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Learning mobility grants and skill (mis)matching in the labour market.

The case of the 'Master and Back' Programme

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The paper looks at the geographical mobility of graduate students and their skill matching in the labour market. The paper assesses the impact of a learning mobility grant scheme funded by the European Social Fund in Sardinia (ex-Objective 1 region in the Italian Mezzogiorno). The scheme aims to foster regional human capital and increase the employability of local graduates by covering the cost of post-graduate studies in other regions or countries. The econometric analysis is based on a unique dataset that combines administrative data on beneficiaries with information from a dedicated survey. The results suggest that learning mobility grants can reinforce skill matching only if the problem of self-selection of the beneficiaries is properly addressed.

1. Introduction

The lack of appropriate human capital – in both quantitative and qualitative terms - has been acknowledged as a relevant bottleneck for EU innovation and economic dynamism (Rodriguez-Pose and Crescenzi, 2008): the average level of higher education attainment among the active population (25-64 years) is 21% in Europe, as compared to 38% in the US and 36% in Japan (Ploeg and Veugelers, 2008). In addition the matching between supply and demand of skills is far from perfect: according to the EU- Labour Force Survey "nearly 15% of European employees are over-qualified, on average, while 21% are under-qualified, implying a total incidence of vertical mismatch in the EU of about 36%" (European Commission 2013, p.17), with significant variations across countries and regions. In his 2014 Annual Central Bank Symposium Speech at Jackson Hall, Mario Draghi (European Central Bank President) concluded that "the analysis of the evolution of skill mismatch suggests a notable increase in mismatch at regional, country and euro area level"[1], placing skill mismatch at the very centre of the policy debate in the European Union.

The EU has identified a number of labour supply and demand factors leading to the observed mismatch: from the provision of education and training curricula more tailored to firms' needs to reforms in labour market institutions and regulations (European Commission, 2013). In this context labour mobility - both geographical and occupational – and the removal of all barriers to its full realisation are presented as key tools to tackle skill mismatch (European Commission 2002). Although the practical policy tools for the active support of labour mobility have remained limited, learning mobility programmes have attracted special (and increasing) attention. By conjugating human capital accumulation (learning) with geographical mobility they are regarded as the ideal response to both quantitative and qualitative skill imbalances (European Commission 2013). Learning mobility programmes can – at the same time - increase the level of human capital of their recipients and reduce their probability of skill mismatch by broadening the geographical scope of their future job search process. Based on this rationale the EU has invested resources in a number of learning mobility schemes (European Commission 2009): from the Erasmus programme launched in 1987 in order to allow EU students to study in universities outside their home country to Marie Curie and Leonardo programmes targeting the mobility of researchers and potential employees respectively.

More recently, EU-wide learning mobility programmes have been complemented by regional-level schemes of similar nature. Individual EU regions - often economically disadvantaged areas - have promoted learning mobility schemes for their residents providing them with financial support to study in other countries or regions. The European Social Fund (ESF) has been progressively more targeted towards these programmes in France, Lithuania, Portugal and Spain. A recent report by the European Commission (2012a) lists and analyses a large number of learning mobility schemes in 34 European Countries. In Italy, several different programmes have been implemented at the regional level in Apulia, Sardinia, Tuscany, Emilia-Romagna, Marche, Friuli-Venezia Giulia and Umbria (European Commission, 2010).

Given the increasing popularity of learning mobility programmes at all levels, the objective of this paper is to assess their ability to improve the skill matching of their beneficiaries. For this purpose the paper looks at the case of a learning mobility programme designed and implemented by the Sardinia Regional Government (Italy) in order to fund Master and PhD-level studies by local residents in other regions or countries ('Master & Back' Programme). The empirical analysis, based on a unique and original database combining administrative and individual-level data on beneficiaries and non-beneficiaries of the

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[1] http://www.ecb.europa.eu/press/key/date/2014/html/sp140822.en.html

programme over several years, aims to single out its impacts on the quality of both vertical and horizontal skill matching.

Notwithstanding the emphasis on over-education, over-skilling and skills mismatch and their determinants very limited attention has been devoted in the existing literature to the impact evaluation of policy programmes aimed at their reduction. The paper shows that learning mobility programmes produce some individual-level benefits, working as people-based policies. However, the regions funding learning mobility programmes might be unable to 'incorporate' their benefits into their local labour markets, suggesting that these tools are not appropriate as place-based policies unless incorporated into balanced local economic development initiatives targeting both demand and supply factors. In addition the paper devotes special attention to the self-selection of individuals into the programme, shedding new light on the importance of the procedures for the identification and selection of the beneficiaries. Once the analysis accounts for the higher propensity of the (a priori) most motivated (and possibly most mobility-prone) individuals to apply for learning mobility grants the positive impact of the M&B programme is substantially weakened.

2. **Skill mismatch, over-education and over-skilling and the rationale for learning mobility grants**

The matching between educational achievements and skills (formally and practically) required on-the-job has been extensively analysed in the existing literature (Iammarino and Marinelli, 2011). The progressive expansion of the supply of skilled workers experienced by almost all developed countries has been only partially matched by new job opportunities, forcing workers to accept jobs with formal qualification requirements below their actual education level (Freeman, 1976; Hartog, 2000; Tselios, 2013). According to McGuinness (2006), 'over-education' identifies the extent to which workers possess a level of education in excess of that formally required for their job. In addition to over-education, the skill mismatch in the labour market can take other forms: workers might be forced to accept jobs in fields different from their own area of specialisation/studies (Wolbers, 2003; Hensen et al, 2009; Devillanova, 2013)

A number of empirical contributions have tried to shed light on the determinants of skill mismatch in the US (Duncan and Hoffman, 1982, Sicherman, 1991), in Europe (Hartog and Oosterbeek, 1988, Sloane et al., 1999) and in the UK (Alpin et al., 1998; Barone and Ortiz, 2011; Battu et al., 1999; Chevalier, 2000; Dolton and Vignoles, 2000; Green and McIntosh, 2007; Kler, 2006; McGuinness, 2002; McGuinness, 2003; McGuinness and Bennett, 2007; McGuinness and Sloane, 2011). In these studies geographical mobility is presented as a key factor for the understanding of both over-education and job satisfaction. The job search process is driven by the simultaneous objectives of wage maximisation and optimal skill matching. However, mobility is highly constrained by a complex set of individual and contextual/geographical characteristics with relevant implications for labour market outcomes (Faggian et al, 2006; 2007a; 2007b; Gagliardi, 2014). For married individuals, for example, the search radius is spatially constrained by the choices of other family members in order to maximise total family welfare (Frank 1978). In response to these constraints, higher-income (usually male) family-members tend to be privileged, forcing their (usually female) partners to restrict their job-search process and accept both sub-optimal skill-matching (over-education) and lower wages (Frank, 1978).

Peripherality and long commuting patterns – as barriers to mobility – also play an important role to explain skill mismatch: geographical accessibility determines the quantity and quality of employment opportunities of local residents leading to a sub-optimal skill-matching in peripheral and rural areas (Büchel and Battu 2003). The density of local labour markets (a proxy for the variety of opportunities available at the local

level) is also a key driver for skill-matching. Individuals located in large labour markets are less likely to be over-educated, even if larger shares of highly skilled individuals are also concentrated in denser markets (Jauhiainen, 2011 for the case of Finland; Tselios 2013 for the EU regions). Geographical mobility is a fundamental mechanism to overcome local labour markets constraints. Individuals search for jobs in close proximity to their place of residence, while trying to make the best possible use of their skill set (Simpson, 1992). When they are unable to find a suitable job within their 'home' regional labour market, they have three alternative options: unemployment, over-education or spatial flexibility (either by commuting or migration). Spatial flexibility reduces the likelihood of over-education while regional unemployment rates do not directly affect over-education, confirming that micro-level mobility might be a key mechanisms affecting skill mismatch (Büchel and van Ham 2003 looking at German workers and Hensen et al. 2009 analysing graduate students in the Netherlands).

Notwithstanding the emphasis placed on geographical mobility the analysis of the impact of active learning mobility policies on over-education and skill matching remains very limited. Some existing contributions looked at the Erasmus programme, suggesting that learning mobility increases the likelihood of labour mobility later in life, possibly mitigating the risk of over-education by expanding the job-search radius of the beneficiaries (Guellec and Cervantes, 2002; Parey and Waldinger, 2011; King and Ruiz-Gelices, 2003; Mc Guiness 2002). In a similar vein, by focusing on the impact of a scheme granting learning mobility scholarships to students resident in the Italian lagging region of Basilicata, Coniglio and Prota (2008) found that students' mobility significantly increases the likelihood of future migration. Similar results have been also produced with reference to the Marie Curie Programme (Van de Sande et al. 2005). However, there are no existing studies directly assessing the impact of mobility grants on skill matching.

3. Master and Back: the programme, stylised facts and data collection

In order to assess the impact of learning mobility grants on the skill matching of the beneficiaries in the labour market, this paper looks at the Master and Back (M&B) programme: a major learning mobility programme launched in 2005 by the Italian region of Sardinia and co-financed by the European Social Fund (ESF) with an overall expenditure of more than 200 million Euros. The M&B programme provides its beneficiaries (residents of the region meeting specific eligibility requirements) with a scholarship (covering both enrolment fees and a monthly stipend) to attend either a Master or a PhD programme in selected highly-ranked universities outside the boundaries of the Sardinia region in Italy or abroad[2].

The scheme was expected to make university education available to regional residents more accessible, more diversified in terms of available courses and of better quality. The scheme was also expected to foster knowledge spillovers towards Sardinia and make its beneficiaries more 'employable' by improving their skills matching in the labour market and reducing over-education and 'brain waste'.

In order to analyse the impact of the M&B programme two different datasets have been collected. The first dataset, made available by the 'Agenzia Regionale per il Lavoro' (Regional Employment Agency) of the

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[2] For the sake of completeness it should be highlighted that the 'Master and Back' Programme consists of two completely independent and separate sections/sub-schemes. The 'Master' section supports either post-graduate studies by regional residents as previously discussed (Higher Education part of the programme), or internships in prestigious Italian or foreign organizations (Internships part of the programme). The 'Back' section provides economic incentives for Sardinian graduates to return to the region after their studies. Involvement in this second section of the programme is not compulsory and completely unrelated with the 'Master' section. This paper is exclusively focused on the Master/Higher Education section of the programme.

Sardinia Region, includes detailed information on all M&B applicants in the calls 2006-2009. In order to be eligible for funding all applicants needed to be aged below 35 and possess a university degree making them suitable for Master or PhD Studies with a final grade of 100/110 or above. When all eligibility criteria were met in the 2006 and 2007 calls, applicants were funded on a first-come first-served basis while in the 2008 and 2009 calls funding was based on a ranking of the applicants based on their CVs and the quality of the proposed destination institution. Almost all applicants have in fact received funding with only 17% of the total applicants (i.e. 414 applicants out of 2,440) failing to obtain the funding mainly for bureaucratic/administrative reasons. The actual beneficiaries of the M&B Programme form the treatment group. The second dataset, made available by the University of Cagliari, includes detailed administrative and personal data (including contact details) of all university graduates over the period 2000-2010 (43,913 records in total). The control group is necessarily identified among the individuals included in this second dataset, given that the number of non-beneficiaries applicants– as discussed above - is too small to form a suitable control group. In order to identify a suitable control group all graduates that received any funding under the M&B scheme have been dropped together with all graduates potentially ineligible for M&B funding because of their final grade (i.e. below 100/110) or because of the typology of their degree. In addition all graduates aged 35 or above have been discarded (as ineligible for M&B funding) together with those who graduated after the application deadline of the last call taken into consideration (2009). The information included in both datasets has been complemented by a dedicated web-survey targeting all M&B beneficiaries and a selected sample of non-applicants (but potentially eligible) graduates from Cagliari University with an average response rate of 44% over the treated group[3] and 21% for the (much larger) control group.

Both samples also refer to individuals in employment in order to assess the quality of the skill matching in the labour market (as customary in the analysis of over-education and skills mismatching). The two groups have been compared along a number of relevant dimensions that could affect self-selection into treatment including individual characteristics (such as gender and date of undergraduate graduation), proxies for individual ability (such as duration of undergraduate studies in excess of the normal degree completion time), field of studies (science and technology vs. other fields) and personal preferences with reference to mobility (captured by the importance attributed by the respondents to quality of life, presence of cultural industries, ethnic and cultural diversity and presence of innovative firms and or centres of excellence in research when making their location choices).

As can be noticed from Table A-1 in Appendix A, there are not statistically significant differences among the treatment and control groups in terms of pre-treatment characteristics.

4. Empirical Analysis

4.1 Methodology

The estimation strategy of the effect of the program on the level of job matching is based on a treatment and control group research design.

The dependent variable is a proxy for the quality of job matching in the period following the completion of the program. The quality of job matching is captured by means of two complementary proxies focusing on vertical and horizontal matching respectively.

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[3] The response rate to the web-survey is close to 40% in 2006 and 2007 and higher than 50% in 2008 and 2009.

The first variable is specified as a dummy that takes value 1 when the formal level of education required by the job specification is equal to the actual level of education achieved by the individual. This measure of over-education is based on the comparison of the formal level of education required for the job with the actual educational level achieved[4]. Hence it represents an objective measure of job matching. Groot and Maassen van den Brink (2000) compare the empirical results obtained by means of different proxies for over-education and confirm the robustness of this indicator as a proxy for 'vertical (mis)matching'.

The second (alternative) dependent variable is based on a dedicated question from the web-survey asking individuals to rank their level of job satisfaction with respect to the matching between their skills and those practically required by their current job[5]. This proxy captures horizontal (mis)matching or 'over-skilling' that is defined as a situation in which individuals are not able to fully utilise their skills and abilities in their current job (CEDEFOP, 2010). It is based on a subjective self-reported measure of job matching that complements the objective measure of vertical matching discussed above. While 'vertical matching' captures the coherence between formal job requirements and formal educational achievements of the individuals, 'horizontal matching' proxies the practical suitability of the workers' skills set for the tasks they are expected to complete as part of their current job. Considering over-education (vertical mis-matching) and over-skilling (horizontal mismatching) at the same time is extremely important, since these concepts capture different aspects of skill matching in the labour market (McGuinness and Sloane, 2011; Green and McIntosh, 2007).

The horizontal matching variable is computed as a dummy variable that takes value one if individuals declared to be satisfied with their skill matching irrespective of the overall level of job satisfaction[6]. The choice to rely on a binary variable (rather than on a discrete scale ordinal scale) has three key motivations[7]. First, the binary structure maximises comparability between the two measures of job matching – i.e. vertical and horizontal. Second, this makes it possible to minimise uncertainty in the interpretation of the results due to the response bias typical of survey data. Finally this allows us to deal with endogeneity (due to self-selection) by means of an instrumental variables approach. The use of a discrete ordinal dependent variable would have made it necessary to rely on ordered probit models (as in McGuinness, 2002) for which the use of IVs remains highly problematic[8](Munkin and Trivedi, 2008).

Building on the above considerations the relation of interest is estimated by means of a linear probability model (LPM) where the endogeneity of the regressor of interest is controlled for by means of an

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[4] The 'level of education required by the current job' as well as the 'level of education achieved' are based on 5 categories (None, High School, Undergraduate, Master, Phd). The variable takes value 1 when the formal level of education required corresponds to the qualification held by each individual and 0 otherwise.

[5] The variable for horizontal matching is based on the answer to the 'skill matching' section of following question: "How satisfied are you, on a scale from 1 to 7, with the following aspects of your employment? …. The matching/coherence between your skills and those required by your current job"

[6] The binary variable takes value 1 if individuals declared to be satisfied with their skill matching (either 'Very satisfied', 'Satisfied' or 'Quite Satisfied') and 0 otherwise.

[7] Note that results for the estimates based on the dummy variable proxy for horizontal matching remain qualitatively unchanged when an ordered logit approach is adopted instead, exploiting the whole range of values from the original question on skills matching (results available on request).

[8] Note that the Linear Probability Model has been preferred to the Probit procedure for this same reasons. Endogeneity concerns, that are crucial in the context of this analysis, are in fact more likely to be efficiently addressed in a linear context. Probit estimations are also reported in Table A-3 in the Appendix as a robustness check with no evidence of any systematic change in the results.

Instrumental Variable approach[9]. The estimation equation of the probability of job matching takes the following form:

$$Job\ matching_{it} = \beta_0 + \beta_1 Treatment_{i,t-1} + \beta X_{it} + \varepsilon_{it} \qquad (1)$$

Where $Job\ matching_{it}$ is a dummy variable taking value one in the case of positive matching, for both vertical and horizontal matching, for individual i at time t; $Treatment_{i,t-1}$ is a dummy taking value 1 if the individual received the treatment (M&B Scholarship) at time t-1; X_{it} is a vector for post treatment controls customary in the literature on over-education discussed above (such as gender, age, marital status, field of studies and sector of employment) and ε_{it} is a well behaving error term. A detailed description of all explanatory variables included in the analysis is reported in Table A-3.

The key challenge in the estimation of equation (1) is the selection bias associated to the treatment status. Some omitted variables – for example in terms of unobserved individual ability – might affect the probability to find a better skill matching after the M&B programme: M&B beneficiaries might differ from the control group in terms of their a priori unobserved capabilities, improving their matching irrespective of the actual benefit (or 'value added') from the programme. In addition, given that M&B programme funds post-graduate studies outside Sardinia, this might lead to additional selection bias: treatment and control groups may differ not only in terms of unobserved ability but also with reference to their attitude toward mobility due to personal or contextual characteristics (e.g. family background or any other peer effect dynamics). In order to address this issue the paper exploits two alternative methodologies.

First the analysis adopts an instrumental variable approach that is customary in the literature on the return to education: it makes use of the level of education of the mother of each individual – measured by the level of formal qualification held – as an instrument for unobserved individual and contextual characteristics (Ashenfelter and Krueger, 1994; Card, 1995; Butcher and Case, 1994; Card, 1999; Currie and Moretti, 2003).

There is a long tradition of empirical analyses using family background information - such as mother's or father's education - to control for unobserved ability and explain the probability to engage in further education. Ashenfelter and Rouse (1998) show that up to 60% of the cross-sectional variation in schooling outcomes in a large sample of twins is explained by family factors. This claim is reinforced by Card (1999) showing that almost 30% of the observed variation in educational achievements among US adults is explained by parental education. In a similar vein the attitude of individuals towards mobility is positively affected by individualism and both parents' and peers' attitudes (Dette and Dalbert, 2005). Individuals from different social backgrounds - in terms of both family and broader social structures - are subject to different incentives with reference to both further investments in education and mobility (the two key features of 'learning mobility' programmes). Individuals living in more (less) stimulating social environments might be more (less) likely to apply for a program that is financing further education outside their 'home' region (Noe and Barber, 1993; Tabuchi and Thisse, 2002; Eliasson, 2003; Arntz, 2005). In our paper the choice of 'mother education'[10] as an instrument builds on the idea that parental education is likely to be a good proxy for unobserved abilities as well as differences in those contextual conditions that may affect the decision to

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[9] Results have been replicated adopting non-linear techniques as well. Table A-4 reports estimates for both horizontal and vertical matching. Our key findings remain qualitatively unchanged.
[10] Note that father's education has also been tested as a possible alternative instrument however its correlation with our variable of interest, the treatment status, is weak in the first stage and it does not satisfy the standard weak instrument tests.

simultaneously invest in further education and move outside the boundaries of the region, in order to exploit the opportunities offered by the M&B programme.

Second, the paper makes use of Propensity Score Matching (PSM) techniques to provide additional support for the key findings of the analysis. Converging results across different estimation procedures, which are aimed at tackling the potential sorting bias in different but complementary ways, provide convincing evidence on the robustness of the results.

4.2 *The impact of M&B on Vertical (overeducation) and Horizontal (overskilling) Matching*

The regression model specified in equation 1 is estimated in order to capture the impact of the M&B program on Vertical (overeducation) and Horizontal (overskilling) Matching. The estimation results are reported in Table 1. Columns 1 to 3 make reference to Vertical Matching while columns 4 to 6 to Horizontal Matching. Columns 1 and 4 can be interpreted as baseline models, presenting the estimation of the effect of the treatment after controlling for standard individual characteristics such as gender, marital status and age. The treatment status appears to be positively correlated to job matching and significant at 5%: M&B beneficiaries benefit from better vertical and horizontal matching in the labour market. The individual controls show the expected signs: women are likely to experience on average a lower probability of job matching as well as older individuals. This is in line with previous studies documenting that women tend to be more influenced than men by overall working conditions and job amenities (such as on-site child care or flexible hours) with a higher probability to accept less qualified jobs (Robst, 2007). The negative impact of age on skill matching is also supported by other recent studies showing that job mismatching tends to be positively associated to a number of factors such as previous unemployment history and age (McGuinness and Sloane, 2011). Conversely, marital status is positively correlated to job matching but not statistically significant. Columns 2 and 5 include controls for individual educational levels (excluding the qualification obtained under the Master and Back funding) through a set of qualification dummies. These controls are of crucial importance in order to correctly identify the effect of the treatment, making it possible to net out the risk of undervaluing the educational level of the control group – i.e. failing to account for the fact that individuals in the control group benefited from additional training after the degree independently from the Master and Back. As expected, additional educational attainments are positively correlated to both vertical and horizontal matching but not statistically significant except for those holding a Master or a PhD for vertical matching only. This evidence generally confirms the benefits of investing in further education in order to reduce the risk of over-education and possibly tackle the concentration of employability disadvantage factors in the intermediate tiers of the skill distribution (Goos et al, 2009). However, these benefits are significantly lower when it comes to the practical tasks pursued on-the-job (horizontal matching). Columns 2 and 5 also control for the typology of qualification acquired by each individual, the sectoral composition of the labour market, for public sector employment and for current employment location distinguishing individuals currently working in Sardinia from those in occupation elsewhere. Individuals with a background in Science (the baseline category) benefit from a better job matching when compared to all other typologies of qualification.. The results also suggest that individuals employed in the public sector have the best vertical and horizontal matching. This probably reflects the legal constraints for access to public sector jobs that require all applicants to possess exactly the same formal qualification as specified in the job advertisement. Finally, the control for Sardinia is negatively associated to the quality of both vertical and horizontal job matching and significant at 10% level: individuals currently employed in Sardinia are more likely to experience a sub-optimal matching. This feature generally supports the idea that

the probability of a better matching is positively associated to the extension of the job search area (Molho, 2001). More interestingly the inclusion of the control regarding the current geographical location of the individuals reduces both magnitude and significance of the treatment status for the horizontal matching equation (column 5), suggesting that the benefits of the program tend to be higher for the beneficiaries that do not return to Sardinia after their studies. M&B improves the quality of the matching on the labour market (positively affecting individual welfare), but this does not necessarily happen within the boundaries of the 'home' region sponsoring the programme with limited localised spillovers and local economic development benefits (contrary to the expectations of the regional government).

The impact of the program remains statistically significant and positively associated to both vertical and horizontal matching despite the relevant number of 'post-treatment' controls added to the specification, suggesting a robust correlation irrespective of individual or contextual characteristics. However, as extensively discussed in section 4.1, the positive effect of the M&B treatment might still be driven by selection bias: individuals selected for M&B funding may differ from their controls in terms of unobserved characteristics. These omitted variables may refer to both the unobserved ability (as customary in the literature) that is assumed to bias the return to education and any other contextual characteristics that may affect the sorting mechanism into the program. In order to deal with this possible bias, the regression model has been re-estimated adopting an instrumental variable (IV) approach adopting parental educational level as an instrument for the treatment status. The selected instrumental variable - mother education - is significantly associated to the regressor of interest at 1% level (Tab. 2), in line with the existing literature that suggests that parental education is strongly correlated to both the decision to invest in further education (Card, 1999) and mobility proneness (shaped by parents' and friends' attitudes towards mobility) (Dette and Dalbert, 2005). The F-statistic for the first stage is close to the customary value of ten (Staiger and Stock, 1997) and generally above the thresholds values identifies by Stock and Yogo (2005). The IV results for the main equation reported in Columns 3 and 6 (Table 1) suggest that - after controlling for the selection bias associated with the sorting mechanism into the program - the impact of the program itself becomes insignificant on both vertical and horizontal matching. In other words, once we account for the mechanisms that might induce certain individuals to apply for M&B funding the additional effect of the funds disappears: M&B beneficiaries benefit from a better matching because of their a priori initial characteristics not necessarily because of the scholarship received from the Regional Government. This evidence seems to suggest that these individuals would have achieved a better matching – lower risk of over-education and over-skilling – even without the M&B programme casting doubts on the economic 'value added' of learning mobility programs. This evidence suggests that part of the effect found in the OLS specification is dependent upon the a priori self-selection of the most 'successful' individuals into these programs, implying that eligibility criteria and actions to support participation might play a crucial role for the generation of value added from the programme (Crescenzi et al. 2013).

The validity of the exogeneity restrictions is confirmed by means of a second instrumental variable, under the constraint of the availability of suitable questions in the web-survey. Information on 'Parental Status' of the individuals is selected as an instrument. The variable 'Parental Status' takes value 1 if the individual has children before the launch of the program and 0 otherwise: individuals with children before the launch of the program are less likely to apply for a grant requiring the enrolment into higher education programs outside Sardinia. Results are reported in table A-5 in the Appendix. As expected 'Parental Status' is negatively and significantly correlated with the instrumented variable while our preferred instrument "Mother education" remains positively and significantly correlated at 1% with the treatment status. The availability of an additional instrument makes it possible to compute the Hansen J Statistic to test for the validity of our IV strategy. With a P-value of 0.17 for the regression on Vertical Matching and 0.26 for

Horizontal Matching we fail to reject the null hypothesis that J =0. This implies that over-identification restriction is satisfied and our IVs are valid. This additional test confirms the exogeneity of our preferred Instrumental Variable, supporting the robustness of our findings.

4.3 Robustness checks and alternative identification strategy

The results presented above are robust to a number of robustness checks[11] that confirm their validity.

However, given the relevance of selection mechanism for the assessment of the overall value added of the programme and in order to further support the Instrumental Variable results, a Propensity Score Matching (PSM) approach is applied as an alternative identification strategy to deal with the potential selection bias in the estimates[12]. Rather than relying on 'mother education' in order to proxy unobservable characteristics that determine selection, the PSM relies on multiple observable characteristics correlated both with the selection into the programme and with the outcome of interest. Table 3 reports the estimate based on a Propensity Score (PS) calculated by using the same variables used for the IV specification including also the square of age and an interaction term between 'married' and 'Sardinia'. For both vertical and horizontal matching the first row reports the so-called naïf effect, which is a simple t-test on the difference in means between treated and control groups, without controlling for selectivity. The second row shows the result with Nearest Neighbour Matching (NNM) with single matching (n=1), the third row with NNM with multiple matching (n=3) and the fourth row with NNM with single matching (n=1) and exact matching on sex (given the importance of gender for the estimation of individual labour market outcomes). Consistently with the results obtained through the IV approach, the PSM provides evidence of a significant selection bias driving the baseline results. Though the naïf effects are positive and highly statistically significant, they tend to become statistically non-significant when the recipients are matched to the non-recipients based on their PS[13]. The analysis based on the PSM confirms that the self-selection of the participants into the programme is a key challenge in order for the programme to generate the expected 'value added'.

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[11] Our results hold with respect to a number of robustness checks. First, the full regression model (with IV and all controls as reported in columns 3 and 6 of table 1) has been re-estimated progressively dropping all controls. Results confirm that the impact of the treatment status after instrumenting through the level of mother education is not systematically affected by the specification of the model and the inclusion of additional regressors. Second, to check whether the impact of the program becomes apparent only when a more comprehensive dimension of job satisfaction is taken into account the entire estimation procedure has been replicated with 'total matching' as the dependent variable (e.g. when both the vertical and horizontal matching variables take value one at the same time). Results with this 'combined' outcome variable are qualitatively unchanged. Finally, we try to account for the role of labour market features by looking at employers' characteristics and the regression of interest has been re-estimated controlling for the size of the firm employing each individual. Despite some weak evidence of a positive correlation between firm size and job matching, the inclusion of these additional controls does not affect the results. All these robustness checks are available upon request.

[12] It is in fact worth noting that the First Stage statistic on the excluded instrument reported in table 2 is close but not above the value of 10 proposed by Staiger and Stock's the rule of thumb. This may raise some minor concerns on the strength of our IV results. The coherence of our results across alternative methodologies to address the sorting bias is thus exploited to complement the IV estimates and interpreted as convincing evidence on their reliability.

[13] Additional tables with the logit model used to compute the propensity score and balancing test are available on request.

5. Conclusions

Very few existing studies have attempted to assess the impacts of active labour market policies aiming to tackle vertical and horizontal mismatching by means of learning mobility programmes (notwithstanding the increasing popularity of these schemes). This paper has filled this gap by implementing a causal analysis of the impacts of the M&B programme on different forms of skill matching in the labour market.

The empirical results suggest that learning mobility programmes have a strong potential to improve the quality of both vertical and horizontal matching. However, this is true with two fundamental caveats: a) the benefits of these programmes might not necessarily be 'appropriated' by the region funding the scheme, in particular if the region shows weak labour market conditions; b) the value added of the programme crucially depends upon the mechanisms and procedures implemented for the selection of the beneficiaries: the key risk of these programmes is to fund individuals who would invest in further education and mobility even without public support.

The evidence produced for the case of the M&B programme suggests that benefits from the programme tend to 'spill out' away from the local labour market of the region sponsoring the programme. Individuals returning to work in Sardinia tend to benefit less from the programme in terms of both vertical and horizontal matching. This is likely to be the result of the weak local labour market conditions in Sardinia and suggests that supply-side labour market policies cannot be decoupled from appropriate demand side policies in lagging regions. If appropriate demand conditions for the 'skills' developed by means of post-graduate courses (Masters or PhDs) are not in place locally, skilled individuals are more likely to move and search for better job opportunities elsewhere. The improvement of local firms' absorptive capabilities in terms of skills is then a crucial pre-condition for the local 'appropriation' of the potential benefits of learning mobility schemes (in particular in economically disadvantaged and peripheral regions). In addition, the diagnosis of local needs in terms of the existing (and future) demand for skills is a key step towards a better matching at the local level (Crescenzi and Rodriguez-Pose 2011). In line with this diagnosis learning mobility grants can be targeted towards disciplines and fields of studies of special relevance to the local context (differently from the M&B programme that offered support for studies in all fields).

Finally, the selection mechanisms of the beneficiaries of these programmes need to be carefully considered and designed. The almost inexistent competition among M&B applicants to get the funding has magnified the self-selection problem. In this regard, information campaigns to promote the scheme and the potential opportunities offered by further education outside the regions should be organised in order to broaden participation among groups and categories that would otherwise not be involved. Transparent and open selection procedures are also important to signal the 'openness' of the scheme to people outside local elites and encourage participation. Improvements in targeting highly talented individuals from socially disadvantaged groups would also increase value added.

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Dep.Var.	Vertical Matching			Horizontal Matching		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	OLS	OLS	2SLS
Treatment status – Participation in 'M&B'	0.0752**	0.0907**	-0.190	0.0904**	0.0851*	0.232
	(0.0307)	(0.0370)	(0.408)	(0.0372)	(0.0442)	(0.470)
Female	-0.0294	-0.0037	-0.0004	-0.0767**	-0.0690**	-0.0707**
	(0.0265)	(0.0266)	(0.0279)	(0.0305)	(0.0321)	(0.0324)
Married	0.0220	0.00250	-0.0140	0.0684*	0.0608*	0.0695
	(0.0316)	(0.0308)	(0.0400)	(0.0350)	(0.0353)	(0.0446)
Age	-0.0086**	-0.0095**	-0.0104**	-0.0148***	-0.0151***	-0.0147***
	(0.0042)	(0.0041)	(0.0043)	(0.00480)	(0.00493)	(0.00514)
Master (first level)		0.0321	-0.0212		0.0431	0.0710
		(0.0720)	(0.106)		(0.0787)	(0.118)
Master (second level)		0.0862***	0.0532		0.0295	0.0468
		(0.0313)	(0.0589)		(0.0371)	(0.0665)
Phd		0.152***	0.111		0.0897*	0.111
		(0.0330)	(0.0697)		(0.0488)	(0.0831)
Economics and Statistics		-0.0970**	-0.0835*		-0.0361	-0.0432
		(0.0427)	(0.0475)		(0.0483)	(0.0533)
Other social sciences		-0.126***	-0.0806		-0.0735	-0.0972
		(0.0396)	(0.0739)		(0.0467)	(0.0878)
Humanities		-0.176***	-0.181***		-0.0938**	-0.0912**
		(0.0320)	(0.0344)		(0.0394)	(0.0402)
Public Sector		0.167***	0.168***		0.111***	0.110***
		(0.0327)	(0.0334)		(0.0365)	(0.0364)
Manufacturing		0.293**	0.305**		-0.0144	-0.0208
		(0.143)	(0.145)		(0.132)	(0.134)
Services		0.183	0.205		-0.0125	-0.0242
		(0.141)	(0.145)		(0.127)	(0.133)
Sardinia		-0.0635*	-0.174		-0.0732*	-0.0152
		(0.0349)	(0.163)		(0.0387)	(0.190)
Constant	1.077***	0.910***	1.061***	1.178***	1.222***	1.143***
	(0.140)	(0.195)	(0.295)	(0.164)	(0.203)	(0.322)
Observations	960	960	960	960	960	960
R-squared	0.012	0.106	0.057	0.024	0.049	0.039

Table 1: Participation into 'Master and Back' Programme and Vertical and Horizontal matching

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 2: First Stage Regression

Dep Var: Treatment status - Participation in 'M&B'	(1) OLS
Female	0.0170
	(0.0241)
Married	-0.0571**
	(0.0220)
Age	-0.0012
	(0.0034)
Master (first level)	-0.1949***
	(0.0422)
Master (second level)	-0.1258***
	(0.0230)
Phd	-0.1539***
	(0.0334)
Economics and Statistics	0.0494
	(0.0374)
Other social sciences	0.1645***
	(0.0355)
Humanities	-0.0137
	(0.0271)
Public Sector	0.0076
	(0.0254)
Manufacturing	0.0562
	(0.0653)
Services	0.0880
	(0.0555)
Sardinia	-0.3892***
	0.0317
Mother Education	0.0326***
	(0.0114)
Constant	0.3740***
	(0.1370)
Observations	960
R-squared	0.329
F (1, 945)	8.24

Robust standard errors in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Propensity Score Matching – Estimates for Horizontal and Vertical Matching

Algorithm	Effect	Standard error	Treat on support.	Treat off support (trimmed)	Control
Outcome: vertical matching					
Naïf effect[1]	.085**	.034	163	18	779
Nnm(m1)[2]	.067	.063	163	18	779
Nnm(m3)[3]	.061	.051	163	18	779
Nnm(m1) sex[4]	.017	.058	163	18	779
Outcome: horizontal matching					
Naïf effect[1]	.103***	.039	163	18	779
Nnm(m1)[2]	.110	.069	163	18	779
Nnm(m3)[3]	.088	.058	163	18	779
Nnm(m1) sex[4]	.123*	.071	163	18	779

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The estimates have been calculated with the Stata module NNMATCH (Abadie et al., 2004). They are based on Nearest Neighbour Matching algorithms (NNM), repetitions are allowed and standard errors are calculated allowing for heteroskedasticity (robust=3).
[1] Effect without matching: simple difference in means.
[2] NNM is implemented with single matching (n=1).
[3] NNM is implemented with multiple matching (n=3).
[4] NNM is implemented with single matching (n=1) and exact matching is carried out on the covariate sex.