INEQUALITY OF OPPORTUNITY IN THE LABOUR MARKET ENTRY

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Abstract

The aim of this work is to test for equality of opportunity in the entry into the italian labour market. By using an Italian survey data on the transition from university to work, we focus on the probability to get a job within two years from the graduation, and we find significant differences across individuals with different family backgrounds. In an attempt to explain whether these differences reflect opportunity inequality, we adopt the Gomulka-Stern decomposition method. This method allows us to decompose differences in the probability to find a job between three groups of people with different family background into two additive components. The first component can be attributed to differences between the three groups in the distribution of individual characteristics (some of them, such as the graduation mark and the subject of the first degree, used as proxy for the level of effort exerted by individuals). The second component is a residual difference which can be attributed to opportunity inequality under the assumption that there is no unobserved heterogeneity between the three groups. In the presence of unobserved heterogeneity this residual component can be thought as an upper bound estimate for the difference in the probability explained by opportunity inequality.

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1. Introduction

The aim of this work is to test for equality of opportunity in the entry into labour market, and more precisely in the probability to find a job within two years from graduation in Italy.

The basic idea of the Equality of Opportunity (EOp) theory is that individuals should be rewarded for differences in outcome due to characteristics for which they are not hold responsible (*circumstances*), while differences arising from different degrees of *effort* exerted by individuals are considered “ethically acceptable” (for a more complete definition of EOp see Arneson R., 1989; Cohen G., 1989; Dworkin R., 1981a, 1981b; Rawls J., 1971; Roemer J., 1998 and Sen A., 1980). The most used approach to check for equality of opportunity consists in: (i) divide the population into *types* according to their circumstances and (ii) checking whether there are differences in outcome within people who exert the same degree of effort but belong to different types.

In this work we follow this common approach adopted in the literature on EOp and we divide new graduates into three *types* according to their family background (*circumstances*). But contrary to the literature on EOp we consider a different statistical method to check whether differences in outcomes between *types* depends only on the *effort* exerted by individuals or whether, instead, it depends also on inequality of opportunity. We adopt an extension of the Oaxaca-Blinder (1973) decomposition method[2] as proposed by Gomulka and Stern (1990).

This method allows us to decompose differences in the probability to find a job (within two years from the graduation) between the three subgroups of the population with different family backgrounds (*types*) into two additive components. The first component can be attributed to difference in the distribution of individual characteristics (some of them, such as graduation mark and the time taken to get the degree, used as proxy for the level of effort exerted by individuals) between the three groups. The second component is a residual difference which can be attributed to opportunity inequality under the assumption that there is no unobserved heterogeneity between the three groups. In the presence of unobserved heterogeneity this residual component can be thought as an upper bound estimate for the difference in the probability explained by opportunity inequality.

A second difference of this paper from the existing literature on EOp is in the outcome variable. In the great part of this literature the outcome variable is the distribution of income or earnings. Clearly, there are some exceptions, especially in the literature which focuses on

[2] Blinder and Oaxaca developed a decomposition method to analyse wage differentials, by using the classical linear regression method. Their decomposition technique is widely used to identify and qualify the separate contribution of groups differences in measurable characteristics, such as education, experience and marital status to racial and gender gaps in outcome.

equality of educational opportunities. For example, Bratti et al. (2008) analyze the impact of the expansion of higher education on the probability of obtaining an university degree for individuals with different family background. Other studies analyze the impact of family background on children schooling choices (Checchi et al, 2007). But also the literature on EOp in educational attainment uses the distribution of income (Peragine and Serlenga,2008) or the distribution of cognitive abilities (Checchi and Peragine, 2005) as outcome variables, and neglects in this way the fundamental passage from school to the labour market. Differently, here we test for EOp in (higher) educational attainment, but, as we said above, the outcome is the probability of been employed two years after the graduation. Testing for equality of opportunity in the entry into the labour market may help also to verify if schooling plays its signalling role in the labour market and to understand how meritocratic the last is.

Assessing the meritocracy in the entry to the labour market is especially of interest in the case of Italy, where about the 70 percent of new graduates declare they receive help from relatives and/or friends to get their first job after graduation (see section 5). Moreover, it seems worthwhile to test for EOp in a country, like Italy, with a low level of intergenerational mobility (Checchi et al, 2002; 2007a; 2007b), which is a concept strictly related to those of EOp.

2. Inequality of opportunity

In this section, we first define Equality of Opportunity and then we briefly describe the methods most commonly used to measure inequality of opportunity in the existing literature.

2.1 Equality of Opportunity: Definition

It is possible to define the Equality of Opportunity theory by comparing it with the Equality of Outcome (EO) theory. The difference between the two is in their answer to the following question: "equality of what?". The EO theory concentrates its attention on the equalization of individuals' outcome, while the EOp theory is based on the so-called "*level the playing field*" ideal, which is on equalization of advantages and opportunity. This difference hides a deeper one, implied in the concept of *personal responsibility*. This concept is absent in the EO theory, which doesn't hold individuals responsible for imprudent actions that may reduce the values of the outcomes they enjoy; on the contrary, personal responsibility is essential in the EOp theory.

Traditionally, equality of opportunity was understood as the absence of legal bar in the access to education, to all positions and jobs, and the fact that all hiring was meritocratic. This way to define EOp was challenged firstly by Rawls (1971) and by Sen (1980). Both of them state that equality of opportunity requires compensating persons for a variety of circumstances whose distribution is morally arbitrary. But they give different definitions of equality. For Rawls, it is attained when social class and family background do not affect people's opportunities for social positions, whereas for Sen there is equality when the personal sets of vectors of functioning[3] are equal.

According to Roemer "*there is, in the notion of equality of opportunity, a "before" and an "after": before the competition starts the opportunities must be equalized,…, but after it begins, individuals are on their own.*" (Roemer 1998, p.83) Thus, EOp levels the playing field in the sense of compensating persons for their deficits in *circumstances*.

Summarizing, EOp is achieved when characteristics beyond individual control, and for which they are not held responsible, do not prejudice the fulfilment of their objectives. According to this view, individuals should be compensated for differences in outcomes due to characteristics for which they are not held responsible (*circumstances*), while differences in outcomes related to characteristics under individual control (*effort*) are considered "ethically acceptable", and should not be compensated[4].

Several problems arise when we try to measure and evaluate EOp. A first problem regards the definition of circumstances: what are the factors which are beyond individual control? Once an agreement on the definition of circumstances is reached, another major issue remains: how can we observe, and then measure, the individual level of effort?

Roemer (1998) is the first one who tried to translate the philosophical idea of equality of opportunity into an economic framework, and to offer a solution to the problem related to the measurement of effort. He claims that there is equality of opportunity in a society when all those who exert the same degree of effort end up with the same outcome, regardless of their circumstances. Thus, EOp is reached when the *playing field* is levelled , meaning that people are compensated for their potential bad circumstances, so that only their effort affect their outcome.

The literature recently developed in the field of normative economics has shown that the concept of EOp can be decomposed into two distinct ethical principles: the *Compensation Principle*, on one side, and the *Reward Principle* on the other. The former states that differences in outcomes due to characteristics beyond individuals' control, and for which individuals can not be held responsible for (*circumstances*) are ethically inacceptable and should be rewarded. The latter takes the view that differences due to characteristics for which individuals can exert a certain control (*responsibility characteristics*) are to be considered ethically acceptable and do

[3] "Functionings represent part of the state of a person, in particular the various things that he or she manages to do or be in leading a life" (A. Sen, 1993, p. 31). Sen called a set of vectors of functioning a capability set, that is the combination of beings and doings that a person can achieve.

[4] For a discussion about this topic see Arneson R., 1989; Cohen G. A., 1989; and Dworkin R., 1981a and 1981b

not need any intervention. As we will see in next section, we can divide the literature on EOp recently developed according to the interpretation given of these criteria

2.2 Methods to measure EOp

In the last years several scholars presented different methods to measure the level of opportunity inequality, and the outcome variable is often, if not always, individual's income/earning, and in some cases cognitive ability. Almost all of them assume that the population is completely described by a list of characteristics which are divided into two groups: characteristics for which individuals are not held responsible (*circumstances*) and characteristics belonging to the sphere of individual's responsibility (*effort*).

As explained in the previous section, one of the difficulties arising in the measurement of inequality of opportunity is in the definition (and then the measurement) of what constitutes circumstances and what constitutes effort.

As regards circumstances, it is possible to say that a kind of agreement has been reached in the literature. That is, it is common to use as circumstances the social and family background of individuals, measured by the education, the income or the occupational positions of parents.

Parents affect final individuals' outcome through different channels, such as:

1) provision of social connections;
2) formation of beliefs and skills in children, through family culture and investments;
3) genetic transmission of native ability;
4) instillation of preferences and aspirations.

Depending on the channel one chooses to represent *circumstances* we have different notions of EOp. After this choice, the population is divided into *types*, each one composed by individuals who share the same set of circumstances.

As regard *effort*, the first one in this literature who tried to give a solution to problems related to its measurement was Roemer (1998). He develops a statistical method to measure the equality of opportunity which we can explain in the following. After dividing the population into *types*, according to individual's set of *circumstances*, he derives the level of effort exerted from each individual by the position individual *i* occupies in the outcome distribution of his own type. In this way, he affirms, it is possible to say that differences in outcome, between individuals of different types but in the same position of their own distribution, are due to inequality of opportunity. At this point, on the basis of the EOp principle, differences within *types* have no influence on social welfare evaluation, only differences between types matter, particularly those between individuals in the same quantile of different types.

Now, we can divide the existing literature into two approaches which differs for the definition of EOp they use and for their interpretation of the two ethical principles presented in the previous section: (i) the ex-ante approach and (ii) the ex-post approach. According to the ex-ante approach, there is EOp if and only if the set of opportunities is the same for all individuals, regardless of their circumstances. In this case, according to the Compensation Principle, individuals should be compensated for differences in the opportunity sets they face, while the Reward Principle is intended as neutrality with respect to the outcome chosen by individuals from their opportunity sets. This approach looks at the opportunities offered to individuals and, consequently, focuses on differences between *types*. On the other side, according to the ex-post approach, there is EOp if and only if all those who exert the same level of effort end out with the same outcome. Here the Compensation Principle is defined in terms of outcomes for individuals who exert the same effort, while the Reward Principle is intended as neutrality with respect to differences in outcome distributions between group of individuals with different level of effort. It follows that this approach is interested in inequalities within *responsibility classes* and, in order to measure EOp, the population is divided in groups (*tranche*) formed by individuals who have exerted the same level of effort.

Within these two approaches, it is possible to further distinguish the existing literature according to the method used in the measurement of EOp. In some cases EOp is tested by using the concept of stochastic dominance, as done in the studies of Lefranc et al. (2006a; 2006b) and Peragine and Serlenga (2008) both based on an ex-ante approach. There are then studies in which opportunity-egalitarian social welfare functions are used to obtain partial rankings of opportunity sets. In this case we can distinguish between studies based on the ex-ante approach (Peragine, 1998, 2004; Van de Gaer, 2003), and studies based on the ex-post approach (Peragine, 2002). Finally, EOp can be measured by using inequality indices by which it is possible to obtain complete rankings of opportunity sets. In this case, when the ex-ante approach is used (Bourguignon et al. 2003; Checchi and Peragine, 2005; Dardanoni et al, 2005; Ferreira and Gignoux, 2008; Pistolesi, 2007), overall inequality is decomposed into two parts, inequality between types, intended as opportunity inequality, and inequality within types, intended as effort inequality. When the approach used is the ex-post (Checchi and Peragine, 2005), overall inequality is again divided into two components, the within tranche, intended as opportunity inequality, and the between tranches, intended as effort inequality.

Our work belongs to the second approach, in the sense that we also control for variable considered as a proxy for the level of effort exerted by individuals, but then we do not make any comparison between effort groups (for a detailed description of the variables used see section 4).

We only compare differences in the probability of finding a job between different types. Moreover, our variable is binary, namely the fact of been employed within two years from the graduation, and this is why we cannot use the methods commonly used to measure the level of inequality of opportunity, they are only suitable to cases in which the outcome variable is continuous. So we use decomposition technique that are more common in the non-discrimination literature.

The description of the decomposition method used to test for equality of opportunity is the object of the following section.

3. Decomposition methods and inequality of opportunity

A way to measure inequality of opportunity is by adopting decomposition methods such as the Oaxaca-Blinder method (1983) or the Gomulka-Stern method (1990).

The Oaxaca-Blinder decomposition method was developed by Oaxaca (1973) and Blinder (1973) and it can be used to decompose the differences in the mean of a continuous outcome (such as earnings or income) between two types (two groups of individuals with different socio-economic background) into two additive components. The first components reflect differences in the distribution of a set of controlled characteristics between the two types, while the second is a residual component which could reflect inequality of opportunity and/or unobserved heterogeneity. The Gomulka-Stern method (which gets its name from the first economists who applied it, Gomulka and Stern, 1990) is an extension of the decomposition method adequate to decompose difference in the mean of a binary outcome (for example the probability to find a job) between two groups.

Both the Oaxaca-Blinder and the Gomulka-Stern method are widely used in the non-discrimination literature. The Gomulka-Stern method has been for example used to study the racial gap in self-employment rates (Fairlie, 2005), in female labour market participation rates (Yun, 2000) or in wage (Yun, 2007); or to analyze gender differences in the probability of finding a job (Nielsen, 1998) or in the labour market participation rates (Booth et al., 1999); or to study differences in job mobility patterns between Scotland and England (Heitmueller, 2004) or in school enrolment between different ethnic groups in India (Borooah and Iyer, 2005). But these methodologies are used not only in this literature. For example, Bourguignon et al. (2002) use a more general version of the Oaxaca-Blinder decomposition method (that they call Generalized Oaxaca-Blinder) in order to compare income inequality in Mexico and in the United States.

We apply this method in order to test for inequality of opportunity in the access to the labour market. More precisely we check whether differences in the probability to find a job (within two years from graduation) depends only on the *effort* exerted by individuals or whether, instead, it depends also on individuals' *circumstances* (family background).

3.1 Decomposition method

In this section we describe how to check for inequality of opportunity in the probability of experiencing a specific event (in our empirical analysis the event is finding a job within two years from the graduation) by using the Gomulka-Stern decomposition technique. The method proceeds in three steps:

(1) dividing the populations of individuals into three subgroups (*types*) with different circumstances (family background);

(2) estimating a model for the probability of the specific event separately for each subgroup;

(3) using the estimate from the second step to decompose the difference in the marginal probability between types in the part due to differences in characteristics and in the residual part due to inequality of opportunity or to unobserved characteristics.

Hereafter we will explain how to implement the above three steps when considering the probability to find a job within two years from the graduation (hereafter find a job). In this empirical case the population of interest is given by new graduates in a given year. Let *T* be a categorical variable defining different types of graduates based on their parental education (*circumstances*). In our empirical analysis we will divide the graduates in three types (T=1,2,3) by considering three levels of parental education (low, medium and high). Let Y_{it} be a dummy variable taking the value one if the individual (new graduate) *i* belonging to type *t* finds a job within two years from the graduation, and zero otherwise.

We assume that the outcome variable Y_{it} is equal to one if the latent variable Y_{it}^* (the unknown propensity to find a job) is positive, and it is 0 otherwise. We assume the following linear model for the propensity to find a job:

$$Y_{it}^* = Z_{it}\gamma_t + u_{it} \quad (1)$$

where Y_{it}^* is the latent variable, Z_{it} is a $k_m \times 1$ vector of characteristics, γ_t is a $k_m \times 1$ vector of parameters and u_{it} is a random error distributed as N(0,1).

If we indicate with P_{it} the probability that the outcome variable is equal to one, and with $(1 - P_{it})$ the probability that Y_{it} is equal to zero, then

$$E(Y_{it}) = P_{it} = \Phi(Z_{it}\gamma_t) \quad (2)$$

where $E(Y_{it})$ denotes the expected value and $\Phi(Z_{it}\gamma_t)$ is the cumulative density function (CDF) from the standard normal distribution. Using the standard normal CDF it is possible to show that the following relationship between Y_t and P_t holds asymptotically:

$$\overline{Y}_t = \overline{\hat{P}} = \overline{\Phi(Z_t \hat{\gamma}_t)} \qquad (3)$$

where $\overline{Y}_t = \sum_{i=1}^{n_t} \frac{Y_{it}}{n_t}$ is the mean of the outcome variable in type t, $\overline{\hat{P}}_t = \sum_{i=1}^{n_t} \frac{\hat{P}_{it}}{n_t}$ is the average of the estimated probabilities, $P_{it} = \Phi(Z_{it}\gamma_t)$ for individual i of type t, and $\overline{\Phi(Z_t \hat{\gamma}_t)} = \sum_{i=1}^{n_t} \frac{\Phi(Z_{it}\hat{\gamma}_t)}{n_t}$.

Differences of the average of computed probability between type 1 and type 2 $(\overline{Y}_1 - \overline{Y}_2)$ are given by

$$(\overline{Y}_1 - \overline{Y}_2) = \left[\overline{\Phi(Z_1\hat{\gamma}_1)} - \overline{\Phi(Z_2\hat{\gamma}_2)}\right] \qquad (4)$$

By adding and subtracting from the right hand side (RHS) of equation (4) the term $\overline{\Phi(Z_1\hat{\gamma}_2)}$ we obtain:

$$\overline{Y}_1 - \overline{Y}_2 = \left[\overline{\Phi(Z_1\hat{\gamma}_1)} - \overline{\Phi(Z_1\hat{\gamma}_2)}\right] + \left[\overline{\Phi(Z_1\hat{\gamma}_2)} - \overline{\Phi(Z_2\hat{\gamma}_2)}\right] \qquad (5)$$

where the second term in brackets on the RHS represents differences in the probability to find a job due to a different distribution of individual characteristics between type 1 and type 2, while the first term in brackets on the RHS represents the effect of different probit "coefficients" between the 2 types.

A similar procedure can be applied to decompose differences between tyep1 and type 3 and between type 2 and type 3, and we get:

$$\overline{Y}_1 - \overline{Y}_3 = \left[\overline{\Phi(Z_1\hat{\gamma}_1)} - \overline{\Phi(Z_1\hat{\gamma}_3)}\right] + \left[\overline{\Phi(Z_1\hat{\gamma}_3)} - \overline{\Phi(Z_3\hat{\gamma}_3)}\right] \qquad (6)$$

$$\overline{Y}_2 - \overline{Y}_3 = \left[\overline{\Phi(Z_2\hat{\gamma}_2)} - \overline{\Phi(Z_2\hat{\gamma}_3)}\right] + \left[\overline{\Phi(Z_2\hat{\gamma}_3)} - \overline{\Phi(Z_3\hat{\gamma}_3)}\right] \qquad (7)$$

that are obtained in the same way we get equation (5).

What we are interested in is the first term on the RHS of equations (5), (6) and (7). Under the assumption that there is no unobserved heterogeneity, it represents the part of the differences in the probability to find a job due to inequality of opportunity. More in general, in the presence of unobserved heterogeneity this kind of decomposition allows us to estimate how much of the total difference is explained by differences in the distribution of individual characteristics and to identify an upper bound for the difference due to inequality of opportunity (the residual difference). Notice that we can only identify an upper bound for the difference due to opportunity inequality, because in the presence of unobserved heterogeneity the first term on the

RHS of equations (5), (6) and (7) represents, at least in part, also differences in probabilities due to differences between types in unobserved individual characteristics.

The results we obtain from the application of the method described in this section are presented in section 5.

4. Data and variable description

In this section we describe the data and variable used to apply the decomposition method shown in section 3.

4.1 Data

As we said before, the outcome variable is a dummy, indicating whether an individual has found a job within the first two years from the graduation. The probability of finding a job within two years from the graduation differs for individuals belonging to different *type*, where each type is formed by individuals who shared the same set of circumstances. As illustrated in section 2, there are several channels through which parents can affect the outcome reached by their children; and the notion of equality of opportunity changes depending on which one of these channel is assumed to represents circumstances. Here, we assume that the channels influencing the probability of finding a job after the graduation are two: provision of social connections and instillation of preferences and aspirations. They represent what we call family background and are both proxied by the level of parental education, which we measure by the highest educational attainment in the couple of parents. According to this criterion, the population is divided into 3 types: the first one is formed by individuals whose more educated parents has at the most a primary school degree; the second is formed by those whose more educated parents has an upper secondary school degree and the third one is formed by individuals who have one or both parents with a bachelor or a higher degree. In the first type we have about 2,500 individuals, in the second type there are 3,400 individuals and 2,600 are in the third type.

The data we use are taken from “Indagine sull’Inserimento Professionale dei Laureati”, a survey on the transition from university to work of a representative sample of Italian graduates, conducted by ISTAT (Italian National Statistical Office) in 2004. This survey is conducted 3 years after the graduation, and the collection method is the C.A.T.I. (Computer Assisted Telephone Interview). The sample is composed by 26,006 individuals (48 percent men and 52 percent women) graduated in 2001 in all the Italian universities. The survey contains information about the individual’s academic curriculum, labour market experience in the 3 years after the graduation, households and individual information.

Our sample is composed only of men with a sample size of 12,153. We also drop-out from the sample those individuals who, at the date of the interview, declare they are not interested in finding a job. Most of them declare they are not looking for a job because they are already engaged in formative activities. Anyway, at the end, the sample is reduced to 10,931 individuals.

4.2 Variable description

The outcome variable is a dummy, indicating if an individual has found a job within two years from the graduation. Four years after the graduation 9,735 individuals, about the 71 percent of the whole sample, work. We choose two years after the graduation as a threshold because it seems a reasonable spell of time to find a job. That is, we can imagine that individuals may not find a job in the first year because they are in a vocational training or for any other reason.

The variables we use in the model are the following:

1) course programme (course programme attended by individuals);

2) course programme change (1 if the graduate moved from one course programme to another during his university studies, 0 otherwise);

3) mark (1 if the graduation mark was between 105 and 110, 0 if the graduation mark was less than 105[5]);

4) first class honours degree (1 if the graduate received a first-class Honours Degree, 0 otherwise);

5) institutional time (1 if the graduate received the degree in the institutional time established for the course programme he or she attended, 0 otherwise);

6) working student (1 if the individual worked during his university studies, 0 otherwise);

7) North-Centre[6] (1 if the current region of residence of the individuals is situated in the North-Centre of Italy, 0 if it is in the South or in the islands);

8) age (1 if the individuals is 26 years old, or less, 0 otherwise);

9) country (1 if individuals would accept to move abroad in order to get a job, 0 otherwise);

10) city (1 if individuals would accept to move in another city in order to get a job, 0 otherwise)

The first group of variables (1-5) contains information about the academic curricula and attainments of individuals with information about the course programme chosen and the graduation mark.

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[5] In the Italian universities the final mark ranges from 66 to 110, but more then the 70 percent of the population has a mark greater than 100. Moreover, 105 is the minimal mark if one wants to apply for a public servant position.

[6] The variable Centre-North is equal to one if individuals live in one of the following region: Piemonte, Valle d'Aosta, Lombardia, Trentino Alto Adige, Veneto, Friuli Venezia Giulia, Liguria, Emilia Romagna, Toscana, Umbria.

As regard the final mark, it does not represents a good indicator of individual's academic ability, as shown by Biggeri, Bini and Grilli (2001). The average mark is equal to 106, and the 26 percent of the population has a mark equal to 110. This is why we also use the variable institutional time, probably more proper when one wants to evaluate the academic ability of individuals. This variable is equal to one only if individuals received their degree in the institutional time established for the course programme they attended. As we can see in table 4 the average institutional time is equal to one only for the 22 percent of individuals in the sample, and this percentage increases by 3 percentage points in the Centre-North ahile falls to 17 percent in the South of Italy.

As regards the variable "course programme", we divide the population into four groups on the basis of the course programme they attended: the first one includes individuals with a degree in arts faculties (Law, Political Science, etc.); the second includes individuals with a degree in science faculties (Chemistry, Biology, etc.); the third one includes those individuals with a degree in medicine and the last includes individual with a degree in sports faculties.

These variables can be seen as a proxi for the level of effort exerted by individuals. But they could be influenced by the parental level of education (for example, parents could influence the final mark through the transmission of native ability). For example, the different distribution of final marks between types is in part visible when we look at the descriptive statistics (Appendix A.1, B.1 and C.1). The same is true if we look at the distribution of the variable First Class Honours Degree (tab. 6) or at those related to the course programme chosen by individuals with different family background.

Our intuition, supported also by previous studies (Checchi at al., op. cit.), seems to be confirmed when we test whether there is independence between the variables in the first group (1-5) and the level of parental education. To test for independence we use the Chi-Squared statistics (Pearson's Test). The results allow us to reject the null hypothesis, i.e. that there is no correlation between the first group of variables and the family background. Nevertheless we decide to use those variables as proxy for the level of effort exerted by individuals, as others authors do (see, for example, Bourguignon et al., 2003), because we consider the impact of family background on them as an indirect effect of *circumstances* on *effort*. Moreover, in this work we are interested in testing for inequality of opportunity in the labour market entry within two years after the graduation net to the effect the family background exerted in earlier stages (i.e. graduation mark, subject of the first degree, time taken to get the degree, and a change in the course programme). So, variables related to individuals' academic curricula and attainments are used not only as proxy for individual's effort, but also to obtain a measure of inequality of opportunity not affected by the influence exerted by the family background in a previous stage.

The second group of variable (6-10) provides other personal information about individuals in the sample, such as age and current residence. We decide to control also for them considering the effect of individuals' age on the probability of finding a job and the differences in the labour market between the Centre-North and the South of Italy.

We tried different definitions of age and eventually we consider a dummy variable, equal to one if the individuals is 26 years old or less at graduation, and zero otherwise. As we can see in tab. 2 only the 37 percent of the population is 26 years old or younger.

The variable Centre-North is introduced to take into account differences in terms of economic development - which also affect the labour market - between northern and southern Italian regions. In fact, in 2004 the unemployment rate was around the 15 percent in the South and the 4,5 percent in the North (ISTAT, Rilevazione sulle Forze Lavoro, 2004). The correlation between the probability of finding a job and the current area of residence is confirmed also by the Chi-Square statistics (Pearson's test). The result of this test (see tab. 9) allows us to reject the null hypothesis of independence between the two variables. Given this result, after testing for equality of opportunity at a national level, we split the sample into two parts (Centre-North and South) according to individuals' area of residence and we conduct separate estimations in order to take into account the existence of regional disparities.

5. Empirical Results

We begin our empirical analysis by testing whether there is independence between the probability of finding a job within two years from the graduation and individuals' family background. We use the Chi-Squared statistic (Pearson's Test) which test whether the two variables are independent. The Pearson's chi-square value is 12.238 with a p-value of .002. In consequence we can reject the null hypothesis of independence between the probability of finding a job and the level of parental education.

Given this result it is of interest to analyze inequality of opportunity in the probability of finding a job after the graduation across groups with different parental background, measured by parental education.

The probit equations was estimated by using the maximum likelihood (ML) method. After the estimations, we also compute marginal effects. As well known, in a binary choice model, as the one we use here, the estimated parameters do not represent the marginal effects (Greene, 2003). So we have to compute them separately, and in the probit model the computation of marginal effects is the following:

$$\frac{\partial E[Y \mid Z]}{\partial Z} = \phi(Z\gamma)\gamma \quad (8)$$

where ϕ is the standard normal density function. But in our empirical case the independent variables are dummy, so the formula we have to use is:

$$\text{Marginal Effect} = \Pr\left[Y = 1 \mid \overline{Z}_d, d = 1\right] - \Pr\left[Y = 1 \mid \overline{Z}_d, d = 0\right] \quad (9)$$

where $\overline{Z}_d$ represents the mode of the other variables in the model, and d is the independent dummy variable for which we want to calculate the marginal effect.

5.1 Estimation Results

We estimate three probit models for the probability of finding a job, one for each type. We use as explanatory variables the set of characteristics defined in section 4: three dummies for course programme in arts, sciences and medicine (the reference category is sports studies); a dummy for course programme change (change); a dummy for graduation mark within 105 and 110 and a dummy for first class honours degree (the reference category are graduate with a mark lower than 105); a dummy for individual graduated without delays; a dummy for people who worked during university; a dummy for people resident in the North-Centre of Italy; a dummy for individuals aged less than 26 years when they got their first degree; and two dummies which consider individuals' willingness to change country or city of residence in order to get a job.

We check for the significance of the variables used in the model, and we find that the final mark and the fact that individuals completed their studies in the institutional time established for their course programme have no impact on the probability of finding a job within the two years from the graduation The same is true for the variable indicating if the individual received a first class honours degree. All these results hold for each type, so we drop all the three variables from the final regressions, and we left only those with a percent level of significance lower than 5. In conclusion our models consider two groups of explanatory variable: a first group describing individual academic curricula and attainments (dummies for different types of course programme, for final mark and for people changing programme) and a second group capturing other socio-demographic variables (age, working while at the university, area of residence, and willingness to move abroad or to change city of residence).

In table 11 and 12 we report estimated coefficients and marginal effects for the probit model for individual of type 1 (individuals with low educated parents). As we can see, the most significant coefficients, among those related to individuals' academic curricula and attainments, are those indicating the course programme chosen by individuals, while a change in the course programme is slightly less significant. From tab. 12 we see that, as regard the course programme, a degree in, for example, Philosophy (Arts Faculties) increase the probability of finding a job by the 33 percent, the same probability is augmented by the 51 and 45 percent if one has a degree in, for example, chemistry (Science Faculties) or medicine, respectively. Changing the course programme, has a negative impact on the probability of finding a job, specifically, this probability is reduced by the 8 percent. These results are slightly different when we split the sample into two parts. As we can see from tables 23 and 35 only the variables indicating the course programme chosen by individuals are strongly significant, among the first group of variable, and this holds both in the Centre-North and in the South of Italy. Some differences emerge when we look at the marginal effects. We see from tales 24 and 36 that a degree in medicine, for example, increases the probability of finding a job by the 42 percent for individuals living in the Centre-North, while the same probability increases by the 51 percent for individuals living in the South. On the other side, a degree in one of the science faculty increases the probability of finding a job by the same amount both in the Centre-North and in the South. As regard the variable indicating a change in the course programme, it is significant only at the 10 percent level of significance in the Centre-North and it is not statistically significant in the South.

Among the second group of variable, those containing personal individuals' information, the most significant variables are the dummies indicating if individuals live in the Centre-North of Italy and if they would change their current residence in order to get a job. Living in the Centre-North increase the probability of finding a job by 11 percent. The age has a lower impact on the probability of finding a job, as it is significant only at the 10 percent level of significance. Finally, working while attending the university has a negative impact on the outcome variable (-5 percent). These results are related to the whole sample, but when we consider the two macro-areas separately, we have that working while attending the university reduce the probability of finding a job by 9 percentage points for individuals who live in the Centre-North, while the same variable seems to have no impact in the South, as it is not significant at the 5 percent nor at the 10 percent level of significance (tables 24 and 36).

In tables 13 and 14 we present estimated coefficients and marginal effects of the probit model estimated for individuals belonging to type 2 (individuals with parents with medium education). In this case the most significant of the coefficients in the first group (individuals' academic curricula and attainments) are those indicating the course programme chosen by individuals. For individuals in type 2 a degree in one of the Arts Faculties increases the probability of finding a job by 9 percent, the same probability is augmented by 40 and 29 percent if the individual has a degree in one of the Science Faculties or in Medicine, respectively. Changing the course programme has a negative but not really strong marginal effect on the probability of finding a job (-6 percent).

Almost all the variables in the second group are strongly significant. The only exception is represented by the age at the graduation, which has no impact on the probability of finding a job within two years from the graduation. On the contrary, the current region of residence has a positive marginal effect on the probability of finding a job (+11 percent), while the opposite holds for the variable indicating if individuals worked while attending the university (-7 percent).

As for individuals in type 1, when we consider separately the Centre-North and the South of Italy, among the first group of variables, only those indicating the course programme chosen by individuals are statistically significant, while a change in the course programme has no impact on the probability of finding a job (tables 25 and 37). Again, by looking at the marginal effect (tables 26 and 38) we see that the same degree increases the probability of finding a job within two years from the graduation in a way that differs according to the macro-area we consider. As an example, the probability is increased by the 42 percent for individuals living in the Centre-North with a degree in one of the science faculties, while the same degree increases the probability of been employed within two years from the graduation by the 33 percent for an individual who lives in the South of Italy. Among the second group of variables, working while attending the university has a statistically significant and negative impact (-8 percent) only for individuals who live in the Centre-North.

Finally, the estimated coefficients and marginal effects for individuals belonging to type 3 (individuals whose parents have high education) are presented in tables 15 and 16, respectively. Again, the dummies for the course programme chosen are the most significant, while a change in the course programme has no impact on the probability of finding a job. An individual belonging to type 3 has a probability 36 percent higher to find a job if he has a degree in one of the Art Faculties, the same probability is augmented by 48 and 28 percent respectively if he has a degree in one of the Science Faculties or in Medicine. Among the second group of variables, the current region of residence and working while attending the university are equally significant, but they act in the opposite way, i.e. living in the Centre-North increases the probability of finding a job by 9 percent, while the same probability is reduced by 8 percent if the individual worked during the university. Again, the age at graduation has no impact on the outcome variable.

Summarizing, the most significant of the coefficients, between those relating to individuals' academic curricula and attainments, are those associated with the course programme chosen by individuals. This is true for individuals belonging to type 1 and type 2, while the coefficients are slightly less significant for individuals belonging to type 3. The differences between *types* are visible also when we observe the marginal effects associated to these coefficients. For example, a degree in Economics or in Political Science (or in any other Arts Faculties) increases the probability of finding a job within two years from the graduation by 33 percent for individuals belonging to type 1, by 29 percent for individuals in type 2 and by 36 percent for those in type 3. The impact of changing course programme is, on the contrary, negative and strong for individuals of type 1, less significant for individuals in type 2 and it has no impact on those in type 3. It seems then interesting to notice that these results hold also when we split the sample into two macro-areas. The differences between the Centre-North and the South emerge clearly when one looks at the marginal effects. As stated above, individuals with the same degree face different perspective in the labour market, and these differences can be attributed not only to family background, but also to the area of residence. As we have seen, individuals with the same degree have different probabilities of finding a job if they live in the Centre-North or in the South of Italy, even if they belong to the same type, that is if they have the same family background.

Among the second group of explanatory variable, the most significant coefficient, in this case for each type, are those indicating the individuals' current area of residence and their willingness to move abroad or in a different city in order to get a job. In this case there is a small difference between *types* also when we look at the marginal effects. Living in a region of the Centre-North increases the probability of finding a job within two years from the graduation by 11 percentage points for individuals in type 1 and by 9 percentage points for individuals in type 2 or 3. Working while attending the university has a negative and statistically significant effect on the probability of finding a job, even if the effect is slightly less significant for individuals in type 1. Finally, individuals' age seem to have no impact on the probability of finding a job within the two years from the graduation, at least for individuals belonging to type 2 and 3. As regard variables indicating whether an individual would change his current residence in order to get a job, they have a negative and strongly significant impact on the probability of finding a job, and these results hold for all types The same result holds when we consider separately individuals living in the Centre-North or in the South of Italy, and in this case the same result is true for individuals in each type. On the contrary, working while attending the university has a strongly significant and negative impact on the probability of finding a job within two years from the graduation for each of the three type, but only in the Centre-North.

After this analysis of the estimation results we can now see what happen when we apply the decomposition method illustrated in section 3.

5.2 Decomposition Results

The results of the decomposition analysis are presented in table 17. When we apply the decomposition method we do not consider the variables we drop in the estimation of the probability of finding a job (i.e. mark, first class honours degree and institutional time).

The observed difference in the probability of finding a job within two years from the graduation between type 1 ("low family background") and type 3 ("high family background") is about four percentage points (4,25 percent when we consider the whole sample; 3,68 percent in the Centre-North and 3,96 in the South), and those between type 1 and type 2 is similar (3,95 in the whole sample; 3,35 in the Centre-North and 5,70 in the South), while there is almost no difference between type 2 and type 3, at least when we look at the whole sample (0,30 percent), while the situation is quite different when we consider the two macro-areas separately (0,34 in the Centre-North and 1,79 in the South).

More than a half of these differences are explained by what we call "differences in coefficients". Looking at tab. 17, we see that only the 32 percent of the difference in the probability of finding a job within two years after the graduation between individuals belonging to type 1 and those belonging to type 2 is explained by differences in characteristics, the remaining 68 percent is attributable to what we call difference in coefficients. The results are slightly different when we consider differences between type 1 and type 3. In this case the 51 percent of the difference is explained by the different distribution of characteristics among *types*, and the remaining 49 percent is explained by differences in coefficients. The decomposition results do not vary significantly when we look at the two macro-areas. Differences in coefficients explain the great part of the differences between types both in the Centre-North and in the South of Italy (see tables 29 and 41). In the Centre-North more than one half of the differences are explained by differences in coefficients. About the 64 percent of the differences between type 1 and type 2 are explained by differences in coefficients. And the same component explains about the 60 percent of the differences between type 2 and type 3. We have a different result only when we look at differences between type 1 and type 3. In this case, differences in coefficients explain about the 31 percent of differences between types. The results are slightly different in the South of Italy. As regard differences between type 1 and type 2, again the great part is explained by differences in coefficients which, in this case, account for the 88 percent of the overall difference. The 46 percent of the difference in the probability of finding a job within two years from the graduation, between type 1 and type 3 are explained by differences in coefficients, and the remaining 54 percent arises from a different distribution of characteristics among the two types. Finally, this component explains about the 85 percent of the differences between type 2 and type 3, so that only the 14 percent is explained by differences in coefficients. In our interpretation, the last component represent the effect of inequality of opportunity between *types*. As we already explained, the decomposition method we use only permits us to identify an upper bound of the difference due to opportunity inequality. Part of the difference in coefficients may be explained by the fact that we do not control for all possible variables determining the probability of finding a job. Nevertheless, it seems reasonable to conclude that at least part of the difference in coefficients is attributable to the presence of inequality of opportunity in the Italian labour market. Our results show that the family background does not exert its effect just through favouring the educational attainment of individuals or through the instillation of belief and skills. This is because we observe difference between *types* in the probability of finding a job even if we control, for example, for the course programme chosen by individuals. It is more probable that, in this case, parents affect the outcome of their children through the provision of social connection, that is, it seems reasonable to assume that social connections are "greater" or "better" for individuals of type 2 or 3 than those provided by parents of individuals of type 1.

In conclusion, our first regressions show a scarcely meritocratic labour market, where the final mark, or other academic individuals' ability, proxied also by the time individuals employ to get their degree, seem to have no impact on the chance one have to be employed after the graduation. And this result holds in the Centre-North as well as in the South of Italy, that is, even if we split the sample into two part, according to the individuals' region of residence, the result doesn't change. Moreover, we find significant differences at regional level. Not surprisingly the less economically developed area suffers of greater inequality of opportunity, which is almost constantly higher in southern regions. Differences between type 1 and type 2 and between type 1 and type 3 are 20 and 15 percentage points greater in the South than in the Centre-Nord, respectively. The only exception is represented by differences between type 2 and type 3, in this case inequality of opportunity is higher in the Centre-North.

Not only, we find that most of the differences between *types* are attributable to inequality of opportunity, and that the most disadvantaged individuals are those with a poorer family background, i.e. the greatest differences are those between type 1 and type 2 and 3. It seems that the role exerted by parents on the final achievements of their children is not limited to the formative years of individuals, when it is reasonable to assume that parents influence the choices of the pupils. The family background seems to play an important role also later on, probably, as we suppose, through the provision of social connections. It seems a reasonable assumption when we consider that about the 75 percent of individuals in the whole sample declare they were helped in find a job by relatives or friends.

6. Conclusion

Our main purpose in this work was to test for Equality of Opportunity in the entry to the labour market in Italy. More precisely, we tested for the influence of parental background on the probability to find the first job within two years from the completion of the first degree, using a representative sample of Italian graduates who received their degree in 2001.

Previous studies on inequality of opportunity focus almost exclusively on cognitive and monetary outcomes and paying no attention to the fundamental passage from school to the labour market. As far as we know, there are no papers which test for EOp in the entry to the labour market and with this work we have tried, at least partially, to fill this gap.

We assume that there are two channels through which parents affect children’s outcomes and ultimately their probability to find a job within two years from the graduation: instillation of preferences and aspirations, and provision of social connections. To divide children in groups with similar circumstances related to their parental background, we consider three different levels of parents’ education.

Our main aim is to measure inequality of opportunity in finding the first job net to the effect of academic choices and attainments taking place during university. For this reason we compare the probability to find a job between individuals with different parental education by controlling for final mark at the graduation and academic curricula choices. In other words, even if these last variables could be related to parental education and could reflect inequality of opportunity operating at an earlier stage, we treat academic choices and attainments as variables measuring individual effort (as previously done by other authors as for example Bourguignon et al., 2003). Moreover, in this work we are interested in testing for inequality of opportunity in the labour market entry within two years after the graduation net to the effect the family background exerted in earlier stages (i.e. graduation mark, subject of the first degree, time taken to get the degree, and a change in the course programme). So, variables related to individuals’ academic curricula and attainments are used not only as proxy for individual’s effort, but also to obtain a measure of inequality of opportunity not affected by the influence exerted by the family background in a previous stage.

After the estimation of the probability of finding a job, conducted using the maximum likelihood (ML) method and separately for each type, we measure inequality of opportunity by using the decomposition method proposed by Gomulka and Stern (1990). This method allows us to decompose differences in probability to find a job between *types* (children with different parental education) into two parts: one attributable to the differences in the distribution of individuals' characteristics across *types* (*difference in characteristics*) and a residual part due to *difference in coefficients.* If, after controlling for individual characteristics (final mark, course programme, change in the course programme, time taken to get the first degree, working while attending the university, area of residence and age) there is no unobserved heterogeneity across types, we can then interpret the residual part as the difference due to inequality of opportunity. On the contrary, in the presence of unobserved heterogeneity, this residual part provides an upper bound for the difference due to opportunity inequality.

Our results show that the most significant variables explaining the probability to find a job are those related to the course programme chosen by individuals and to the area of residence, and this holds for any type of parental background. On the contrary the final mark does not seem to have any significance in explaining the probability to find a job.

The decomposition results seem to confirm our hypothesis, i.e. that the probability to find a job does not depend solely to individuals' effort. They show that the most part of the differences in the probability of finding a job between individuals with different background (*types*) depends on opportunity inequality. More than one half of the differences between *types* are due to "differences in coefficients". It means that, even if the assumption on individual heterogeneity does not hold, it is reasonable to think that these differences are, at least in part, due to opportunity inequality.

As expected, the most disadvantaged individuals are those with parents with low education (type 1). These individuals have lower probability to find a job compared to individuals with parents with medium and high education (type 2 and 3). On the contrary, the difference in this probability between type 2 and type 3 is negligible.

Given the differences between the Centre-North and the South of Italy, after testing for independence between the area of residence and the probability of been employed within two years from the graduation, we decide to split the sample into two parts. Not surprisingly we find significant differences between the two areas. First of all we find that individuals with the same degree face different perspective in the labour market, the probability of finding a job within two years from the graduation differs between individuals belonging to the same type and with the same degree if they live in the Centre-North or in the South. Moreover, as shown also by previous studies on EOp in Italy (Checchi and Peragine, 2005; Peragine and Serlenga, 2008), the level of inequality of opportunity is almost constantly higher in southern regions, and this is especially true when we look at differences between the most disadvantaged type and the other two.

We can use our results on inequality of opportunity to draw some final conclusions on the level of meritocracy in the Italian labour market and to verify if the educational system really plays its signalling role. Unfortunately, our results are not encouraging. We can not consider meritocratic a labour market where the probability of being employed after graduation seems to be independent from the final mark or other academic individuals' ability (such as time taken to get the degree). Moreover, the decomposition results show that the family background have a direct effect on the probability to find a job as well as an indirect effect through the channels of educational attainments and curricula choices. The direct effect reflects probably another channel through which the parents affect their children outcome, which is the provision of social connection. It seems reasonable to assume that social connections are "greater" or "better" for individuals of type 2 or 3 than those provided by parents for individuals of type 1.

Differences in the probability of finding a job between types could also be explained by different skills, not directly reflected in the variables we use. It seems plausible to think that individuals whose parents have high education are endowed with better skills. Unfortunately, our data do not allow us to control for this.

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APPENDIX A (ITALY)

A. 1 Descriptive Statistics

Tab. 1 Variables Description

Variables	Mean
Age	.2887202
Art faculties	.3644680
Science Faculties	.5232824
Medicine	.0846217
Course Programme Change	.1351203
Woking Student	.6754185
Mark*	.3998719
Institutional time	.2206568
Centre-North	.6099435
Mark_1	1.062.473 (3.631.988)
Country	.1732687
City	.0913915

Standard dev. in brackets

***** dummy variable: it is 1 if the mark is equal to 105 or greater, it is 0 otherwise

Tab. 2 Age

Age (classes)	Freq.	Percent.	Cum.
≤ 24	486	5.72	5.72
25 & 26	2,670	31.40	37.12
≥ 27 and ≤ 29	3,330	39.16	76.28
≥ 30	2,017	23.72	100.00
Total	8,503	100.00	

Tab. 3 Year of starting working and Family Background

Empl_2	**Family Background**			**Total**
	Low	**Medium**	**High**	
0	1,472 (59.55%)	1,879 (55.26%)	1,473 (55.62%)	4,788 (56.62%)
1	1,000 (40.45%)	1,521 (44.74%)	1,147 (44.39%)	3,668 (43.38%)
Total	2,472 (100.00%)	3,400 (100,00%)	2,584 (100,00%)	8,456 (100,00%)

Pearson's Chi-Squared = 12.238 Pr. = 0.000

Tab. 4 Institutional time and family background

Institutional Time	**Family Background**			**Total**
	Low	**Medium**	**High**	
0	2,018 (81.63%)	2,675 (78.68%)	1,913 (74.03%)	6,606 (78.12%)
1	454 (18.37%)	725 (21.32%)	671 (25.97%)	671 (21.88%)
Total	2,472 (100.00%)	3,400 (100.00%)	2,584 (100.00%)	8,456 (100.00%)

Pearson's chi-square = 43.7382 Pr. = 0.000

Tab. 5 Mark and Family Background

Mark	Family Background			Total
	Low	Medium	High	
< 105	1,363	1,927	1,312	4,602
	(55.14%)	(56.68%)	(50.77%)	(54.42%)
≥105	1,109	1,473	1,272	3,854
	(44.86%)	(43.32%)	(49.23%)	(45.58%)
Total	2,472	3,400	2,584	8,456
	(100,00%)	(100.00%)	(100,00%)	(100.00%)

Pearson's chi-square = 21.3407 Pr. = 0.000

Tab. 6 First Class Honours Degree and Family Background

First Class	Family Background			Total
	Low	Medium	High	
0	2,053	2,880	2,019	6,952
	(83.05%)	(84.71%)	(78.13%)	(82.21%)
1	419	520	565	1,504
	(16.95%)	(15.29%)	(21.87%)	(17.79%)
Total	2,472	3,400	2,584	8,456
	(100.00%)	(100.00%)	(100,00%)	(100.00%)

Pearson's chi-square = 10.5858 Pr. = 0.005

Tab. 7 Year of Starting Work

Year of starting work	Freq.	Percent	Cum.
1	2,066	27.48	27.48
2	2,724	36.23	63.71
3	1,631	21.69	85.40
4	1,098	14.60	100.00
Total	7.519	100.00	

Tab. 8 Course Programme and Family Background

Course Programme	Family Background			Total
	Low	Medium	High	
Art	913	1,224	893	3,030
	(38.46%)	(37.24%)	(35.13%)	(36.94%)
Science	1,278	1,859	1,287	4,424
	(53.83%)	(56.56%)	(50.63%)	(53.93%)
Medicine	183	204	362	749
	(7.71%)	(6.21%)	(14.24%)	(9.13%)
Total	2,374	3,287	2,542	8,203
	(100.00%)	(100.00%)	(100.00%)	(100.00%)

Pearson's chi-square = 121.9009 Pr. = 0.000

Tab. 9 Year of starting work and current area of residence

Empl_2	Area of residence		Total
	South	Centre-North	
0	2,619 (62.16%)	3,441 (52.23%)	6,060 (56.11%)
1	1,594 (37.84%)	3,147 ($7.77%)	4,741 (43.89%)
Total	4,213 (100.00%)	6,588 (100.00%)	10,801 (100.00%)

Pearson's chi square = 102.9585 Pr. = 0.000

Tab. 10 Chi-Square Test

Variables	Pearson's Chi Square	P-value
Mark	102.9585	0.000
First Class Honours Degree	0.0008	0.977
Institutional time	97.1104	0.000
Course Programme	4.2090	0.122

The Pearson's chi-square is used to test for independence between the variables related to the individuals' academic curricula and the variable Centre-North

A.2 Empirical Estimation (ITALY)

Tab. 11 Probit model for individuals with low educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.142254	.062776	0.023
Art	.8670065	.191295	0.000
Science	1.459343	.189708	0.000
Medicine	1.24051	.208346	0.000
Change	-.210703	.079804	0.008
Age	.111951	.066990	0.095
Centre_North	.287655	.055780	0.000
Country	-.210877	.072836	0.004
City	-.366066	.091315	0.000
_cons	-1.423874	.198175	0.000

Number of obs. = 2449
Log likelihood = -1527.3921
Pseudo R2 = 0.0763

Tab. 12 Probit model for individuals with low educated parents: Marginal Effects
Y= Pr(empl_2) (predict)
= .39318613

Variable	dy/dx*	St. Error	P-value
Work-student	-.0551708	.02452	0.024
Art	-.0551708	.06988	0.000
Science	.51494	.05596	0.000
Medicine	.4516661	.05859	0.000
Change	-.0790408	.02906	0.007
Age	.0434028	.02615	0.097
Centre-North	.1092694	.02084	0.000
Country	-.0792395	.02663	0.003
City	-.1333705	.03098	0.000

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 13 Probit model for individuals with medium educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.178208	.050484	0.000
Art	.738099	.150594	0.000
Science	1.062769	.148939	0.000
Medicine	1.764961	.171613	0.000
Change	-.148109	.067915	0.029
Age	.009156	.051242	0.858
Centre_North	.244274	.047461	0.000
Country	-.338450	.061336	0.000
City	-.437599	.076959	0.000
_cons	-.949884	.198175	0.000

Number of obs. = 3369
Log likelihood = -2206.746
Pseudo R2 = 0.0475

Tab. 14 Probit model for individuals with medium educated parents: Marginal Effect
Y= Pr(empl_2) (predict)
= .44307461

Variable	dy/dx*	St. Error	P-value
Work-student	-.0706225	.02004	0.000
Art	.2876999	.0563	0.000
Science	.3980139	.05033	0.000
Medicine	.2926476	.05865	0.000
Change	-.0578965	.02622	0.027
Age	.0036166	.02025	0.858
Centre North	.0956343	.01836	0.000
Country	-.1300542	.02278	0.000
City	-.164816	.02699	0.000

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 15 Probit model for individuals with high educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.204421	.053315	0.000
Art	.934572	.271867	0.001
Science	1.300193	.270537	0.000
Medicine	.739167	.277547	0.008
Change	-.046699	.076778	0.543
Age	.055856	.055088	0.311
Centre_North	.226217	.052453	0.000
Country	-.390936	.071942	0.000
City	-.226217	.052453	0.000
_cons	-1.151626	.272897	0.000

Number of obs. = 2543
Log likelihood = -1655.7312
Pseudo R2 = 0.0523

Tab. 16 Probit model for individuals with high educated parents: Marginal effect
Y= Pr(empl_2) (predict)
= .43976489

Variable	dy/dx*	St. Error	P-value
Work-student	-.0806188	.02099	0.000
Art	.3597014	.0973	0.000
Science	.4796512	.08671	0.000
Medicine	.2865513	.09983	0.004
Change	-.0183656	.0301	0.542
Age	.0220524	.02177	0.311
Centre North	.0887926	.02044	0.000
Country	-.1489432	.02607	0.000
City	-.1826127	.03311	0.000

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 17 Decomposition

	Differences in Characteristics	Differences in “Coefficients”	Total
Type1-Type2	-.0137	-.0288	-.0425
	(32.23%)	(67.77%)	(100.00%)
Type1-Type3	-.0202	-.0193	-.395
	(51.14%)	(49.86%)	(100.00%)
Type2-Type3	-.0035	.0065	.0030
	(35.00%)	(65.00%)	(100.00%)

APPENDIX B (CENTRE-NORTH)

B. 1 Descriptive Statistics

Tab. 18 Year of starting working and Family Background

Empl_2	Family Background			Total
	Low	Medium	High	
0	825 (55.15%)	1,137 (51.47%)	757 (51.81%)	2,719 (52.63%)
1	671 (44.85%)	1,072 (48.53%)	704 (48.19%)	2,447 (47.37%)
Total	1,496 (100.00%)	2,209 (100,00%)	1,461 (100,00%)	5,166 (100,00%)

Pearson's Chi-Squared = 5.3818 Pr. = 0.068

Tab. 19 Institutional time and family background

Institutional Time	Family Background			Total
	Low	Medium	High	
0	1,172 (78.34%)	1,675 (75.83%)	1,037 (70.98%)	3,884 (75.18%)
1	324 (21.66%)	534 (24.17%)	424 (29.02%)	1,282 (24.82%)
Total	1,496 (100.00%)	2,209 (100.00%)	1,461 (100.00%)	5,166 (100.00%)

Pearson's chi-square = 22.3334 Pr. = 0.000

Tab. 20 Mark and Family Background

Mark	Family Background			Total
	Low	Medium	High	
< 105	843 (56.35%)	1,332 (60.30%)	827 (56.61%)	3,002 (58.11%)
≥105	653 (43.65%)	877 (39.70%)	634 (43.39%)	2,164 (41.89%)
Total	1,496 (100,00%)	2,209 (100.00%)	1,461 (100,00%)	5,166 (100.00%)

Pearson's chi-square = 7.6100 Pr. = 0.022

Tab. 21 First Class Honours Degree and Family Background

First Class	Family Background			Total
	Low	Medium	High	
0	1,247 (83.36 %)	1,892 (85.65%)	1,190 (81.45%)	4,329 (83.80%)
1	249 (16.64%)	317 (14.35%)	271 (18.55%)	837 (16.20%)
Total	1,496 (100.00%)	2,209 (100.00%)	1,461 (100,00%)	5,166 (100.00%)

Pearson's chi-square = 11.7210 Pr. = 0.003

Tab. 22 Course Programme and Family Background

Course Programme	Family Background			Total
	Low	Medium	High	
Art	547	777	503	1,827
	(38.49%)	(36.43%)	(34.95%)	(36.59%)
Science	760	1,215	715	2,690
	(53.48%)	(56.96%)	(49.69%)	(53.88%)
Medicine	114	141	221	476
	(8.02%)	(6.61%)	(15.36%)	(9.53%)
Total	1,421	2,133	1,439	4,993
	(100.00%)	(100.00%)	(100.00%)	(100.00%)

Pearson's chi-square = 84.6981 Pr. = 0.000

B.2 Empirical Estimation (CENTRE-NORTH)

Tab. 23 Probit model for individuals with low educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.228354	.081119	0.005
Art	.875128	.211609	0.000
Science	1.40451	.210011	0.000
Medicine	1.178071	.236191	0.000
Change	-.270425	.104990	0.010
Age	.045564	.080635	0.572
Country	-.128861	.096195	0.180
City	-.368930	.080605	0.005
_cons	-1.027836	.198175	0.000

Number of obs. = 1496
Log likelihood = -959.70097
Pseudo R2 = 0.0674

Tab. 24 Probit model for individuals with low educated parents: Marginal Effects

Y= Pr(empl_2) (predict)
= .44000865

Variable	dy/dx*	St. Error	P-value
Work-student	-.0905462	.0322	0.005
Art	.3381211	.07693	0.000
Science	.5117505	.06463	0.000
Medicine	.4208248	.06378	0.000
Change	-.104248	.03922	0.008
Age	.0180025	.03191	0.573
Country	-.0503862	.03722	0.176
City	-.1396133	.04721	0.003

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 25 Probit model for individuals with medium educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.211391	.062419	0.001
Art	.838987	.184904	0.000
Science	1.11137	.183084	0.000
Medicine	.816828	.210029	0.000
Change	-.161887	.084337	0.055
Age	.051791	.059968	0.388
Country	-.229399	.078062	0.003
City	-.255831	.101055	0.011
_cons	-.788822	.188596	0.000

Number of obs. = 2209
Log likelihood = -1478.5627
Pseudo R2 = 0.0337

Tab. 26 Probit model for individuals with medium educated parents: Marginal Effect
Y= Pr(empl_2) (predict)
= .48264811

Variable	dy/dx*	St. Error	P-value
Work-student	-.0841749	.02476	0.001
Art	.3241437	.06674	0.000
Science	.4197122	.06197	0.000
Medicine	.3026997	.06601	0.000
Change	-.0641692	.03315	0.053
Age	.0206478	.02391	0.388
Country	-.0906083	.03039	0.003
City	-.1006379	.0389	0.010

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 27 Probit model for individuals with high educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.25096	.070307	0.000
Art	5.869011	.106750	0.000
Science	6.180849	.100367	0.000
Medicine	5.598569	-	-
Change	-.067754	.100471	0.500
Age	.022404	.070808	0.752
Country	-.241299	.099067	0.015
City	-.364803	.133497	0.006
_cons	-5.801280	.098740	0.000

Number of obs. = 1461
Log likelihood = -963.42983
Pseudo R2 = 0.0477

Tab. 28 Probit model for individuals with high educated parents: Marginal effect
Y= Pr(empl_2) (predict)
= .45242535

Variable	dy/dx*	St. Error	P-value
Work-student	-.0994183	.02777	0.000
Art	.9837324	.00206	0.000
Science	.997971	.00034	0.000
Medicine	.8330788	.00839	0.000
Change	-.0267453	.0395	0.498
Age	.0088768	.02806	0.752
Country	-.0940027	.03772	0.013
City	-.1393832	.04831	0.004

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 29 Decomposition

	Differences in Characteristics	Differences in "Coefficients"	Total
Type1-Type2	-.0131	-.0237	-.0368
	(35.60%)	(64.4%)	(100.00%)
Type1-Type3	-.0231	-.0104	-.0335
	(68.95%)	(31.05%)	(100.00%)
Type2-Type3	-.0064	.0098	.0034
	(39.51%)	(60.49%)	(100.00%)

APPENDIX C (SOUTH)

C. 1 Descriptive Statistics

Tab. 30 Year of starting working and Family Background

Empl_2	Family Background			Total
	Low	Medium	High	
0	631	723	655	2,009
	(66.21%)	(62.33%)	(60.54%)	(62.88%)
1	322	437	427	1,186
	(33.79%)	(37.67%)	(39.46%)	(37.12%)
Total	953	1,160	1,082	3,195
	(100.00%)	(100,00%)	(100,00%)	(100,00%)

Pearson's Chi-Squared = 7.2313 Pr. = 0.027

Tab. 31 Institutional time and family background

Institutional Time	Family Background			Total
	Low	Medium	High	
0	831 (87.20%)	975 (84.05%)	843 (77.91%)	2,649 (82.91%)
1	122 (12.80%)	185 (15.95%)	239 (22.09%)	546 (17.09%)
Total	953 (100.00%)	1,160 (100.00%)	1,082 (100.00%)	3,195 (100.00%)

Pearson's chi-square = 32.5177 Pr. = 0.000

Tab. 32 Mark and Family Background

Mark	Family Background			Total
	Low	Medium	High	
< 105	509 (53.41%)	582 (50.17%)	471 (43.53%)	1,562 (48.89%)
≥105	444 (46.59%)	578 (49.83%)	611 (56.47%)	1,633 (51.11%)
Total	953 (100,00%)	1,160 (100.00%)	1,082 (100,00%)	3,195 (100.00%)

Pearson's chi-square = 20.9944 Pr. = 0.000

Tab. 33 First Class Honours Degree and Family Background

First Class	Family Background			Total
	Low	Medium	High	
0	790 (82.90%)	962 (82.93%)	801 (74.03%)	2,553 (79.91%)
1	163 (17.10%)	198 (17.07%)	281 (25.97%)	642 (20.09%)
Total	953 (100.00%)	1,160 (100.00%)	1,082 (100,00%)	3,195 (100.00%)

Pearson's chi-square = 35.1885 Pr. = 0.005

Tab. 34 Course Programme and Family Background

Course Programme	Family Background			Total
	Low	Medium	High	
Art	351 (37.74%)	432 (38.47%)	368 (34.65%)	1,151 (36.95%)
Science	510 (54.84%)	629 (56.01%)	554 (52.17%)	36.95 (54.35%)
Medicine	69 (7.42%)	62 (5.52%)	140 (140%)	271 (8.70%)
Total	7.42 (100.00%)	1,123 (100.00%)	1,062 (100.00%)	3,115 (100.00%)

Pearson's chi-square = 43.2482 Pr. = 0.000

C.2 Empirical Estimation (SOUTH)

Tab. 35 Probit model for individuals with low educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.015533	.100351	0.877
Art	.894295	.466773	0.055
Science	1.595907	.463746	0.001
Medicine	1.401049	.485171	0.004
Change	-.132064	.123683	0.286
Age	.266864	.120886	0.027
Country	-.311027	.112885	0.006
City	-.364266	.127405	0.004
_cons	-1.635697	.468902	0.000

Number of obs. = 953
Log likelihood = -563.60352
Pseudo R2 = 0.0754

Tab. 36 Probit model for individuals with low educated parents: Marginal Effects
Y= Pr(empl_2) (predict)
= .32055318

Variable	dy/dx*	St. Error	P-value
Work-student	-.0055681	.03603	0.877
Art	.3261847	.16645	0.050
Science	.5152282	.12297	0.000
Medicine	.5125504	.13921	0.000
Change	-.0462193	.04225	0.274
Age	.0990644	.04616	0.032
Country	-.1059168	.03626	0.003
City	-.1216819	.03914	0.002

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 37 Probit model for individuals with medium educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.124372	.086753	0.152
Art	.538455	.261352	0.039
Science	.944753	.258042	0.000
Medicine	.656016	.301014	0.029
Change	-.136625	.115309	0.236
Age	-.091358	.100402	0.363
Country	-.518642	.101528	0.000
City	-.695107	.121889	0.000
_cons	-.760162	.265359	0.000

Number of obs. = 1160
Log likelihood = -719.29605
Pseudo R2 = 0.0639

Tab. 38 Probit model for individuals with medium educated parents: Marginal Effect
Y= Pr(empl_2) (predict)
= .36641461

Variable	dy/dx*	St. Error	P-value
Work-student	-.0471822	.03315	0.155
Art	.2046822	.09889	0.038
Science	.3396454	.08554	0.000
Medicine	.2568038	.11527	0.000
Change	-.0504784	.04174	0.226
Age	-.0340395	.03701	0.358
Country	-.1813405	.03221	0.000
City	-.2300524	.03358	0.000

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 39 Probit model for individuals with high educated parents: Coefficient Estimates

Empl_2	Coef.	Std. Error	P-value
Work-student	-.151048	.082443	0.067
Art	.281558	.337318	0.404
Science	.731534	.334657	0.029
Medicine	.200907	.350449	0.566
Change	-.020317	.120465	0.866
Age	.102068	.088232	0.247
Country	-.565371	.105886	0.000
City	-.646099	.146636	0.000
_cons	-.567296	.338617	0.000

Number of obs. = 1082
Log likelihood = -683.02366
Pseudo R2 = 0.0589

Tab. 40 Probit model for individuals with high educated parents: Marginal effect
Y= Pr(empl_2) (predict)
= .38630591

Variable	dy/dx*	St. Error	P-value
Work-student	-.0577336	.03146	0.066
Art	.1086948	.13081	0.406
Science	.2736141	.11977	0.022
Medicine	.0782021	.13813	0.571
Change	-.0077569	.04589	0.866
Age	.039243	.03406	0.249
Country	-.2007632	.03389	0.000
City	-.2188543	.04155	0.000

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tab. 41 Decomposition

	Differences in Characteristics	Differences in “Coefficients”	Total
Type1-Type2	-.0048	-.0345	-.0396
	(12.12%)	(87.88%)	(100.00%)
Type1-Type3	-.0308	-.0262	-.0570
	(54.03%)	(45.97%)	(100.00%)
Type2-Type3	-.0215	.0036	-.0179
	(85.65%)	(14.35%)	(100.00%)