Evaluating the Effectiveness of Axis 3-LEADER Grants on Job Creation

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Abstract

This study investigates the relationship between the number of jobs created and funding granted as part of the Community Led Local Development element within the Northern Ireland Rural Development Programme. Analysis is carried out using *ex-post* application-level data associated with Axis 3-'improving the quality of life and the management of economic activity' during the 2007-2013 period. A two-step procedure is used to estimate a negative binomial model and correct for sample selection. A joint estimation was performed to allow for correlation between the structural and selection equations. Results indicate that there is a positive and statistically significant relationship between the number of created jobs and the amount of awarded grant per application and, moreover, that this relationship depends on the categories, or Measures, within Axis 3. The more economic-focused Measures (*Diversification into non-Agricultural Activities, Business Creation and Development*, and *Encouragement of Tourism Activities*) showed a statistically significant link between the amount of public funds and job creation. No such relationship was found for the other Measures. Finally, in cases where public funds are linked to job creation, we found that this happens only above a given threshold, namely two or three jobs.

Key Words: Public spending, job creation, rural development programme, count data models, sample selection.

JEL Code: Discrete Regression Models C35, Agricultural Policy Q18.

1. INTRODUCTION

The objective of this work is to generate evidence that can be used by stakeholders to improve the economic outcomes of Community Led Local Development (CLLD) approaches to rural development. In this context, the stakeholders of interest include policymakers designing rural development policy and delivery agents such as local governments or community groups. The use of CLLD is formalised in the Common Agricultural Policy (CAP) framework and therefore information on how existing approaches deliver economic objectives, in this specific case employment, will be of interest across the European Union (EU). One could argue, that the impending exit of the United Kingdom (UK) means that such information may be even more important to British stakeholders as there may be a dramatic re-working of agricultural and rural policy after the close of the current round of CAP, and, inclusion of CLLD within that context may be fundamentally questioned as a strategic approach to develop the wider rural economy. Given Northern Ireland (NI) will need to assert its policy agenda within the UK restructuring of rural affairs, evidence on what has worked previously in the local context will be extremely important, so that NI can argue for locally relevant policy revision within national frameworks.

This study investigates the relationship between the number of jobs created and funding granted as part of CLLD element within the NI Rural Development Programme (NIRDP). Analysis is carried out using *ex-post* application-level data associated with Axis 3-'improving the quality of life and the management of economic activity' during the 2007-2013 period. The resulting evidence is used to form recommendations on potential approaches to future iterations of policy focusing on creating rural employment opportunities.

2. BACKGROUND AND LITERATURE REVIEW

2.1 Background

The NIRDP 2007 – 2013 was divided into three main axes and two administrative/support axes (Northern Ireland Department of Agriculture and Rural Development, 2015). Axis 3 was tasked with 'improving the quality of life and the management of economic activity' and was delivered through CLLD, or Axis 4 'the LEADER method of delivery'. Axis 3 is further subdivided into six Measures that have a different focus or target a different group of rural stakeholders including: Measure 3.1 *Diversification into Non - Agricultural Activities*, Measure 3.2 *Business Creation and Development*, Measure 3.3 *Encouragement of Tourism Activities*, Measure 3.4 *Basic Services for the Economy and Rural Population*, Measure 3.5 *Village Renewal and Development*, and Measure 3.6 *Conservation and Upgrading the Rural Heritage*. All Measures except for 3.6 had an initial target set for 'gross number of jobs created' at the outset of the programme. Local Action Groups, or LAGs, function as delivery agents in cooperation with local government and are allocated a programme and operating budget according to their size and strategic objectives (Department of

Agricultural Environment and Rural Affairs, 2016). During NIRDP 2007-2013 seven LAGs were operating in NI[1] to deliver the LEADER approach.

A review of the LEADER methodology only broadly categorised the economic and social impacts in its evaluation (such as economic regeneration, community cohesion/ empowerment and rural development (RSM McClure Watters, 2013). The Mid-Term Evaluation of the NIRDP 2007-2013 in 2010 found that the economic impacts were un-measureable due to the early stage of the projects (NISRA, 2010b) and a similar conclusion reach in a 2013 follow up report (NISRA, 2013). The Ex-Post evaluation carried out by the Northern Ireland Statistics and Research Agency (2016) report that £105.8 million of total public expenditure was carried out as part of Axis 3/4 creating 1,194 jobs. The ability to meet targets set by the then Department of Agricultural and Rural Development (DARD) on number of jobs created for each Measure is reported and discussed. Some interesting avenues to consider are revealed just by looking at a simple comparison of the *expected* number of jobs per £ of public funds (implied by dividing DARD's job target by their public funding target) and the actual rate of job creation (by dividing the actual jobs created by the final position in terms of public spending) for each Measure. For instance, Measures 3.1 and 3.2 are both related to business development, with the main difference being that 3.1 targets farmers and family members of farmers while 3.2 is more general. However, patterns related to a range of application-level characteristics are not fully explored. Therefore, this paper provides complementary analysis by introducing quantitative analysis of the relationship between the application of public funds and the number of jobs created at an individual application and project level.

2.2 Literature review

The relationship between public funding and employment is complex, as public bodies are often concerned with both efficiency and distributional issues (as understood through the First and Second Theorem of Welfare Economics). In general, some sectors of the economic activity are traditionally more suitable to create jobs than others. For instance, manufacturing, tourism, and retail sectors exhibit, on average, the highest rates of job creation when there is an economic growth (Van Stel & Storey, 2004). Similarly, agriculture can have high seasonal rates of job creation depending on the weather and market conditions (Singh, Squire, & Strauss, 1986). Finally, some sectors can exhibit a local multiplier effect. A local multiplier effect indicates the presence of positive spill-over effects that a particular job has on the local economy. Jobs in the tradable sector have usually a high chance to create jobs through an increased demand for goods and services in the local market and in the surrounding areas (Moretti, 2010). Thus, if the goal of the policy-maker is to increase the employment level, an effective selection of what types of recipients to solicit in the first instance is fundamental to increase the efficiency of funding allocation (Coady & Skoufias, 2004). This is closely related to how funds are made available. Considering the context of CLLD within the NIRDP, it can be expected that certain Measures will exhibit different rates of job creation due to the underlying objectives related to both efficiency and distributional issues as decided by the administering body. Each Axis Measures is

[1] In Northern Ireland the definitions of LAGS increased from seven to ten from the 2007-13 period to the 2014-2020 period (Rural Network NI 2017) to coincide with local government districts.

characterized by a different budget and allocative rules ideally designed to enhance the use of the limited public resources (Department of Agricultural Environment and Rural Affairs, 2016).

Another complicating factor to consider is the range of responses possible in reaction to an increase in labour demanded. For instance, Oi indentifies the quasi-fixity of labour as the costs associated with the recruiting and training process (Oi, 1983). In general, the firm specific human capital represents the level of know-how necessary to perform specific tasks, and tends to be associated with relatively high-skilled jobs more likely to be present in large companies (Lazear, 2009). Thus, a large firm that demands more skilled jobs may use the over-time labour of the specialized personnel already present in its staff to absorb the excess of demand rather than incur in the agency costs for hiring new staff (Oi, 1983). Similarly, small farmers and local entrepreneurs are usually characterized by a smaller degree of labour specialization, but they also exhibit more flexibility. For instance, small farmers need basic skills in farming, business administration, trade and tax regulations (Lazear, 2009) and therefore may satisfy increased demand with their own time and that of their families (Singh et al., 1986) instead of taking on employment responsibilities and the associated costs.

Another important factor to allocating public funds effectively for job creation relates to application-level characteristics. For example, public funding choices are often subject to evaluating the trade-off between risk and return (Myles, 1995). On one hand, studies indicate that start-up companies tend to create more jobs than pre-existing businesses (Haltiwanger, Jarmin, & Miranda, 2012). This would suggest promoting the selection and the allocation of funds towards these companies. However, the failure rate among the start-up companies is also high, namely because of liquidity constraints and difficulties with product strategies faced during the early stages (Haltiwanger et al., 2012). Thus, the choice among different applications can be brought back to the problem of the optimal investment policy under uncertainty and budget constraint. In this case, the optimal choice will depend on the risk-return distribution of the applications and on the preferences of the social planner (Myles, 1995). In general, analyzing which factors drive job creation is a prerequisite to design more effective policies. The next section explains our approach based on examining the role of application-level characteristics including the methodological approach employed in the analysis.

3. METHODOLOGY

To estimate the relationship between the number of created jobs and the amount of public funds we employ a count data model. Count data models directly consider the nature of the dependent variable which is a non-negative integer. This allows handling the main shortcoming of linear regression models, namely that they can generate a negative number of created jobs. In particular, we will estimate a Negative Binomial (NB) model. The NB model has a more general and flexible form than alternatives such as the Poisson model that imposes an equality condition on the expected value (average) and variance of the observed number of created jobs ($VAR[Y] = E[Y]$). In contrast, the NB model allows for over-dispersion ($VAR[Y] > E[Y]$) a far more realistic assumption in our case considering the expected high level of variance amongst application-level data. Thus, the estimated equation is the following:

$$Prob[Y = j_i|\boldsymbol{X}_i] = \frac{\Gamma(\theta + j_i)}{\Gamma(j_i + 1) \cdot \Gamma(\theta)} r_i^{j_i} (1 - r_i)^{\theta},$$

$$\lambda_i = \exp\,(\boldsymbol{X'}_i \boldsymbol{\beta}), \qquad (1)$$

$$r_i = \lambda_i / (\theta + \lambda_i).$$

Where $\Gamma(.)$ is the gamma function, $E[Y = j_i|\boldsymbol{X}_i]=\lambda_i$ and $VAR[Y = j_i|\boldsymbol{X}_i]=\lambda_i\left(1 + \frac{\lambda_i}{\theta}\right)$ and j_i is a non negative integer[2]. In the literature, this is the standard NB and it is often known as NB 'type 2' (Cameron & Trivedi, 1986; Greene, 2010a).The model can be estimated by maximum likelihood and a test for over-dispersion can be carried out by testing the hypothesis $\alpha = \frac{1}{\theta} = 0$ with a Wald test or a Likelihood Ratio test (LR test)[3]. Moreover, the overall fit of the model to the data can be tested through the deviance test to see if the model is capable to properly reproduce the data generating process.

If the applications to be funded were randomly selected we could estimate a standard count data model. However, the nature of LEADER grants mean that there is a selection process performed by the delivery agents. Because the evaluation process includes criteria related to expected job creation, the outcome we are interested in, a standard count data model will produce biased and inconsistent parameters and incorrect standard errors. In addition, public authorities may prefer to approve existing businesses with respect to new ones due to fact their risk profile is lower and their chances to succeed higher (Evans & Leighton, 1989; Haltiwanger et al., 2012). Moreover, an existing business can face a lower opportunity cost to create new jobs than a new activity, especially because it is already paying for the fixed costs and it may also benefit of economies of scale (Evans & Leighton, 1989). Thus, applications from existing businesses can have more chances to be approved and, moreover, they can have more chances to generate new jobs.

The approach employed in this study was originally developed by Greene (W. Greene, 1998; W. H. Greene, 1994) and (Terza, 1998) and it consists of modifying the structural equation, i.e. the NB Model, to allow for sample selection. In particular, we will follow Greene's approach by adding the Inverse of Mills Ratio (IMR) as an extra covariate to $\boldsymbol{X'}_i\boldsymbol{\beta}$ in equation (1). This approach is similar to the Heckman model, but instead of a linear regression in the structural equation, we have a count data model, namely a NB model[4]. Thus, in essence, this approach is a two-stage estimation. In the first stage, a probit model between approved and not approved applications is estimated and the IMR is calculated[5]. Then, the IMR is added as a covariate to $\boldsymbol{X'}_i\boldsymbol{\beta}$**,** and the NB model is estimated relating jobs created and explanatory factors.

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[2] Throughout, we use bold type to denote vectors and non-bold type to denote scalars.

[3] For estimation purposes, $\log(\alpha)$ is estimated to allow for the fact that α must be greater than zero.

[4] Theoretically, there is no reason to assume that the IMR should linearly enter into $\boldsymbol{X'}_i\,\boldsymbol{\beta}$ as in the traditional Heckman model since the structural equation is not linear (Terza, 1998). However, Greene (W. H. Greene, 1994) showed that this corresponds to a first degree Taylor approximation of the conditional mean function under selection as in Terza (Terza, 1998) and, moreover, this produces consistent estimates of the coefficients given that the model is correctly specified and the sample size sufficiently large.

[5] The inverse of Mills ratio corresponds to $\phi(Z_i'\hat{\gamma})/\Phi(Z_i'\hat{\gamma})$ where Z is the matrix of independent variables of the selection equation and $\hat{\gamma}$ the relative estimated coefficients while $\phi(.)$ and $\Phi(.)$ are the density function and the cumulative density function of the standard normal distribution, respectively.

The shortcoming of a two-stage estimator is that the standard errors are inefficient due to the fact that the parameters of the NB model depend on the parameters of the probit model through the IMR. Murphy and Topel (1985) developed the structure of the variance of the parameters estimated with maximum likelihood when the number of observations is the same in the first stage as in the second stage. When the number of observations is different, one has to follow the correction developed by Karaca-Mandic and Train (2003) for nested data. The complicated part of this procedure is that it requires taking the derivative of the second stage scores with respect to the first stage parameters. However, this is analytically equivalent to jointly estimating the first and the second stage equations[6]. Moreover, the joint estimation should still be more efficient than the two-stage estimation with the Karaca-Mandic and Train's correction (Greene, 2010a). Thus, we will jointly estimate the selection and the sample equation.

Finally, because we expect the relationship between public funds and the number of created jobs to depend on the Measure, we employ binary variables to generate slope shifters of the coefficient of the amount of funds per application. This will represent our *Extended Model* as opposed to the *Baseline Model* that does not consider any slope shifter. Overall, a test on the hypothesis that the relationship between public funds and number of created jobs depends on the Measures of the Leader Project can be carried out with a Wald test and LR test between the *Baseline model* and the *Extended model*. If we fail to reject the null hypothesis that the slope shifters are jointly equal to zero, there is evidence that the effect of public funds on job creation is differentiated by Measure.

With respect to the effect of funds on job creation *differentiated* by Measure, following Greene (Greene, 2010b), we study how the partial effect changes with respect to the categorical variables. We do not directly study the interaction effect/cross-partial derivative between funds and the Measures because, although it is correct, this does not necessarily have an economically meaningful interpretation. The problem is that when the model contains numerous variables, interpreting the outcome is difficult at best. As the next section will show, the model is populated with several variables to control for the application's characteristics. In this case, any number of different combinations of the independent variables can interact with the amount of funds per application and the Measure binary-indicator to statistically equate to zero the interaction effect/cross-partial derivative.

Consider, for simplicity, that there are only two Measures, *A* and *B*. The interaction effect between the amount of funds per application and the Measures will be:

$$E[y_i] = \exp\left(\boldsymbol{Z}_i^{'}\boldsymbol{\delta} + b_1 x_{1i} + b_2 x_{2i} + b_{12} x_{1i} x_{2i}\right) = \exp\,(A_i) \qquad (2)$$

Where x_1 is the continuous variable (funds), x_2 is the categorical variable equal to 1 if the Measure is *A* and 0 if it is *B*, $\boldsymbol{Z}_i$is a set of other variables including the constant term, and A_i is called an index function. Our goal is to study how the relationship between x_1 and $E[y_i]$ changes

[6] If we jointly estimate the LLF of the NB model (LLF_{NB}) plus the LLF of the probit model (LLF_{Probit}), the difference with respect to the uncorrelated case is that the derivative of the total LLF with respect to the parameters of the probit model has an extra term: the derivative of $LLF_{NB}$with respect to IMR multiplied by the derivative of IMR with respect to the parameters of the probit model. This corresponds to the matrix $\boldsymbol{B}$ in Karaka-Mandic and Train (Karaca-Mandic & Train, 2003) . The equivalence holds asymptotically since in finite samples the gradient of a two-stage estimator is not exactly the same of the gradient calculated by jointly estimating the two equations.

when x_2 changes from 0 to 1. This is called the second cross partial derivative and it estimated by taking the discrete difference of following equation (3):

$$\frac{\partial E[y_i]}{\partial x_{1i}} = E[y_i] \cdot (b_1 + b_{12}x_{2i}) = \exp(A_i) \cdot (b_1 + b_{12}x_{2i}) \tag{3}$$

$$\frac{\Delta\left[\frac{\partial E[y_i]}{\partial x_{1i}}\right]}{\Delta x_{2i}} = E[y_i|\boldsymbol{Z}_i, x_{1i}, x_{2i} = 1] \cdot (b_1 + b_{12}) - E[y_i|\boldsymbol{Z}_i, x_{1i}, x_{2i} = 0] \cdot \mathrm{b}_1 \tag{4}$$

$$= e^{\boldsymbol{Z}_i^{'}\delta + b_1 x_{1i}} \cdot [e^{b_2 + b_{12}x_{1i}}(b_1 + b_{12}) - \mathrm{b}_1]$$

where the last part of equation (4) was obtained by factoring out the common part of $E[y_i|\,.\,]$.

In general, the interaction effect highlighted in equation (4) depends on all variables in the model and a test of zero interaction effect can be carried out based simply on $b_{12} = b_2 = 0$. However, this would imply removing the categorical variable x_2 that indicates the Measure the application is submitted under. Alternatively, one could test if equation (4) statistically equates to zero for a specific application and for the average application as well without imposing $b_{12} = b_2 = 0$, but it is unclear what this hypothesis means with respect to the *overall* significance of the interaction. Thus, Greene suggested studying how the partial effect changes with respect to the categorical variable. In particular, the partial effect is calculated by conditioning the categorical variable equal to 1 for a specific Measure and zero for all the other ones. Traditional statistical tests of the partial effect for different Measures can be carried out by calculating their standard errors with the delta method (Greene, 2010a). In addition, graphical inspection can provide a further understanding on how the effect of public funds on job creation is differentiated by Measure.

Finally, we will study the partial effect of funds on the *probability* to create jobs instead of the partial effect of funds on the *expected number* of created jobs as highlighted in equation (3). This is made for three reasons. First, once the partial effect in (3) is conditioned to a specific Measure, a variation of some units in the index function $A_i|Measure$ can imply a difference of hundreds or even thousands in the number of expected jobs $exp(A_i|Measure)$, a figure that difficultly can make sense[7]. To make a comparison with the probit and logit models, although the condition to test the presence of the interaction effect is the same as for the count data models[8], the analogous of the partial effect given in (3) for a binary model has $\phi(A_i|Measure)$ and $\Lambda(A_i|Measur) \cdot \left(1 - \Lambda(A_i|Measur)\right)$ instead of $exp(A_i|Measure)$, where $\phi(.)$ is the standard normal density bounded between 0 and 0.39 while $\Lambda(.) \cdot \left(1 - \Lambda(.)\right)$ is the logistic density function bounded between 0 and 0.25. In contrast, $\exp(.)$ is not upper bounded and, moreover, it grows really fast. Thus, if we studied the partial effect of funds on the expected number of created jobs by different Measures, we would have predictions that do not have an economic interpretation although they are analytically correct. Conversely, the probability to create jobs is bounded by construction between zero and one and thus its partial effects will have a meaningful economic interpretation (Greene, 2010b). This approach will also allow analyzing two additional aspects.

[7] As shown in Table 2, the maximum amount of created jobs observed in the 2007-2013 period was 41 jobs per application.

[8] Being this condition $b_{12} = b_2 = 0$ (Greene, 2010b).

First, it will be possible to study the probability to create jobs, that is $\mathrm{Prob}[Y \geq 1]$. This is useful from a policy perspective since it is a benchmark between job creation ($Y \geq 1$) and non job creation ($Y = 0$). Second, this approach will allow studying the probability to create a given number of jobs, that is $\mathrm{Prob}[Y = j]$ for any non negative integer j. This goes beyond the dichotomous analysis between job creation vs. non job creation typical of a binary model and it will allow studying the patterns of the job creation and thus formulate more detailed policy recommendations.

4. DATA SOURCE AND MODEL SPECIFICATION

4.1 Data Source

The data-set was provided by the Department of Agriculture, Environment, and Rural Affairs Northern Ireland (DAERA), previously DARD, and it consists of all applications submitted under Axis 3 of the NIRDP between 2007 and 2013. Application information that was used in this analysis includes basic data about the individual or organization applying for the grant, and details of the proposed project such as description, aims, anticipated costs, grant requested, and, proposed start and end dates.

Applications can be made via the public website or on a hard copy application which is transferred to the electronic management system (System2007). If an application is approved, all claims against letters of offer are also recorded over the life of the project. A Post Project Evaluation (PPE) is carried out two years after project ends and also logged on to System2007. This provides *ex-post* information such as amount of total grant paid, total project expenses, duration of the project, and, moreover, the realized outcome against initial targets at the time of application. Thus, the data employed in this study such as paid grant, capital share, duration of the application, number of payments, and the number of created jobs are all *ex-post* variables. Overall, the data-set contains 5,973 applications of which 29% were approved and granted funding to support the projects outlined.

4.2 Model Specification

We model the selection process and the job creation considering several factors. First, we consider if there are differences due to the Measures associated with each application. Applicants select which Measure their project is most related to as part of the submission process.

Some Measures can roughly be associated with different industries (e.g. 3.1 with food processing, 3.3 with hospitality and recreation, and 3.4 with services) and so we should expect a potential effect on the pattern of job creation by economic sector (Van Stel & Storey, 2004). Moreover, by programme design, Measures have different minima and maxima of grant awards and different rates of support in proportion to applicant's projected spending on the project (Department of Agricultural Environment and Rural Affairs, 2016)[9] which we expect to have implications for what applications are selected for funding. Therefore the binary variables indicating the Measure associated with each application are included as *intercept shifters* in the selection equation and in the structural equation. Similarly, we consider if there are differences due to the associated LAG.

[9] The grant aid ranges from £225 to £250,000 per application while the public coverage of the project cost ranges from 50% to 75% (Rural Network NI 2017).

With respect to the applicant, we employ binary variables to describe the organization characteristics such as the legal type - private, public, or charity – its formation – new rather than existing business – and its structure – in partnership rather than sole company. We also employed continuous variables to describe the agricultural characteristics of the local area (electoral ward) associated with each application[10]. Two variables related to agricultural characteristics were considered: the share of farms located in less favoured areas (LFA) and the average standard gross margin per farm (SGM) taken from the Farm Survey (NISRA, 2010a) . A LFA is an EU definition to describe an area with natural handicaps such as lack of water, short crop season and tendencies of depopulation (OECD, 2002). Similarly, the SGM is a measure of the production or business size of an agricultural firm (Eurostat, 2016). These variables were employed to control if the job creation was also related to the agricultural and economic characteristics of the region.

With respect to the approved application, we consider both the number of payments and the duration of the project. This distinction is made for two reasons. First, once an application is approved, a claim against the funding awarded can only be submitted after payment has been completed for the purchases of goods and services[11]. Since the purchased recourses cannot be diverted from an approved application, the retrospective payment system should foster an active behaviour of the applicant to carry out the project and, *ceteris paribus*, and increase its effort on the project (Grossman & Hart, 1983). In addition, a payment of public funds can only be made once all the necessary documents such as invoices, signed receipts, copies of the issued cheques, and bank statements are presented to the public authority (Department of Agricultural Environment and Rural Affairs, 2016; Rural Network NI 2017). Thus, a payment represents a moment of screening where the public authority acquires a better understanding about the status of the project. In the principal-agent problem, a higher effort of the agent, that is the applicant, and a better informative status of the principal, that is the public authority, are associated with a better outcome (Grossman & Hart, 1983). Thus, we should expect to see that more payments imply higher chances of job creation.

Second, the duration of the grant is employed separately because the applications have different temporal length and the NB model assumes that the same amount of time is observed for each i (Greene, 2010a). We do not set the coefficient of the duration variable equal to 1 as if it were an *exposure variable*, but we estimate it from the data. This is done because we should expect that an application with a longer duration may have more chances to create jobs and setting its coefficient

[10] This was possible because the data-set contains the coordinates of each application. Since information from Agricultural Census is collected at the electoral ward level in the U. K. and in Northern Ireland in particular, each application was matched with the corresponding electoral ward. Overall, 5,973 applications involved 73% of the electoral wards. The attribution of an application to the corresponding ward was made with the 'sp' package of the R-project (Bivand R. S., Pebesma, & Gomez-Rubio, 2013; Pebesma & Bivand, 2005).

[11] The only exception are the *phased payments* that are allowed before the applicant pays, but they cannot be more than five, they require that at least 20% of the total project is already developed and they must be linked to the tangible outputs describe on the Letter of Offer (Department of Agricultural Environment and Rural Affairs, 2016; Rural Network NI 2017).

equal to 1 represents a particular case (Greene, 2010a). In general, using separately the number of payments and the duration allows deriving other specifications of the model as special cases[12].

Finally, we employ the proportion of the total cost due to the capital investment such as building and equipment purchases. Note that the sign of this variable is not predetermined. First, the sign can be positive if the proportion of the capital investment represents an indicator of the firm size and the labour demand increases with the firm size (Kumar, Rajan, & Zingales, 1999). Second, it can be positive if the proportion of capital investment indicates that the labour demand is more oriented towards skilled jobs (Hijzen, Görg, & Hine, 2005; Lazear, 2009). Finally, the sign of this variable can be negative if the marginal rate of technical substitutions between labour and capital is substantial, that is by far a common situation in agriculture (Arrow, Chenery, Minhas, & Solow, 1961; Mas-Colell, Whinston, & Green, 1995).

With respect to the amount of funds per application, we use the natural log. This transformation was made for two reasons. First, count data models estimates the parameters by taking the exponential of the index function and the exponential of hundreds and thousands is not practically computable. Second, this allowed handling the positive skewness of the funds distribution (Mihaylova, Briggs, O'Hagan, & Thompson, 2011). Finally, this has a useful interpretation in terms of partial effect since we will study how the *percentage change* of the amount of funds per application affects the probability to create jobs (Greene, 2010a). Table 1 indicates the variable definitions while the associated summary statistics is shown in Table 2. As highlighted by Table 2, the average number of created jobs per application is 0.67 while the standard deviation is 2.37. This indicates that the dependent variable is over-dispersed. The next section introduces the results.

5. RESULTS

The results of the *Baseline* model are shown in Table 3 and Table 4. In particular, Table 3 shows the first stage estimates of the probit model while Table 4 shows the second stage estimate of the NB model.

5.1 Selection Equation- First Stage

Regarding the application process, Table 3 indicates that if an application is from a public organization (government department and other public agency), the probability to be approved is higher (partial effect equal to 0.18, 1% statistically significant). In contrast, if an application involves a new business, the probability to be approved decreases by 0.14 (1% statistically significant). In addition, Table 3 indicates that the selection process is affected by the Measure and by the LAG as well. In particular, if an application was submitted under *Business Creation and Development (*Measure 3.2), the probability of approval decreases by 0.07 (1% statistically significant). In contrast, if an application interests *Village Renewal and Development* (Measure 3.5), the probability to get approved increases by 0.20 (1% statistically significant).

[12] As we assume that the log of the number of payments and the log of the duration linearly enter in $\boldsymbol{X}'\boldsymbol{\beta}$ with coefficients γ_1 and γ_2, when the duration is used as an exposure variable γ_2 is set equal to 1. Similarly, if the log of the frequency of payments is used, γ_2 is set equal to $-\gamma_1$.

With respect to the associated LAG, Table 3 indicates that if an application falls within the Down Rural Area Partnership (DARP), the Southern Organization for Action in Rural Areas (SOA), and the Southern Organization for South West Rural Development (SWARD), the probability to get approved decreases by 0.02 (5% statistically significant). In contrast, if an application falls within the remit of the Generating Rural Opportunity within South Antrim group (GROW), the probability to get approved increases by 0.04 (10% statistically significant). We did not find any statistical significance of the variables relating to the agri-economic characteristics of the region from where an application is from, namely the percentage of farms classified as less-favoured (LFA) and the average amount of the standard gross margin per farm of the region (SGM)[13].

5.2 Job Equation – Second Stage

5.2.1 Baseline Model

Table 4 shows the estimates of the job equation for the *Baseline Model*. Preliminarily, the log-likelihood function of the model estimated as in equation (2) corresponds to -4,683.61. If we separately estimate the probit model over the entire sample (5,973 observations) and the NB model over the sample of the approved applications (1,723 observations), the sum of these log-likelihood functions is -4,683.83, basically the same value. In addition, Table 4 shows that the corrected standard errors estimated are usually not smaller that those estimated by assuming zero correlation, as we should expect (Karaca-Mandic & Train, 2003). Finally, Table 4 indicates that the coefficient of the IMR is statistically significant at the 5% level. These results indicate strong evidence of correlation between the selection process and the job creation process[14].

With respect to the overall fit of the model, Table 4 shows at the bottom that the LR test on the parameter of over-dispersion (alpha) is highly significant with a p-value basically close to zero. Note also that the deviance test that does not reject the null hypothesis for the NB model, but it does for the Poisson model. This indicates that the NB model properly represents the data generating process.

Regarding the partial effect of the variables specific to the job equation, Table 4 shows a positive relationship between the number of created jobs and the capital expenses per application. In particular, if the proportion of capital expenses such as construction of buildings and fixed capital investments increases by 1%, the probability to create at least 1 job increase by 0.07 (5% statistical significance). This means that applications characterized by a high incidence of fixed capital were suitable to generate more jobs. If we consider that the median turnover of the approved applications was £214,000 per year and that large companies usually demand more skilled jobs, this may provide suggestive evidence about the nature of the jobs that were created (Kumar et al., 1999).

A similar result is estimated for the number of payments where the average partial effect is equal to 0.03 and statistically significant at the 1% level. This can indicate that the recursive payment

[13] We employed additional variables to test if the selection and the job creation processes were affected by the regional characteristics such as the unemployment rate and the share of population under job seeker's allowances, but we did not find any statistical significance.

[14] This is also confirmed by the correlation between the parameters of the probit model and those of the NB model that ranges from -0.91 to 0.98.

system may stimulate agent effort, improve the monitoring activity of the public authority, and eventually create more jobs (Grossman & Hart, 1983).

Finally, the amount of public funds has a positive effect on the probability to create jobs. Overall, the estimated partial effect is equal to 0.06 and 1% statistically significant. This means that if the amount of funds per application increases by 17%, we should see the probability to create at least one new job close to 1. This suggests two implications. First, this confirms previous studies on the positive link between public funds and job creation of the CLLD approach (Haven-Tang & Jones, 2012). Second, the magnitude of this partial effect seems particularly reasonable in terms of costs benefit analysis. For instance, the average amount of funds per applications is £34,217. Thus, an increase of 17% corresponds to £5,817 more per application. If compared with the average annual salary in the UK and in NI in particular, the required increase of the public expenditure may generate benefits larger than costs (Department for the Economy, 2016).

5.2.2 Extended Model

Table 5 shows the estimates of the *Extended Model* with slope shifters for the interaction between the amount of funds and the Axis 3 Measure where Measure 3.4 was taken as base (*Basic Service for the Economy and Rural Population*). Preliminarily, Table 5 shows that all the coefficients of the slope shifters are 1-10% statistically significant. In addition, the sign of the coefficients of the Measures 3.1, 3.2, 3.3, and 3.5 is positive and this could indicate that the effect of funds on the job creation is higher for these Measures than for the Measure 3.4. In contrast, the sign of the slope shifter of the Measure 3.6 (*Conservation and Upgrading of the Rural Heritage*) is negative indicating that this measure probably performs worse than the other ones. This is not unexpected as this measure is not conceived to deliver job creation, as indicated by the choice not to associate a job-creation target at the outset of the NIRDP 2007-2013. Finally, Table 5 at the bottom shows the LR test and the Wald test to test the null hypothesis that all the slope shifters are jointly equal to zero. The LR test rejects the null hypothesis at the 4% significance level and, similarly, the Wald rests rejects the null hypothesis at the 3% significance level. Overall, these results indicate that there is evidence that the effect of public funds on job creation is differentiated by the Axis 3 Measure.

In terms of *overall* job creation, Table 6 shows the observed and the predicted probability to create jobs by Measure. Table 6 shows that some Measures are more productive in terms of creating jobs than others regardless of the public funds. This is expected considering not all Measures are concerned with generating employment outcomes directly such as Measures 3.5 - *Village Renewal and Development* and Measure 3.6- *Conservation and Upgrading of the Rural Heritage* creating only one or no job based on the data set. In contrast, Measure 3.2 - *Business Creation and Development* - has the highest probability to create jobs, followed by the Measure 3.1 – *Diversification into Non–Agricultural Activities*, Measure 3.4 – *Basic Services for Economy and Rural Population*, and Measure 3.3 - *Encouragement of Tourism Activities*.

With respect to the public funds, Table 7 shows the statistical significance of their average partial effect (APE). This was calculated by taking the derivative of equation (1) with respect to $log\ (funds)$ and then *conditioning* it to the Measure indicator. The statistical significance was assessed with the delta method (Greene, 2010a). Preliminarily, we should notice that if a Measure is suitable to create new jobs we should observe that the APE for $j = 0$ is negative since

$Prob[Y \geq 1] = 1 - Prob[Y = 0]$ and $\frac{\partial \text{Prob}[Y \geq 1]}{\partial Funds} = -\frac{\partial \text{Prob}[Y=0]}{\partial Funds}$. Apart from Measure 3.6-*Conservation and Upgrading of the Rural Heritage*, this happens for all the other measures. However, while the Measure 3.4 and the Measure 3.5 did not exhibit any statistical significance, the first three Measures show statistically significant APEs.

In particular, Measure 3.1, *Diversification into Non–Agricultural Activities* (APE 0.07), shows the highest effect followed by the Measure 3.3, *Encouragement of Tourism Activities* (APE 0.05), and the Measure 3.2, *Business Creation and Development* (APE 0.03). This means that if the amount of funds per application increase by 14%, 20%, and 33% for Measures 3.1, 3.3, and 3.2, respectively, the probability to create at least one new job per application should be close to 1. It is also interesting to notice that the effect of these Measures is not statistically significant for the first units of labour, namely the first one and two jobs. This can indicate that firms internalize the increased demand for labour through the over-time of the personnel already present in their staff and sustain the agency costs of recruiting and training only when their labour capacity is not sufficient to satisfy the increased demand for labour (Lazear, 2009; Oi, 1983). Finally, the statistical significance of the APEs disappears for more than 5 jobs. This suggests that the positive effect of public funds on job creation is suitable to generate between three and five new jobs. A possible explanation is that if an application generates a substantial amount of new jobs, probably other factors such as the capital investment and economies of scale can be better drivers for job creation (Haltiwanger et al., 2012; Oi, 1983).

These results indicate that some Axis 3 Measures were able to create jobs in NI in the period 2007-2013, but that this was not solely related to the amount of public funds. For instance, Measure 3.2 has the highest observed and predicted probability to create jobs, but once the effect of public funds is considered, this is more limited than for the Measures 3.1 and 3.3. Similarly, although the Measure 3.4 has the third highest out of six observed and predicted probabilities to create jobs, this is not related to public funds at all since its APE is not statistically different from zero.

Figure 1 plots the APEs from Table 7 and it can be a useful tool to assess the robustness of the results. In general, the APE of the first three Measures is the only one that shows the expected pattern. In particular, the APE is negative for zero created jobs, it becomes immediately positive, and then it quickly approaches to zero only for the Measures 3.1, 3.2, and 3.3. For the other Measures, the APEs show an insignificant or inconsistent pattern[15].

Finally, Figure 2 plots the partial effect on the probability to create one or more jobs with respect to the amount of funds per application. This corresponds to the first row in Table 7 and the first point of each panel in Figure 1 where, apart from $log(funds)$, all the covariates were fixed at the median values[16]. Figure 2 confirms the previous analysis. First, the APE of Measure 3.6 is close to zero regardless of the funds per application. Second, for Measure 3.4 the APE is a horizontal line slightly above zero that does not show any change with respect to the public funds. Third, the APE of the Measure 3.5 shows some variability (green line). However, the dashed vertical lines

[15] For the Measures 3.4 and 3.6 the APEs are basically zero, while the APE of the Measure 5 is negative from zero to ten created jobs.

[16] The median is usually chosen for the binary variables. In addition, the median was also chosen for the continuous variables because it gives a better idea of centrality for skewed distributions (Mihaylova et al., 2011).

drawn in correspondence of $\pm$ one standard deviation from the average of $log\ (funds)$ indicate that the variability is more limited where it matters (Greene, 2010b). Thus, the graphical inspection of Figure 2 confirms the analysis carried out from Table 7 and Figure 1 about the limited effect of public funds on job creation for the Measures 3.4, 3.5, and 3.6.

In contrast, Measures 3.1, 3.2, and 3.3 show large positive variability along the central part of the distribution. In particular, for applications with an amount of funds below the average, Measure 3.1 shows a higher partial effect than Measure 3.2 and, especially, Measure 3.3. However, for applications utilising an amount of public funds above the average, Measure 3.3 shows a higher partial effect than Measure 3.2 and, especially, Measure 3.1. It is interesting to notice that the APE of the Measure 3.1, *Diversification into Non–Agricultural Activities*, is positive, but it decreases if the amount of funds per application increases. In contrast, Measure 3.2, *Business Creation and Development*, and especially Measure 3.3, *Encouragement of Tourism Activities*, exhibit an increasing marginal product of public funds on the probability to create jobs. This result confirms previous studies and it suggests that these Measures can have spill-over effects (Moretti, 2010) which resulted in job creation particularly in the tourism sector (Haven-Tang & Jones, 2012; Moretti, 2010). This also suggests a final remark.

We have seen that the APE on $Prob[Y \geq 1]$ is higher for Measure 3.1 than for Measure 3.3 and this led us to conclude that public funds exhibit a higher capability to create jobs if the application is addressed to the *Diversification into Non–Agricultural Activities* (Measure 3.1) rather than if it is addressed to the *Encouragement of Tourism Activities* (Measure 3.3). However, Figure 1 and Table 7 also indicate that a) the APE on $Prob[Y = j]$ for the Measure 3.3 is actually higher than for the Measure 3.3 for j that ranges from 1 to 20; b) the magnitude and the statistical significance of the APEs quickly approach to zero for $j > 5$. Thus, the fact that APE on $Prob[Y \geq 1]$ is higher for the Measure 3.1 than for the Measure 3.3 is due the partial effect on the probability to create 21 and more jobs, a quite rare event given the distribution of the outcome in this data-set[17]. This makes us conclude that public funds increase the chance to create jobs for Measure 3.1, *Diversification into Non–Agricultural Activities*, but their effect is probably more limited than for the Measure 3.3, *Encouragement of Tourism Activities*.

6. CONCLUSIONS AND POLICY RECCOMENDATIONS

This study analyzed the effectiveness of Axis 3 delivered through the LEADER/LAG approach on job creation in NI. We employed individual level observations to analyze the applications of the last concluded round covering the 2007-2013 period. After correcting for sample selection and controlling for the socio-economic characteristics of the application, we found that there is a positive relationship between public funds and job creation. In addition, this study found that the relationship is differentiated by the Measure. In particular, Measure 3.1, *Diversification into non-Agricultural Activities*, Measure 3.2, *Business Creation and Development*, and the Measure 3.3, *Encouragement of Tourism Activities*, showed that public funds increase the probability to create one or more jobs. No significant effect was found with respect to the other Measures, but this is not surprising considering these are less concerned with generating economic outcomes directly.

[17] The observed probability of an application to create 21 or more jobs is to 0.004.

Finally, this study found that when public funds effectively stimulate job creation, they do so only *above a threshold*, namely two jobs.

A possible explanation of this result is that in NI the Axis 3 Measures created jobs typically for the existing businesses that invest in fixed capital. In general, a significant incidence of fixed capital is characteristic of large companies with a high demand for high-skilled jobs (Kumar et al., 1999; Lazear, 2009). Thus, the absent impact of public funds on job creation for the first units of labour seems due to middle-large size firms that can use the over-time of the specialized personnel already present in their staff to absorb the excess of the demand for labour (Lazear, 2009; Oi, 1983; Singh et al., 1986).

From a policy perspective, two alternative approaches are possible. If the program administrators will follow the same pattern by approving pre-existing businesses rather than new companies, they should allocate more funds where the chances of a positive outcome are higher. In terms of job creation, this means applications that operate in the tourism sector and that foster farm diversification. In addition, the program administrators should allocate funds to the applications most suitable to generate a minimum number of jobs, namely more than two. The risk is that if the excess of the demand for labour is not sufficiently *high*, firms could absorb it with their current staff and the allocation of public funds would be less efficient in terms of job numbers.

Alternatively, CLLD approaches to the rural development in NI can promote new businesses and initiatives rather than the pre-existing ones. This would require to re-design the selection and the allocation mechanisms, a policy choice that can be implemented only after the current round of the NIRDP concludes in 2020 and when alternative rural development strategies will be necessarily adopted (Boulanger & Philippidis, 2015). This policy choice could take advantage of the fact that the start-up companies usually create more jobs than pre-existing companies, but it will also have to consider that their failure rate is high as well (Haltiwanger et al., 2012). Thus, if policy-makers will decide to promote young businesses rather than the pre-existing ones, they would have to deal with the trade-off between chances of success vs. chances of job creation from a different prospective (Myles, 1995).

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Table 1. Variable Names and Definitions

Variable	Definition
Jobs	Number of created jobs per application (headcount).
Funded Application	Binary variable equal to One if the application was funded; Zero otherwise.
Private Business	Binary variable equal to One if the applicant was a private business (limited company, sole trader, and business partnership); Zero otherwise.
Public Organization	Binary variable equal to One if the applicant was a public body (government department and agency, other public sector organization); Zero otherwise.
Other Type of Organization	Binary variable equal to One if the applicant was neither a private business nor a public body; Zero otherwise.
New Business	Binary variable equal to One if the application involves a new business/enterprise; Zero if the application involves an existing business/enterprise.
Company Link	Binary variable equal to One if the applicant's company is a linked company; Zero Otherwise.
Share LFA	Percentage of farms located in areas (electoral wards) classified as less-favoured (Source: Farm Surveys, 2010).
SGM	Average standard gross margin (SGM) per farm in British sterling (Source: Farm Surveys, 2010) [a].
MEASURE 1	Binary variable equal to One if the application was presented as Measure 3.1 (Diversification into Non - Agricultural Activities); Zero otherwise.
MEASURE 2	Binary variable equal to One if the application was presented as Measure 3.2 (Business Creation and Development); Zero otherwise.
MEASURE 3	Binary variable equal to One if the application was presented as Measure 3.3 (Encouragement of Tourism Activities); Zero otherwise.
MEASURE 4	Binary variable equal to One if the application was presented as Measure 3.4 (Basic Services for the Economy and Rural Population); Zero otherwise.
MEASURE 5	Binary variable equal to One if the application was presented as Measure 3.5 (Village Renewal and Development); Zero otherwise.
MEASURE 6	Binary variable equal to One if the application was presented as Measure 3.6 (Conservation and Upgrading of the Rural heritage); Zero otherwise.
ARC	Binary variable equal to One if the Local Action Group is ARC North West (Assisting Rural Communities); Zero otherwise.

Table 1. Continued

Variable	Definition
DARP	Binary variable equal to One if the Local Action Group is Down Rural Area Partnership (DARP); Zero otherwise.
GROW	Binary variable equal to One if the Local Action Group is Generating Rural Opportunities within South Antrim (GROW); Zero otherwise.
LRP	Binary variable equal to One if the Local Action Group is Lagan Rural Partnership (LRP); Zero otherwise.
NER	Binary variable equal to One if the Local Action Group is North East Region (NER); Zero otherwise.
SOAR	Binary variable equal to One if the Local Action Group is Southern Organization for Action in Rural Areas (SOAR); Zero otherwise.
SWARD	Binary variable equal to One if the Local Action Group is Southern Organization for South West Action for Rural Development (SWARD); Zero otherwise.
Paid Grant	Paid funds per awarded application[b].
Capital Share	Percentage of total cost per application due to capital expenses rather than resources expenses[c].
Number of Payments	Number of payments the awarded grant was paid.
Duration	Duration in months of the awarded application.

[a]: Average exchange rate Euro/British sterling 2010 equal to 1.1657 (Source: bank of England 2017).
[b]: In 2010 British sterling based on the Consumer Price Index for the United Kingdom (source: Federal Reserve Bank, 2017).
[c]: Capital expenses = expenses for construction and refurbishment of buildings/premises and fixtures; Purchase of equipment/plant, and land.
Resources Expenses = marketing costs, professional consultancy, training costs, labour costs, travel expenses, running costs, evaluation costs.
Where not specified, the data source is from the RDP Axis 3 Dataset Northern Ireland (DAERA, 2016).

Table 2. Descriptive Statistics

Variable	Average	Standard Deviation	Minimum	Maximum
Jobs	0.67	2.37	0	41
Funded Application	0.29	0.45	0.00	1.00
Private Business	0.75	0.43	0.00	1.00
Public Organization	0.07	0.25	0.00	1.00
Other Type of Organization	0.18	0.39	0.00	1.00
New Business	0.36	0.48	0.00	1.00
Company Link	0.10	0.30	0.00	1.00
Share LFS	0.65	0.36	0.00	1.00
SGM (British Sterling)	33,613	20,115	3,497	228,261
MEASURE 1	0.33	0.47	0.00	1.00
MEASURE 2	0.36	0.48	0.00	1.00
MEASURE 3	0.13	0.33	0.00	1.00
MEASURE 4	0.10	0.30	0.00	1.00
MEASURE 5	0.06	0.23	0.00	1.00
MEASURE 6	0.03	0.18	0.00	1.00
ARC	0.18	0.38	0.00	1.00
DARP	0.15	0.36	0.00	1.00
GROW	0.09	0.29	0.00	1.00
LRP	0.08	0.27	0.00	1.00
NER	0.15	0.36	0.00	1.00
SOAR	0.17	0.37	0.00	1.00
SWARD	0.18	0.39	0.00	1.00
Paid Grant (British Sterling)	34,217	41,897	209	239,271
Capital Share	0.78	0.38	0.00	1.00
Duration (Months)	17.74	11.38	0.33	68.17
Number of Payments	7.75	20.82	1.00	480.00
Number of Applications	5,973	---	---	---

Table 3. First Stage Estimates of the Baseline Model: Probit Model

Dependent Variable	Funded Application	
Independent Variable	Coefficient	Robust Standard Error
Private Business	0.01	0.06
Public Organization	**0.60*** **	0.08
New Business	**-0.43*** **	0.04
Company Link	0.02	0.06
Share LFS	0.01	0.07
Log(SGM)	0.02	0.03
MEASURE 1	0.12	0.08
MEASURE 2	**-0.22*** **	0.08
MEASURE 3	-0.09	0.08
MEASURE 5	**0.66*** **	0.09
MEASURE 6	0.04	0.11
DARP	**-0.16** **	0.07
GROW	**0.16** **	0.07
LRP	0.00	0.08
NER	0.04	0.06
SOAR	**-0.16*** **	0.06
SWARD	**-0.12** **	0.06
Constant	**-0.68* **	0.38

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4. Second Stage Estimates of the Baseline Model: Negative Binomial Model

Dependent Variable	Number of Created Jobs (Headcount)		
		Asymptotic Standard Errors	
Independent Variable	Coefficient	Corrected[a]	Uncorrected[b]
Private Business	1.51	1.12	0.32
Public Organization	**7.41***	4.08	2.96
New Business	**-7.74****	3.31	2.59
Company Link	0.85	1.04	0.27
Share LFS	-0.03	1.22	0.29
Log(SGM)	0.25	0.67	0.19
MEASURE 1	2.60	1.81	0.84
MEASURE 2	-2.23	1.93	1.29
MEASURE 3	-1.75	1.42	0.63
MEASURE 5	5.92	4.32	3.10
MEASURE 6	**-20.26*****	1.83	0.63
DARP	-2.39	1.62	0.96
GROW	**2.22****	1.10	0.72
LRP	0.63	1.40	0.36
NER	-0.28	0.99	0.46
SOAR	-2.24	1.60	0.92
SWARD	-1.42	1.35	0.73
Log(Paid Grant)	**0.62*****	0.07	0.07
Capital Share	**0.74****	0.32	0.32
Log(Number of Payments)	**0.35*****	0.08	0.08
Log(Duration in Months)	-0.08	0.13	0.13
Inverse Mills Ratio	**22.75****	9.67	7.70
Constant	**-36.87****	15.74	9.58
α	**1.02*****	0.32	0.31
Observations	5,973		
Log-Likelihood Function	-4,683.61		
AIC	9,415.22		
Deviance Test Negative Binomial Modell[c]	0.49		
Deviance Test for Poisson Model[d]	0.00		
LR Test for α = 0[e]	1,324.56 (0.00)		

[a]: The gradient of the LLF is defined allowing for correlation between the parameters of the NB model and probit model.
[b]: It is assumed that the parameters of the NB model and probit model are uncorrelated.
[c]: 1,699 degrees of freedom, p-value Chi2 distribution in parenthesis.
[d]: 1,700 degrees of freedom, p-value Chi2 distribution in parenthesis.
[e]: 1 degree of freedom, p-value Chi2 distribution in parenthesis
***, **, * indicate statistical significance at the 1%, 5%, and 10% level, with respect to the corrected standard errors.

Table 5. Second Stage Estimates of the Extended Model: Negative Binomial Model

Dependent Variable	Number of Created Jobs (Headcount)		
		Asymptotic Standard Errors	
Independent Variable	Coefficient	Corrected[a]	Uncorrected[b]
Private Business	1.48	1.18	0.30
Public Organization	**8.33****	4.08	2.92
New Business	**-8.57****	3.28	2.55
Company Link	0.91	1.15	0.26
Share LFS	0.03	1.34	0.28
Log(SGM)	0.34	0.72	0.18
MEASURE 1	-3.74	3.06	2.60
MEASURE 2	**-6.88****	2.97	2.55
MEASURE 3	**-10.61****	4.30	4.08
MEASURE 5	1.72	5.71	4.18
MEASURE 6	**-12.51*****	3.16	2.57
DARP	-2.71	1.71	0.96
GROW	**2.40****	1.21	0.72
LRP	0.60	1.52	0.33
NER	-0.25	1.09	0.45
SOAR	-2.54	1.67	0.91
SWARD	-1.64	1.44	0.72
Log(Paid Grant)	0.17	0.21	0.21
Log(Paid Grant) · MEASURE 1	**0.63****	0.24	0.24
Log(Paid Grant) · MEASURE 2	**0.40***	0.22	0.22
Log(Paid Grant) · MEASURE 3	**0.81***	0.37	0.37
Log(Paid Grant) · MEASURE 5	**0.48***	0.27	0.25
Log(Paid Grant) · MEASURE 6	**-0.76*****	0.24	0.24
Capital Share	**0.61***	0.34	0.34
Log(Number of Payments)	**0.34*****	0.08	0.08
Log(Duration in Months)	-0.06	0.13	0.13
Inverse Mills Ratio	**25.12*****	9.57	7.59
Constant	**-35.51****	25.96	11.57
α	**2.71*****	0.31	0.30
Observations		5,973	
Log-Likelihood Function		-4,677.50	
AIC		9,403.00	
LR Test Baseline Model = Extended Model[c]		11.41 (0.04)	
Wald Test Baseline Model = Extended Model[d]		12.11 (0.03)	

[a]: The gradient of the LLF is defined allowing for correlation between the parameters of the NB model and probit model.
[b]: It is assumed that that the parameters of the NB model and probit model are uncorrelated.
[c]: 5 degrees of freedom, p-value Chi2 distribution in parenthesis.
[d]: Based on the bootstrapped variance-covariance matrix. 5 degrees of freedom, p-value Chi2 distribution in parenthesis.
***, **, * indicate statistical significance at the 1%, 5%, and 10% level, with respect to the corrected standard errors.

Table 6. Observed and Predicted Probability by Measures

Observed Probability[a]							
Jobs	Overall	Measure 3.1	Measure 3.2	Measure 3.3	Measure 3.4	Measure 3.5	Measure 3.6
0	0.78	0.76	0.53	0.93	0.89	1.00	1.00
1	0.10	0.13	0.18	0.04	0.04	0.00	0.00
2	0.05	0.04	0.13	0.00	0.03	0.00	0.00
3	0.02	0.02	0.05	0.01	0.01	0.00	0.00
4	0.01	0.01	0.03	0.00	0.00	0.00	0.00
5	0.01	0.01	0.02	0.00	0.01	0.00	0.00
6	0.01	0.01	0.01	0.00	0.01	0.00	0.00
7	0.00	0.00	0.01	0.00	0.01	0.00	0.00
Predicted Probability[a]							
Jobs	Overall	Measure 3.1	Measure 3.2	Measure 3.3	Measure 3.4	Measure 3.5	Measure 3.6
0	0.78	0.74	0.61	0.90	0.84	1.00	1.00
1	0.10	0.12	0.14	0.06	0.10	0.00	0.00
2	0.04	0.05	0.07	0.02	0.03	0.00	0.00
3	0.02	0.03	0.04	0.01	0.01	0.00	0.00
4	0.01	0.02	0.03	0.00	0.01	0.00	0.00
5	0.01	0.01	0.02	0.00	0.00	0.00	0.00
6	0.01	0.01	0.02	0.00	0.00	0.00	0.00
7	0.00	0.00	0.01	0.00	0.00	0.00	0.00

[a]: The predicted probability to have *j* jobs by measure is calculated with equation (1) and averaged by measure.

Table 7. Average Partial Effect (APE) of Δ% $Funds$ on $P[Y = j \ Jobs]$ by Measure

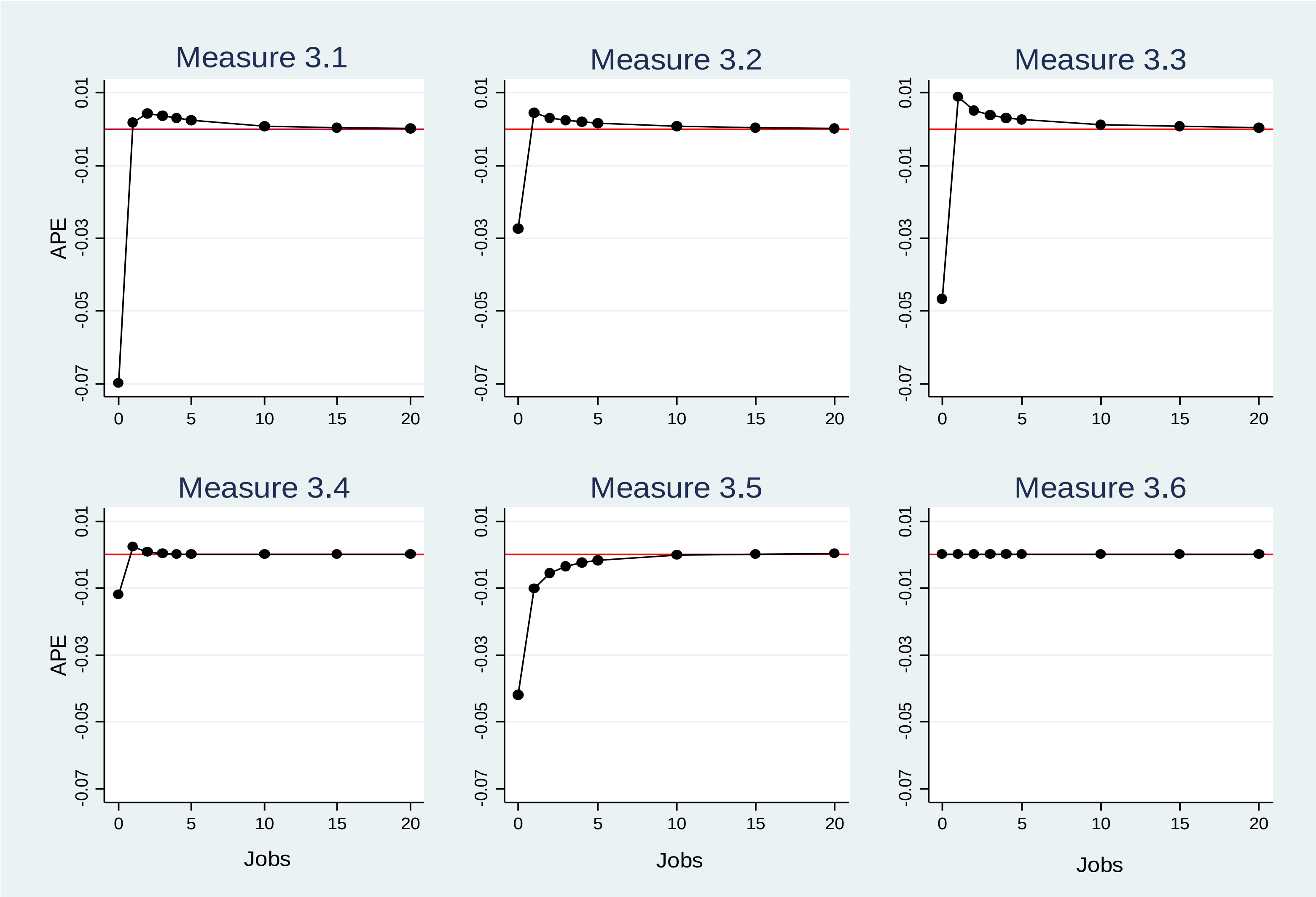
$$\frac{\partial P[Y=K]}{\partial \log(Funds)} \cdot 100$$

(Standard Errors in parenthesis)[a]

Jobs	Overall	Measure 3.1	Measure 3.2	Measure 3.3	Measure 3.4	Measure 3.5	Measure 3.6
0	**-6.40*****	**-6.99*****	**-2.74*****	**-4.67*****	-1.20	-4.18	1.76E-04
	(1.62)	(1.78)	(0.87)	(1.27)	(2.35)	(8.58)	(6.26E-04)
1	**1.02***	0.19	0.46	0.88	0.24	-1.01	-1.76E-04
	(0.61)	(0.60)	(0.51)	(1.38)	(0.81)	(1.36)	(5.67E-04)
2	**0.96*****	0.43	0.31	0.52	0.08	-0.54	-2.29E-08
	(0.31)	(0.30)	(0.20)	(0.79)	(0.57)	(0.47)	(1.77E-04)
3	**0.75*****	**0.38***	**0.25***	**0.39*****	0.02	-0.34	-4.32E-12
	(0.24)	(0.22)	(0.13)	(0.17)	(0.45)	(0.55)	(1.40E-04)
4	**0.59*****	0.30	**0.21***	**0.31****	0.01	-0.23	-1.12E-15
	(0.21)	(0.20)	(0.11)	(0.15)	(0.39)	(0.63)	(1.18E-04)
5	**0.47****	0.24	**0.17***	**0.26****	0.00	-0.16	-3.61E-19
	(0.19)	(0.19)	(0.09)	(0.13)	(0.34)	(0.66)	(1.03E-04)
10	0.18	0.09	0.08	0.13	0.00	-0.02	-3.86E-36
	(0.13)	(0.14)	(0.06)	(0.24)	(0.22)	(0.54)	(6.72E-05)
15	0.08	0.04	0.05	0.08	0.01	0.01	0.00
	(0.10)	(0.12)	(0.05)	(0.20)	(0.17)	(0.39)	(5.22E-05)
20	0.04	0.02	0.03	0.05	0.01	0.02	0.00
	(0.08)	(0.10)	(0.04)	(0.17)	(0.15)	(0.28)	(4.36E-05)

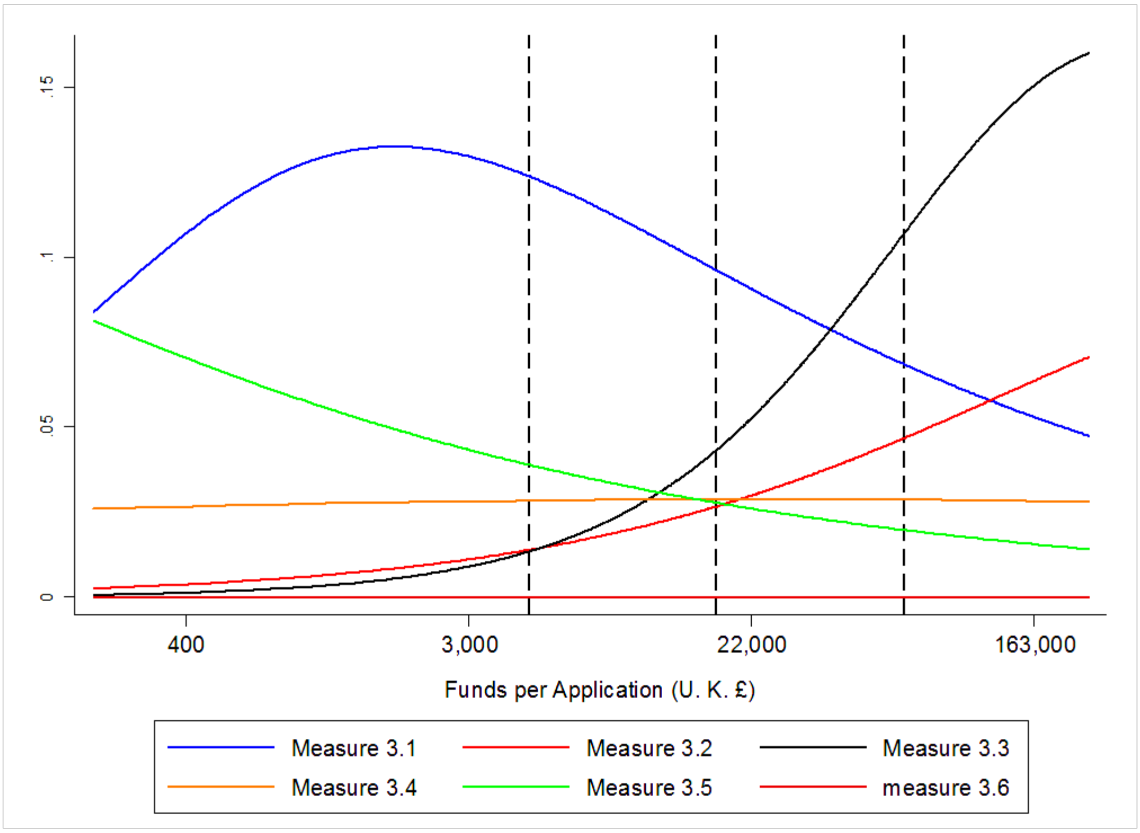
[a]: ***, **, * indicate statistical significance at the 1%, 5%, and 10% level. Standard errors estimated with the delta method.

Figure 1. Average Partial Effect (APE) of Δ% $Funds$ on $P[Y = j\ \ Jobs]$ by Measure



The red horizontal line is drawn for APE=0.

Figure 2. Partial Effect (PE) of Δ% $Funds$ on $P[Y = 1\ or\ more\ Jobs]$ by Measure



$$\frac{\partial \mathrm{Prob}[Y = j \geq 1]}{\partial \log(Funds)} = -\frac{\partial \mathrm{Prob}[Y = 0]}{\partial \log(Funds)}$$