Italy
[5] There are 45 different industrial sectors.
[6] There are nine size categories based upon number of employees.
[7] Although SMEs are legally identified as firms with fewer than 250 employees, INPS data are aggregated by firm size classes that yield employment information only for firms with fewer than either 200 or 500 employees. The analysis focus on firms in size classes with fewer than 200 employees with very little loss of generalibility as, in the Italian regions with Obj.2 areas, much less than one percent of SMEs have between 200 and 250 employees.

categorized into those that occurred in Obj.2 areas and non-Obj.2 areas and those that are accounted for by SMEs and large firms. Because the focus of the analysis is limited to SMEs, geographic problems that plague larger firms are avoided. INPS EO data measure firm-level rather than establishment-level employment. Thus, all employment is attributed to the administrative offices. For large, mulit-establishment firms, this can be very misleading, particularly if the establishments are in disparate locations. The overwhelming majority of SMEs have only one location, thus avoiding the coding problem.

Data for the analysis cover all the provinces in each Italian region containing at least one Obj.2 area. All of southern Italy (i.e., the regions of Abruzzo, Campania, Molise, Puglia, Basilicata, Calabria, Sicilia e Sardenia) is excluded from the analysis due to the extremely severe economic distress that qualifies those regions for the more generous and geographically comprehensive Obj. 1 incentives. These incentives and very different economic conditions make the southern-Italian provinces bad comparisons for the Obj.2 areas.

Information on the location of the Obj.2 areas is obtained from EU documents and brochures by the regional governments administering the program. Unfortunately, the boundaries of Obj2 areas do not entirely coincide with those of the Italian province boundaries. Because of this, a coding scheme must be used to assign each province *p* as a treatment Obj.2 area province or a control province. A number of alternative assignment rules are used to assure that the estimated program impacts are not a function of miscoding. Under a first rule, a province is coded as an Obj.2 area only if at least 80% of the province population resides within the boundaries of an actual Obj.2 area. Provinces with an Obj.2 area coverage of less than 80% are excluded from the analysis, and only provinces with 0% Obj.2 area coverage are coded as non-Obj.2 areas. Under a second rule, treatment areas are coded by a continuous rather than binary variable. The Obj.2 area status of each province is coded directly as the percentage of the province population residing within the boundaries of the actual Obj.2 area. Under a third rule a province is coded as an Obj.2 area if 100% of the province population resides within the boundaries of an actual Obj.2 area. The use of this range of alternative coding rules allows the robustness of the results to be tested.

Table 3 illustrates the pre-intervention 1986-1991 and treatment 1995-1998 employment growth recorded in Obj.2 area provinces for the eligible industrial sectors and the employment growth recorded in non-Obj.2 area provinces. The assignment rule illustrated in the tables is the first one in which the Obj.2 area provinces are those with at least 80% of residents living within the boundaries of the Obj.2 area zone.

Table 3

For both the treated and non-treated province-sector pairs, employment growth was much faster in the pre-treatment 1986-1991 period. While the growth rates were similar in that period (approximately 15%), the treated province-sector pairs grew more rapidly (5.62%) than the non-treated pairs (2.49%) during the 1995-1998 period. This faster growth rate, however, does not necessarily imply that the Obj.2 business incentives were successful because province-level and industrial sector heterogeneity has not been accounted for. Also, t-tests of the means indicate that none of the differences between the treated and non-treated province-sector pairs are statistically significantly different at the 0.1 level.

Pre intervention province level characteristics are measured using 1991 decennial census data available from the Italian national statistical agency, ISTAT. These measures include the percentage of residents with high-school or college degree, the number of crimes per thousand residents, the business closure rate, the population density and the percentage of jobs in manufacturing sectors. Table 4 illustrates the distribution of the ISTAT pre-intervention characteristics of the provinces in the data set by Obj.2-area status.

Table 4

Based upon the 1991 decennial census data, the Obj.2 provinces had a higher fraction of residents with a high school or college degree and were much more densely populated (380 versus 174 residents per square kilometer) than the non-Obj.2 provinces. However, the Obj.2 provinces also had higher crime rates, higher business closure rates, and a smaller fraction of jobs in the manufacturing sector. Only the crime rate and population density differences are statistically significantly different at typical levels.

Data measuring the amount of the Obj.2 investment subsidies received by each assisted SME are taken from either program monitoring reports produced by consulting firms[8] or from archives maintained by the regional Obj.2 program administrators. The data used in the analysis are the business investment incentive payments that occurred between 1995 and early 1998 in the Obj.2 areas of the following regions: Piemonte, Liguria, Veneto, Friuli-Venezia-Giuglia, Emilia-Romagna, Toscana, Marche, Umbria and Lazio. These payments are referred to as those of the "1994-1996" programming sub-period. Although they actually occurred with certainty between 1995 and early 1998, the exact payment dates within such period, however, were not recorded in the documentation available for the analysis, which only includes the total value of the subsidies received by each assisted firms in the entire 1995-1998 period.

The payments referred to as those of the "1989-93" programming sub-period, which actually took place mainly only after 1991, and the "1997-1999" sub-periods, which actually took place only after 1998, are instead unusable for the analysis. The former lacks retrospective information concerning both the exact dates and amounts of the subsidies, and the latter is unusable because no incentive payment was actually received by the assisted firms before 1998, the last year for which employment information are available. Such incomplete information on the program incentive payments limit the usable portion of the INPS employment data to the years prior to 1992 and the years 1995-1998. Data for the 1992-1994 years have to be excluded in order to avoid potentially serious omitted variable biases and endogeneity problems due to the lack of information on the incentive payments that occurred in the first programming round, referred to as the "1989-93" sub-period.

5. Empirical model

It is quite possible to construct econometric models that yield unbiased employment impact estimates under the assumption that employment growth outcomes (with and without treatment) are independent of treatment assignment conditioned on the industrial sector, region and unobserved fixed effects of the units of observations (p-j) [i.e., under the assumption that by controlling for the industrial sector, region and any time-invariant unobserved characteristics of the unit of observation, treatment assignment becomes independent from any factor that may affect employment growth outcomes]:

[8] E.g., Viatec (1997, 1999) for the Piemonte and Liguria regions.

$? Y^0_{pj}, ? Y^1_{pj} \perp T_{pj} \mid S_j, R_p, \alpha_{pj}$ (1)

where:

$? Y^0_{pj}, \Delta Y^1_{pj}$ = employment growth between a period *t* and a period *t-r* in region p and sector j without and with treatment, respectively;

T_{pj} = treatment assignment which equals 1 if treated in the period [t-(t-1)] and 0 otherwise;

S_j = industrial sector;

R_p = region;

α_{pj} = time-invariant fixed-effects.

By exploiting the ISTAT 1991 decennial census data and the 1986-1991 portion of the INPS EO data, it is possible to construct econometric models that yield unbiased employment impact estimates under the weaker condition:

$? Y^0_{pj}, ? Y^1_{pj} \perp T_{pj} \mid S_j, R_p, X91_p, GRW_{pj}, \alpha_{pj}$ (2)

where:

$X91_p$ = set of pre-intervention province-specific observed characteristics from 1991 decennial census;

GRW_{pj} = p-j-specific pre intervention (1986-1991) employment growth.

As the usable data for the analysis do not include the single years within the incentive payment period (1995-1998), models like the random growth rate of Heckman and Hotz (1989), Papke (1993, 1994), Boarnet and Bogart (1996) and Bondonio and Engberg (2000) cannot be estimated. Such models would yield unbiased impact estimates even if unobservable p-j specific growth trend (for example, formalized in linear form as $\beta_{pj}t$) were correlated with treatment assignment, but they require more than two consecutive time periods to be estimated. The available data only offers relevant information on a single pre- and post- intervention time (1995 and 1998, respectively). While data also exist for the period prior to 1992, that period is too distant from the intervention. Random growth rate models would yield unbiased impact estimates under the weakest condition of[9]

$$? Y^0_{pj}, ? Y^1_{pj} \perp T_{pj} \mid S_j, R_p, X91_p, GRW_{pj}, \alpha_{pj}, \beta_{pj}\mathbf{t} \qquad (3)$$

where:

$\beta_{pj}t$ = unobservable province-sector (p-j) specific growth trends;

Given the features of the actual selection process, however, retrieving unbiased impact estimates of the program intervention should not require estimating models based on the weakest assumption of equation (3). Assuming dependence between $\beta_{pj}t$ and T_{pj} would require that the program officials designate the treated p-j units of observations (pairs province-sector) based on information unknown to the evaluator that would allow them to forecast which industrial sector and in which province would grow the least or the most. Such hypothesis is very unlikely because the Obj.2 area selection into treatment process is based on three separate stages that do not allow direct selection of specific province-sector (p-j) pairs to take place. At the first stage, Obj.2 areas are designated based on area-designation proposals made by regional governments and presented to the EU by each respective national government. Obj.2-area designation rewards areas with declining industrial production from 1975 to the date of the designation round. At the second stage, each separate regional government administering Obj.2 areas selects a range of eligible industrial sectors based on its specific regional programming goals. At the third stage, eligible firms submit investment proposals to their regional governments. At a later time, the selection of the assisted firms is operated by the regional government based on a ranking of investment proposals that rewards high ratios between the amount of own resources invested by the firm and the amount of the capital grant requested. Thus, at first, locations are designated as Obj.2 areas without specific considerations being given to the selection of specific industrial sectors as well. At a second time, and through a separate selection process, a wide range of industrial sectors are made eligible for the program incentives within each designated Obj.2 area. Finally, based on different criteria and at a later time, assisted firms are selected within the already designated industrial

[9] Random growth rate models are estimated through a double differencing procedure in which data are first-differenced, and then the model is estimated with a panel data fixed effects estimator (differences from the mean).

sectors and areas. As a result, the overall selection process tends to reward, on the one hand, areas and sectors with difficult economic prospects, and, on the other hand, firms that are willing to risk a large portion of their own financial resources in the proposed investment project.

5.1 The baseline model

The estimated baseline longitudinal parametric model, which yields unbiased employment impact estimates under condition (2), is as follows:

$$\Delta Y_{pj} = \lambda + \sum_{\boldsymbol{J}} \beta_{\boldsymbol{J}} S\_\boldsymbol{J}_{j} + \sum_{\boldsymbol{r}} \omega_{\boldsymbol{r}} R\_\boldsymbol{r}_{p} + \delta FIN_{pj} + \gamma GRW_{pj} + \sum_{\boldsymbol{n}} \psi_{\boldsymbol{n}} X91\_\boldsymbol{n}_{p} + \delta STK94_{pj} + e_{pj} \qquad (4)$$

where:

ΔY_{pj} = province-sector (p-j) 1995-1998 employment growth;

$\sum_{\boldsymbol{J}} S\_\boldsymbol{J}_{j}$ = sector dummies (non-eligible sectors are excluded) [$\boldsymbol{J}$=1, 2…$\boldsymbol{N_J}$;]. $\boldsymbol{N_J}$ = number of sectors receiving Obj.2 program assistance in at least one region];

$\sum_{\boldsymbol{r}} R\_\boldsymbol{r}_{p}$ = region dummies;

FIN_{pj} = linear treatment variable expressing the monetary value of the incentives paid to the province-sector p-j [= 0 if the province-sector p-j was not assisted by the program];

GRW_{pj} = province-sector p-j pre-intervention (1986-1991) employment growth;

$\sum_{\boldsymbol{n}} X91\_\boldsymbol{n}_{p}$ = set of *n* pre-intervention province-specific characteristics [*n*=5]: 1) percentage of residents with high-school or college degree; 2) number of crimes per 1,000 residents; 3) business closure rate; 4) population density 5) percentage of jobs in industrial sectors);

$STK94_{pj}$ = p-j stock of employment at the end of 1994;

e_{pj} = random error term

The model of equation (4) is obtained through long differencing equation (5). Long differencing was preferred to the more standard differencing from the mean or first differencing procedures due to the lack of reliable information on the exact dates of the incentive payments that occurred within the period 1995-1998,[10]

$$Y_{pjt} = \lambda \mathbf{t} + \mathbf{t}[\Sigma_{\boldsymbol{J}}\beta_{\boldsymbol{J}}\, S\_\boldsymbol{J}_j] + \mathbf{t}\, [\Sigma_{\boldsymbol{r}}\omega_{\boldsymbol{r}} R\_\boldsymbol{r}_p] + \beta \mathbf{t} FIN_{pj} + \boldsymbol{\gamma} \mathbf{t} GRW_{pj} + \mathbf{t}[\Sigma_{n}\psi_{n} X91\_n_p] + \delta \mathbf{t} STK94_{pj} + \alpha_{pj} + e_{pjt} \qquad (5)$$ [11]

where:

$\mathbf{t}$ = time;

α_{pj} = province-sector (p-j) fixed effects.

To deal with possible heteroskedasticity due to the lack of independence among the cross-section areas (p-j) clustered within a same province *p* or a same sector *j*, estimation of the coefficient standard error of the model are also obtained through the "robust cluster estimator" of STATA (Statcorp 2003), which is based upon estimators derived by Huber (1967) and White (1980, 1982). Adequate modeling of multi-level clustering of observations can improve the estimates of the standard errors on the coefficients and provide more reliable t-statistics (e.g., Pepper 2002 and Wooldridge 2003). Often, theory suggests grouping cross-sectional data based upon clusters of provinces, states or regions. In this case, however, the nature of the clustering is not obvious and clustering by same geographic areas (provinces or regions) is supported neither by strong geographic differences in administrative and tax rules nor by strong economic differences between provinces and/or regions. Firms composing the industrial sectors *j* of the cross-section areas are predominantly manufacturers that operate in national and international markets rather than in local or regional markets. In Italy, administrative and tax rules are very similar across the provinces and regions in which firms are located. As a result, geographic clustering hypotheses are not supported by any much stronger economic rationale than other alternative clustering hypotheses, such as by sector, by same prevailing workers' union affiliation, or by firm size. We choose to estimate regression coefficients with robust standard errors (e.g. Hubert 1967, White 1980, 1982, Royall 1986, Lin and Wei 1989) and to test the robustness of the results by replicating the analysis with

[10] While all payments were made between early 1995 and the end of 1998, information regarding exact payment dates are unreliable.
[11] Coefficient of (5) are to be considered ¼ of those of (4) to allow exact correspondence between (4) and (5).

both uncorrected standard errors and standard errors retrieved from robust cluster procedures (Statacorp 2002, Rogers 1993, Williams 2000) that adjust for possible correlation of observations within the same provinces or sectors.

5.2 Model specifications

The baseline model of equation (4), which estimates the mean impact of the program incentives, is also implemented through two other specifications that estimate the impacts by industrial sector [equation (6)] and degrees of pre-intervention decline of the target cross-section areas [province-sector p-j pairs, equation (7)];

$$\Delta Y_{pj} = \lambda + \sum_{\boldsymbol{J}}\beta_{\boldsymbol{J}}S\_\boldsymbol{J}_{j} + \sum_{\boldsymbol{r}}\omega_{\boldsymbol{r}}R\_\boldsymbol{r}_{p} + \sum_{\boldsymbol{J}}\delta_{\boldsymbol{J}}FIN\_\boldsymbol{J}_{pj} + \gamma GRW_{pj} + \sum_{\boldsymbol{n}}\psi_{\boldsymbol{n}}X91\_\boldsymbol{n}_{p} + \delta STK94_{pj} + e_{pj} \qquad (6)$$

where:

$\sum_{\boldsymbol{J}}FIN\_\boldsymbol{J}_{pj}$ = set of ***J*** linear treatment variables expressing the cost of the incentives paid to the treated (p-j) areas by industrial sectors [***J***=18: total number of 2-digits industrial sectors containing assisted firms]. E.g., if ***J*** = "DA-food industries," then FIN_DA_{pj} = cost of the incentives paid to the pair p-j if j ="DA-food industries"; = 0 otherwise];

$$\Delta Y_{pj} = \lambda + \sum_{\boldsymbol{J}}\beta_{\boldsymbol{J}}S\_\boldsymbol{J}_{j} + \sum_{\boldsymbol{r}}\omega_{\boldsymbol{r}}R\_\boldsymbol{r}_{p} + \sum_{\boldsymbol{g}}\delta_{\boldsymbol{g}}FIN\_\boldsymbol{g}_{pj} + \gamma GRW_{pj} + \sum_{\boldsymbol{n}}\psi_{\boldsymbol{n}}X91\_\boldsymbol{n}_{p} + \delta STK94_{pj} + e_{pj} \qquad (7)$$

where:

g = 1^{st} quartile, 2^{nd} quartile, 3^{rd} quartile and 4^{th} quartile of the 1986-1994 total employment change distribution for the treated p-j areas;

$\sum_{\boldsymbol{g}}FIN\_\boldsymbol{g}_{pj}$ = set of [***g***=4] linear treatment variables expressing the cost of the incentives paid to the treated (p-j) areas by quartile of pre-intervention employment growth [e.g., if ***g***="1^{st} quartile (I_qrt)", $FIN\_I\_qrt_{pj}$ = cost of the incentives paid to the area p-j if p-j experienced an employment growth within the 1^{st} quartile of the 1986-1994 employment growth distribution of all treated pairs; = 0 otherwise];

Each of the estimated specifications of equation (4), (5) and (7) is estimated following three different coding rules used to operationalize the Obj.2 area status of each province p included in the data set. Table 5 summarizes the complete set of specifications.

Table 5

Depending on the Obj.2 area coding rule used, the number of treatment provinces varies from four to 27. Note that the total number of provinces included in the analysis varies across the different coding rules because the number of excluded provinces varies based upon how restrictive the coding rule is.

6. Results

Table 6 reports results from the model of eq. (4), which yields mean impact estimates of the Obj.2 area incentives. Every 1,000 € worth of incentives paid to the treated p-j (province-sector) pairs generates 0.047 additional jobs. Using different Obj.2 area coding schemes for the treated areas produces little changes in the impact estimates. Mean impact estimates for all specifications vary from 0.034 to 0.062 additional jobs for each 1,000 € worth of incentives (0.034 jobs for specification II, in which Obj.2 area status is granted as percentage of the province residents located within the boundaries of an actual Obj.2 area, and 0.062 jobs for specification III, in which Obj.2 area status is granted only to provinces with 100% of residents located within the boundaries of an actual Obj.2 area).

Such point estimates imply that generating one additional job required 21,413 € worth of program incentives (with results from other model specifications yielding a cost per additional job in a range from 15,873 € and 29,411 €). Counting the entire budget of the program interventions that benefit SMEs (about 509.6 million €), the impact estimates highlight that the Obj.2 area business investment incentives from the “1994-1996” programming sub-period (which were generated a total of about 23,800 additional jobs between 1995 and 1998 that would not have existed otherwise (with results from different model specifications yielding estimates in a range from 17,327 to 32,106 additional jobs).

Table 7

Table 7 summarizes the industrial sector coefficients from estimation of the model of eq. (6) which allows impact estimates to vary according to the industrial sector of the treated areas. Results are quite inconclusive, as standard errors are often large compared to the coefficient point estimates. Indeed, only five of the sector-specific treatment variables reach statistical significance levels consistently across the three estimated specifications: 'DA-food industries', 'DB-textile industries', 'DI-processing of non-metalling minerals'[12], 'DJ-metal and metallic products', 'DL manufacturing of electrical machinery'. Impact estimates for the 'DA-food industries' and 'DI-processing of non-metalling minerals' sectors are negative, perhaps indicating that for these sectors the subsidized capital investments are primarily aimed at shifting the production process toward more automatized (and less labor intensive) procedures. For the other three sectors that reach statistical significance (i.e. 'DB', 'DJ' and 'DL'), impact estimates are all positive, with the 'DB-textile industries' and 'DL manufacturing of electrical machinery' sectors showing coefficient estimates of more than double the size of the mean impact estimates of Table 6.

Table 8

Table 8, finally, reports the impact estimates by degrees of pre-intervention decline (measured as the 1986-94 total employment change) of the treated units. Results show that the Obj.2 area incentives are effective only on treated units p-j that experienced the most positive pre-intervention employment change (i.e. treated units belonging to the 4th quartile of the employment distribution). The point impact estimates for those p-j units are in a range from 0.048 to 0.067 additional jobs for each 1,000 € worth of program incentives. For treated units in the 2nd and 3rd quartile of the pre-intervention employment change distribution, the program incentives are not shown to have any significant impact in all three estimated specifications (specs. VII, VIII, and IX), with point estimates close to zero and standard errors of similar size than the point estimates). Impact estimates are also shown to be non-significant for the treated units in the 1st quartile of the pre-intervention employment change distribution. In this case however, the coefficient point estimates are positive throughout the three estimated specifications (in a range from 0.025

[12] For the coefficient of the DI-treatment variable statistical significance is only at the 0.1 level in one of the estimated specification (i.e. spec. VI).

to 0.072 jobs for each 1,000 € worth of program incentives), and the estimated p-values are not too far from the standard significance thresholds.

For a very large portion of all estimated specifications, replicating the analysis with either uncorrected standard errors or robust cluster estimators yields results with unchanged significance level for the coefficient estimates of all treatment variables.

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Table 1. EU "Obj.2 Area" Programs

Country	"1989-1993" programming sub-period EU contribution (millions of euros)	"1994-1996" programming sub-period EU contribution (millions of euros)	"1997-1999" programming sub-period EU contribution (millions of euros)	Percent population covered by Obj.2 areas[(a)]	Percent contribution devoted to SME incentives[(a)]
Austria[(b)]	-	-	108.2	7.5	12.5
Belgium	214.0	160.0	216.2	14.2	74.2
Denmark	25.0	56.0	68.2	8.5	68.3
Finland[(b)]	-	69.2	135.3	25.1	78.5
France	1225.0	1763.3	2246.3	25.1	72.4
Germany	581.0	733.0	901.1	8.8	50.9
Italy	387.0	808.0	967.8	11	65.7
Luxembourg	12.0	7.0	9.8	34.6	68.5
Netherlands	165.0	300.0	442.2	17.4	78.9
Spain	1506.0	1130.0	1485.0	20.4	47.6
Sweden[(b)]	-	-	160.0	11.5	63.7
United Kingdom	2015.0	2142.0	2675.8	30.9	54.2
MEAN	681.1	716.8	784.7	16.4	59.7
TOTAL	6130.0	7168.0	9415.9	-	-

(a) Values based on Obj.2 areas in existence for the 1994-1996 programming sub-period.

(b) Austria, Finland, and Sweden all joined the EU in January 1995. Obj.2 programs were decided for Finland in July 1995 and for Austria and Sweden in November 1995.

Table 2. "Obj.2 Area" Incentives in Italy:

EU Support by Region and Type of Intervention
1994-1996 Programming Sub-Period

Region[a]	Total EU contribution (millions of euros)	Percent contribution devoted to SME incentives	Incentive[b]			
			Research & Development	Infrastruc-ture	Environ-mental protection	Tourism
Piemonte	205	55.28	x	x	x	x
Liguria	96	56.74		x	x	
Veneto	70	45.51			x	
Friuli Ven. Giulia	24	72.79	x	x		
Emilia Romagna	12	88.12	x			
Toscana	251	78.72	x	x	x	x
Marche	21	54.41		x		x
Umbria	35	87.58			x	
Lazio	64	66.05		x	x	x

[a] Lombardia's and Valle d'Aosta's Obj.2 areas are excluded from the analysis.
[b] All regions provide industrial SME capital expenditure incentives, human resources training, and business technical assistance.

Table 3. Employment Growth by Treatment Status of the Province-Sector (p-j) Pairs

	N	Absolute change (Total number of jobs)		Percentage change[a]	
		1986-1991	1995-1998	1986-1991	1995-1998
Treated (p-j) pairs[b]	99	291.20 (944.49)	248.62 (811.93)	14.57 (31.24)	5.62 (19.84)
Not-treated (p-j) pairs[c]	542	419.21 (1001.75)	137.65 (677.71)	15.57 (36.68)	2.49 (26.52)

(Standard deviations are in parantheses.)

[a] Percentage growth based on the average stock of employment between the beginning and the end of the two time periods.
[b] At lest 80% of the province resident population lives within Obj.2 boundaries.
[c] None of the province population lives within Obj.2 boundaries.

T-tests of the means indicate that none of the differences between the treated and non-treated province-sector pairs are within statistically significant levels.

Table 4. Pre-intervention Characteristics of Provinces by "Objective 2" Status[a]

Variable	Obj.2 Provinces[b]	Non-Obj.2 Provinces[c]
Percent of residents with high school or college degree	23.51 (3.18)	21.91 (2.47)
Number of crimes per 1000 residents	47.29 (25.18)	31.39** (10.63)
Business closure rate (number of business clusures/ number of active businesses)	4.08 (2.44)	3.29 (1.57)
Population density (residents per KM^2)	380 (36.92)	174*** (11.81)
Percent of jobs in manufacturing sector	34.33 (8.15)	37.77 (8.53)
N	8	27

(a) Data are from the 1991 decennial census by ISTAT.
(b) At lest 80% of the province resident population lives within Obj.2 boundaries.
(c) None of the province population lives within Obj.2 boundaries.

Tests of the equality of means between obj.2 provinces and non-obj.2 provinces:
* P-value = 0.1 ** P-value = 0.05 *** P-value = 0.01

Table 5. Model Specifications

	Obj.2 area coding rule		
Treatment variable/s	Provinces are coded as Obj.2 areas if at least 80% of their residents are located within the boundaries of Obj.2 areas	Obj.2 area status = percentage of province residents located within the boundaries of Obj.2 areas	Provinces are coded as Obj.2 areas if 100% of their residents are located within the boundaries of Obj.2 areas
FIN_{pj} = cost of the incentives paid to the province-sectors (p-j) pairs	Specification (I)	Specification (II)	Specification (III)
$\sum_j \delta FIN\_J_{pj}$ = set of linear treatment variables (cost of the incentives paid to p-j) by industrial sectors	Specification (IV)	Specification (V)	Specification (VI)
$\sum_g FIN\_g_{pj}$ = set of linear treatment variables (cost of the incentives paid to p-j) by quartile of pre-intervention employment growth	Specification (VII)	Specification (VIII)	Specification (IX)
Number of Obj. 2 provinces	8	27[a]	4
Number of non-Obj. 2 provinces	27	19[b]	27

[a] Number of provinces in which the percentage of province residents located within the boundaries of Obj.2 areas is greater than zero.
[b] Number of provinces in which the percentage of province residents located within the boundaries of Obj.2 areas equals zero.

Table 6: Mean impact of the program incentives.
[Results from Equation 4. Dep.var.: employment change 1=1 job]

Variables		Specification (I)		Specification (II)		Specification (III)	
Treatment							
Cost of the incentives paid to treated (p-j) pairs [1=1,000 Euros]	**FIN[(a)]**	**0.047**	**0.0164(std) 0.004(P-val.)**	**0.034**	**0.012(std) 0.008(P-val.)**	**0.063**	**0.018(std) 0.001(P-val.)**
(p-j)-specific control variables							
Employment stock at the beginning of 1994	STK94	-0.004	0.018(std) 0.792(P-val.)	0.022	0.010(std) 0.031(P-val.)	-0.006	0.021(std) 0.778(P-val.)
Pre-intervention employment growth (1986-91)	GRW	0.410	0.088(std) 0.000(P-val.)	0.335	0.050(std) 0.000(P-val.)	0.391	0.056(std) 0.000(P-val.)
(p)-specific control variables							
% of residents with high-school or college degree [1=1%]		11.726	9.374(std) 0.211(P-val.)	6.167	5.416(std) 0.255(P-val.)	5.721	11568(std) 0.621(P-val.)
N. of crimes per 1,000 residents		0.020	1.796(std) 0.991(P-val.)	-0.407	1.461(std) 0.781(P-val.)	0,799	2.452(std) 0.745(P-val.)
Business closure rate (N. clusures/ N. active businesses)		6.517	8.308(std) 0.433(P-val.)	11.633	4,917(std) 0.018(P-val.)	23,860	11.118(std) 0.032(P-val.)
population density (residents per Km^2)		-106.616	152.789(std) 0.486(P-val.)	-110.70	107.056(std) 0.301(P-val.)	-77,234	308.504(std) 0.802(P-val.)
% of jobs in manufacturings		-369.527	225.142(std) 0.101(P-val.)	29.549	175.431(std) 0.866(P-val.)	-496,225	304.526(std) 0.104(P-val.)
Number of observations		641		840		569	
R^2		0.597		0.605		0.616	

(a) Coefficient estimates for FIN are the number of jobs for each 1,000 Euros worth of incentives paid to assisted firms

Table 7: Impacts by industrial sector of the treated units
[Results from Eq. 6. Dep.variable: employment change 1=1 job]

Treatment variables by industrial sector	**Specification (IV)**		**Specification (V)**		**Specification (VI)**	
[(a)] Value of incentives paid to (p-j) if j=						
CB [Non energetic mineral extraction]; =0 otherwise.	-0.007	0.169 (std) 0.965(P-val)	-0.022	0.088 (std) 0.805 (P-val)	-0.105	0.239 (std) 0.661 (P-val)
DA [Food industries]; =0 otherwise.	-0.041	0.019 (std) 0.038 (P-val)	-0.046	0.021 (std) 0.035 (P-val)	-0.055	0.027 (std) 0.041 (P-val)
DB [Textile industries]; =0 otherwise.	0.137	0.044 (std) 0.002 (P-val)	0.092	0.033 (std) 0.006 (P-val)	0.150	0.041 (std) 0.000 (P-val)
DC [Hide and leather industries]; =0 otherwise.	0.005	0.010 (std) 0.664 (P-val)	-0.013	0.007 (std) 0.063 (P-val)	0.005	0.012 (std) 0.642 (P-val)
DD [Wood industry]; =0 otherwise.	0.089	0.095 (std) 0.349 (P-val)	0.036	0.090 (std) 0.690 (P-val)	0.081	0.113 (std) 0.476 (P-val)
DE [Paper, printing and publishing]; =0 otherwise.	0.012	0.010 (std) 0.266 (P-val)	0.005	0.007 (std) 0.508 (P-val)	0.028	0.027 (std) 0.153 (P-val)
DF [Coke manufacturing and refineries]; =0 otherwise.	0.883	0.378(std) 0.020 (P-val)	0.211	0.315 (std) 0.503 (P-val)	0.632	0.664 (std) 0.342 (P-val)
DG [Chemical product manufacturing]; =0 otherwise.	0.008	0.006 (std) 0.167 (P-val)	0.010	0.005 (std) 0.052 (P-val)	0.068	0.190 (std) 0.002 (P-val)
DH [Rubber and plastics]; =0 otherwise.	0.015	0.027 (std) 0.592 (P-val)	0.021	0.022 (std) 0.351 (P-val)	0.058	0.017 (std) 0.001 (P-val)
DI [Processing of non-metallic minerals]; =0 otherwise.	-0.009	0.004 (std) 0.021 (P-val)	-0.022	0.008 (std) 0.011 (P-val)	-0.008	0.004 (std) 0.085 (P-val)
DJ [Metal and metallic products]; =0 otherwise.	0.057	0.022(std) 0.010 (P-val)	0.039	0.0154 (std) 0.012 (P-val)	0.065	0.021 (std) 0.003 (P-val)
DK [Manufacturing and repair of machinery]; =0 otherwise.	0.055	0.040 (std) 0.169 (P-val)	0.046	0.033 (std) 0.165 (P-val)	0.081	0.031 (std) 0.010 (P-val)
DL [Manufacturing of electrical machinery]; =0 otherwise.	0.132	0.022 (std) 0.000 (P-val)	0.129	0.020 (std) 0.000 (P-val)	0.144	0.0144 (std) 0.000 (P-val)
DM [Vehicle manufacturing]; =0 otherwise.	0.052	0.037 (std) 0.170 (P-val)	0.039	0.0293 (std) 0.180 (P-val)	0.051	0.037 (std) 0.169 (P-val)
DN [Other manufacturing industries]; =0 otherwise.	-0.011	0.069 (std) 0.877 (P-val)	-0.003	0.065 (std) 0.966 (P-val)	-0.048	0.072 (std) 0.506 (P-val)
F [Construction]; =0 otherwise.	0.209	0.196 (std) 0.288 (P-val)	0.182	0.164 (std) 0.270 (P-val)	0.225	0.188 (std) 0.232 (P-val)
G [Commerce]; =0 otherwise.	-0.049	0.066 (std) 0.461 (P-val)	0.055	0.118 (std) 0.645 (P-val)	-0.057	0.067 (std) 0.398 (P-val)
K [Business services]; =0 otherwise.	0.107	0.101 (std) 0.295 (P-val)	0.019	0.070 (std) 0.788 (P-val)	0.103	0.103 (std) 0.318 (P-val)
N		641		840		569
R^2		0.615		0.618		0.632

(a) Two-digits Ateco_91 industrial sector classification by ISTAT.
Coefficient estimates are number of jobs for each 1,000 Euros worth of incentives paid to assisted firms

Table 8: Impacts by degree of pre-intervention decline of the treated units (results from eq. 7) [Dep.variable.: employment change 1=1 job]

Treatment variables	Specification (VII)		Specification (VIII)		Specification (IX)	
Value of the incentives paid to the tretated units (p-j) if (p-j) belongs to the:						
1st quartile of the 1986-94 employment growth distribution; =0 otherwise.	0.038	0.026(std) 0.150(P-val)	0.025	0.019(std) 0.191(P-val)	0.072	0.036(std) 0.052(P-val)
2nd quartile of the 1986-94 employment growth distribution; =0 otherwise.	-0.008	0.015(std) 0.592(P-val)	-0.023	0.022(std) 0.318(P-val)	-0.004	0.019(std) 0.823(P-val)
3rd quartile of the 1986-94 employment growth distribution; =0 otherwise.	-0.009	0.007(std) 0.184(P-val)	-0.012	0.008(std) 0.139(P-val)	-0.001	0.009(std) 0.876(P-val)
4th quartile of the 1986-94 employment growth distribution; =0 otherwise.	0.060	0.018(std) 0.001(P-val)	0.048	0.016(std) 0.004(P-val)	0.067	0.019(std) 0.001(P-val)
N		641		840		569
R^2		0.602		0.609		0.619

Coefficient estimates are number of jobs for each 1,000 Euros worth of incentives paid to assisted firms