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Doctoral Thesis

Student geographical mobility and labour market outcomes: evidences from Italy

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I, , declare that this thesis titled, and the work presented in it are my own. I confirm that:

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- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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Signed: Alessandro D'Ambrosio

Date: 28/06/2018

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Abstract

The aim of this thesis is to discover the association between geographical mobility and labour markets outcomes of Italian early graduates.
Even if is an argument widely trated in literature, I'll try to investigate the evolution of the "Brain Drain" process in light of recents event: the financial crisis of 2007-2008 and the cut back in higher education.

Migration decisions are closely related to degree of social mobilty in a country, especially where there are strong interregionals differences as in Italy where, analyse migration path evolution of human capital might be very useful to policy makers intent to reduce regional gaps and improve the "equality of opportunity" level.

Take into account migration endogeneity, the results suggest a positive effect of spatial mobility on economic performance with differences according to movement trajectories. However some limits, due also to the lack of adequate data, indicate that further researchs are necessary in order to identify a causal relation.

The thesis is strutured as follows: the first chapter explains push and pull factros related to migration and the connection with social mobility, wage inequality and regional development. The chapter two presents an estimation of the return to geographical mobility of early graduates wages while the third chapter present the estimation of return from geographical mobility in terms of employment condition using a dataset summarizing information coming from three different sources: Almalaurea, Infostud and Ministry of Labor.

1

The reasons behind geographical mobility

1.1 The migration model and its application

As in human capital theory, migration is to be considered a form of private investment with effects on lifetime earnings and on labour market outcomes (Sjaastad, 1962; van Ham et al., 2001)

A large volume of existing studies on migration focused on the utility maximization framework and micro-econometric analysis attempts to provide information on factors affecting the costs and benefits characterizing spatial mobility. In migration studies, individual utility is a function of origin, destination characteristics and expected earnings (Dahl, 2002; Dotti et al., 2013) and varies in importance in accordance with individual preferences.

A very simple formalization with an earnings additive function and individual preferences assumes that a movement between origin i and destination j can be explained by the follow equation:

$$V_{ijk} = y_{ik} + t_{ijk} \qquad\qquad \text{k=1,......,N}$$

where:

$$\text{t}_{ijk} = f(\textit{origin characteristics},\ \textit{destination characteristics},\ \textit{individual controls})$$

V_{ijk} is a utility index, y_{ik} are earnings and t_{ijk} is a vector containing both individual characteristics shaping the utility function (age, gender, education etc.) and external factors such as differences in income taxation, the local labour market, public serivices, climate and crime which impacts on the costs and benefits of mobility, correlated with migration decision as push or pull factors.

Since rational individuals try to maximize overall lifetime migration returns, the preferred perspective in this kind of analysis is long term. However, there are no particular reasons preventing this model from being used in order to evaluate the short term effects of spatial mobility, especially when the target population is made up on a selected group, with higher human capital (they are graduate), a higher propensity to move (they are young) and when there are strong differences between local labour markets (as in Italy).

In a shock-free labour markets, classic human capital theory implies that education increases worker productivity and that employers will pay higher wages for this higher productivity (Becker, 1962). In the same way migration is an investment which is justified on both supply and demand sides. On the supply side it is a searching process in which individuals stop moving when their individual preferences are satisfied[1]. From the demand side, migration can be understood using job market signaling theory (Spence, 1973) where employers may consider migration positively or negatively in terms of productivity, motivation and abilities.

In the follow discussion, and in the empirical part of this dissertation, much greater attention will be paid to individual utility, leaving aside debates on how geographical mobility might be evaluated by employers.

In this framework, the primary factors evaluated are mainly pecuniary. Thus it is assumed that migration depends on expected wages, employment probabilities and net migration costs (Gabriel and Schmitz, 1995).
Thus the net present value of migration's economic returns is defined as:

$$NPV_i = \sum_{t=0}^{T} \frac{(P_D W_D - P_O W_O)_t}{(1+r)^t} - C$$

where:

P_D	=	probability of employment at destination
P_O	=	probability of employment at origin
W_D	=	expected wage at destination
W_O	=	expected wage at origin
r	=	discount factor [2]
t	=	time index[3]
C	=	direct and indirect costs of migration.

Migration costs are expressed as:

$$C = \delta W_O + DC + IC$$

where δ is a positive constant and DC are the direct costs[4].
If we assume constant employment probabilities and constant wages, we can resolve the internal rate of return from migration obtaining:

[1]Considering migration's economic returns alone, this happens when a wage offer exceeds or equals the reservation wage.

[4]In reference to Da Vanzo (1976) and Kratx (2011) we can synthesize the costs of migration as follows: direct costs (pecuniary and non-pecuniary costs like transport, rent, information costs and costs in leaving partners, relatives and friends) and indirect costs (opportunity costs).

$$r = \frac{(P_D W_D - P_O W_O)_t}{\delta W_O + DC + IC}$$

The internal rate of return indicates that the decision to relocate is beneficial if r exceeds the direct and indirect costs of migration. This value is positively correlated with P_D and W_D and negatively correlated with δ P_O, W_O DC and IC[5].

The existing relationship between the variables cited above varies in accordance with different migration scales (local, regional or international migration), and it is mainly regional migration which is considered here, since transnational or short distance movement requires alternative hypotheses[6].
As far as regional migration is concerned, this model has been used to show that relocation decisions are frequently driven by income differences between regions (Sjaastad, 1962; Venhorst and Cörvers, 2015) and that migration to work is recognizable as a tool with which to escape the unemployment trap (Pissarides and Wadsworth, 1989).

However the reasons behind migration are not solely economic since typically individuals are trying to satisfy one's own preferences which are also strongly influenced by facilities, services, and more generally, by the quality of life. The presence of these "hidden preferences" and the possibility that may interact differently with external and cultural factors has led to discussions around the need to reconsider human capital, migration and the rational expectation theory together (Gambetta, 1987).
Furthermore, in order to take this specificity into account, temporal autocorrelation in migration decisions should be considered. In fact, relocation decision are strongly influenced by previous migration experience. To take a specific example, a decision to move at beginning of university is strongly correlated with mobility to work and many of the factors underlying both decisions are common. Since migration decisions are taken before starting university or directly after human capital investments (Cutillo and Ceccarelli, 2012), exploit this particularity and analyzing migration and remigration processes helps us to clarify how different utility functions respond to external factors.
In fact, it is plausible to assume that "hidden preferences" and the non-economics factors play a greater role than calssic economic components for the young and those with greater human capital since they can be attracted by learning opportunities, innovative contexts and dynamic locations, meaning that they can decide to move also for "consumption reasons"(Marinelli, 2011a). Furthermore, they react more to differences between regions and are more incline to take on migration costs.
This has been shown in studies of workplace mobility (Mocetti et al., 2010), and may also be true of student migration flows, especially with increases in college access for those coming from lower social classes (Argentin and Triventi, 2011) and with new higher education resources and differentiation between regions (Viesti, 2016).

Considering a restricted sample (the young and those with greater human capital) adds complexity to the model but generates some advantages:

[5] Relocation costs can be reduced in various ways: financial and psychological support (by families for example), migration experience, social capital. These factors are strictly correlated with contextual and personal characteristics and this makes it difficult to isolate their effects (Kratz et al., 2011).

[6] Here, in the geographical mobility for study purposes context, I am specifically referring to the decision to move to a region other than one's home region, whether for work reasons or after high school graduation, to attend university.

- analyzing student mobility helps us to understand regional disparity in greater depth (Dotti et al., 2013);

- analyzing student mobility helps us to understand differences in labour market functioning since in Italy, the choice of university impacts on wage and employment conditions (Cutillo and Ceccarelli, 2012; Makovec, 2006).

Studying migration process through the association between work and study mobility entails consideration of issues such as diverse educational supply quality and relative clusterization, differences in resource assignment between universities and variances in access to education, all factors which are directly controllable by policy makers.

I would argue that this kind of analysis can give indications on how to deal with migration's effects on economic development but it is advisable from a theoretical point of view to discuss some of the mechanisms influencing individual choices (such as family background, social capital and wage inequality) which can be linked to migration first.

1.2 Wage inequality, social mobility and migration

In general wage inequality studies have attempted to understand earnings polarization between individuals with different levels of skills and human capital ("between inequality") and between individuals with the same level ("within inequality")[7].

From the first contributions (Atkinson, 1970) to recent work (Piketty, 2015), there have been various debates about the causes and consequences of this phenomenon. In Italy some analysis moved the debate to the role played by "within wage inequality" (Franzini and Raitano, 2011) with some indications of theoretical arguments potentially useful in policy term. Summarizing, it might be argued that inequality (in terms of economic outputs and opportunities) can be generated by the functioning of the labour market ("demand side") and by differences in educational supply ("supply side"). However only a few studies have taken into account the role played by migration choices on the geographical distribution of ovearall wage inequality (Lilla, 2005) and, in turn, on the rising "within wage inequality".

If it is true that labour markets evolution (especially from a legislative point of view) may be ranked such a key factor, it should be also be considered that workers (especially better educated workers) can choose where to work, and at least for Italy, the economic differences between regions drives spatial mobility (Mocetti et al., 2010). "Within wage inequality" and "between spatial inequality" are, then, strictly interconnected since differences in wage premiums (for the same level of human capital) is a push factor in migration models and the spatial sorting of skills affects inequalities between places (Nakajima et al., 2014).

The existing literature, with its attempt to explain the different labour market outcomes between early graduates, has focused its attention to both demand side and supply side related factors. Regarding supply side factors, for example, diverse economic conditions may be attributed to differences in university quality (Chevalier, 2011; Pietro and Cutillo, 2006), subject

[7]See Baldini and Toso (2004).

(Ballarino and Bratti, 2009; Buonanno and Pozzoli, 2009)[8], individual ability and family background. On the last point, Ordine and Rose (2015), looking at the Italian data, have investigated the causes of "within wage inequality" among early graduates taking into account the effects of family background, education quality and educational mismatches on earnings, using a quantile regression. Their results are interesting: across different quantiles the highest exploit "rent" derived from the interaction of socioeconomic background and subject chosen. They conclude that university quality and family background are important factors in top wage earnings and that there is a pool of workers confined to the bottom of the earnings distribution scale due to family constraints.
At same time, from a macro prospective, growth in enrollment rates has led to graduates in the same subject obtaining very different jobs, increasing the wage disparity among them. For example Lindley and McIntosh (2015) have shown that the rise in earnings variance may be due to an increase in enrollment rates of individuals from lower ability categories, by subject choice or due to a combination of the two.

For Italy, too, it has been shown that there has been an increase in enrollment rates in higher education over the last decade (Triventi and Trivellato, 2009) but the effects on labour market performances has not been analyzed in depth.

On the other hand, some theories argue that there are demand side factors affecting differences in economic conditions between early graduates. For example differences in employability and earnings can be due to demand shifts which have led to remuneration disparities, affecting wage inequality. One of the main drivers in this case is technological progress and there has been much debate on the effects of "Skill bias thecnological change" (Acemoglu et al., 2001) on rising inequality (Card and DiNardo, 2002), also considering early graduates as the target population[9].

Differences amongst early graduates can be also due to changes in labour market regulation. For example, using a sample of U.S. 500 labour markets in 1990, Mccall (2000) has linked rising "within group inequality" to more flexible and insecure jobs (e.g., flexibilization and short-term contracts). In Italy Ballarino and Bratti (2006) have discussed the implications of two reforms, "Pacchetto Treu" (Law no. 196, 24th June 1997) and "Riforma Biagi" (Law no. 30, 14th February 2003), on labour market outcomes, suggesting a possible correlation between this reform and the worsening of graduates employment conditions.

Once again, with reference to Italy, some recent works (Fana et al., 2015; Sestito and Viviano, 2016) has begun analyzing the first effects of a further measure adopted in Italy, i.e. law 183 of 2014 named the "Jobs Act", that introduced new types of contracts (mainly temporary) and new incentives for firms. Here it has been suggested that this measure could have negative economic effect on the working conditions of younger, although a longer timeframe and more up-to-date data will be needed to verify this thesis.

However, whether we consider the causes of wage inequality from the supply or the demand side, it is plausible to assume a differentiated effect by region or by local labour market, especially in strongly heterogeneous contexts such as Italy.

[8]Buonanno (2008), investigating the causal link between field of study and subsequent outcomes in the labour market for Italian early graduates, shows that the quantitative fields increase not only the speed of transition into the first job and employability but also earnings at the outset of careers.

[9]For Italy higher variability in earnings is evident among different fields of study, even between and within regions (Brunello and Cappellari, 2008), while for other countries such the U.S. the differences between "S.T.E.M." (Science Technology Engineering Mathematics) and non STEM graduates is much clearer (Carnevale et al., 2011).

The interaction between the factors referred to above act as push and pull factors shaping individual relocation choices, which, in turn, could make differences in earnings most heavily dependent on geographical factors.
Following this hypothesis it has been shown that there is a wage premium resulting from the agglomeration economy (Chang, 2015; Matano and Naticchioni, 2016), and this effect is strongly related to migration. For example Kanbur (2005) has argued that highly skilled worker mobility results in increasing wage level in the destination countries while Marinelli (2011 A) has argued that this effect is greater where differences between places are very strong and where there are unidirectional movements between regions, such as in Italy.

There is a reverse causality relationship between human capital agglomeration and wage inequality and there has been much debate over the possibility that policies which aim to reduce wage inequality are strictly related to human capital distribution (Acciari and Mocetti, 2013; Acemoglu et al., 2001; Rodríguez-Pose and Tselios, 2009)[10].
In fact, encouraging student and worker mobility is a goal of the EU itself ((EC), 2010) and has positive effects on regional development and labour market efficiency[11]. Students' geographical mobility has positive externalities, too, since it can be a way of avoiding "market failures", or sub-optimal investment in education choices allowing individuals to find a good match between educational supply and their preferences.
It is precisely in the latter example that efficiency means that migration, especially for younger people and for those coming from disadvantaged family contexts or from poor areas, is a social condition improvement tool (Impicciatore and Tuorto, 2011; Scarlato, 2007).

Considering the role played in relocation decisions by economic disparities between places, it should be stressed that costs and benefits of migration depend on an inidividual's own economic condition and family background, which are in turn affected by cultural and social capital in their places of origin. This shapes preferences, risk aversion, motivation and perception regarding job satisfaction and job quality. In the utility maximization framework described in the previous paragraph this implies a t_{ijk} factor value which differs more by geographical area than by "starting condition". I would argue that differences in starting conditions acquires importance as the reason behind spatial differences and it is relevant to trace a connection between migration models and concepts such as "equality of opportunity" and "intergenerational mobility".

Studies on intergenerational mobility have attempted to understand to what extent actual economic condition correlate with individual family background features (Nietzsche, 2011).

Generally, the family background effect operates via three large scale channels: income, education and social network (Argentin and Triventi, 2011); analyzing relocation decisions may be useful in ruling out two of these channels: income effect, because we can assume that strong financial support helps to mitigate the direct and indirect costs of migration and social network effects, because we can assume that migration paths are influenced by family ties and by "neighborhood effects".

Whilist many studies regarding intergenerational mobility (Mocetti, 2007) show a strong correlation between parents and children's labour outcomes, none of these studies take into account (at least for Italy) that different patterns of social mobility can be found in different areas[12].

[10]Investigating the role of spatial educational distribution on income inequalities Karahasan (2009) has argued that a more equal distribution of human capital could guarantee more equal income distribution without capital distribution.

[11]Exchanging new ideas and collaboration between individuals contributes to increasing innovation and research through "spillover effects" (Strathman, 1994).

[12]Taking the British census for 1966 to 1981 into account, for example, Savage (1988) has enquired into

Incorporating "individual migration history" into this framework may help us to grasp the reasons behind different employment conditions.

At same time it is possible, at least theoretically, to connect the concept of equality of opportunity to migration literature if we assume that equality between individuals should imply the potential for the same chances and opportunities (Fromm, 2013).

Some of migration's direct and indirect costs are psychological and moneraty and both have impact on academic performance and working careers. While for monetary costs the connection with family income should be clear the connection with family income (more financial support implies lower monetary costs), for psychological costs we have to consider that these can be strictly dependent on personal socioeconomic status (Eddy, 2011)[13].
Thus, implying that migration depends on starting conditions, is true for those who decide where (and whether) to attend university (Karlson, 2013):

"migration is a choice that implies consideration of the consequences. These are constrained by family background and academic performance. In this way choice is naturally bound by constraints that are at least partially determined by factors beyond indiviudal students' control".

In the equality of opportunity concept discussed in the literature (Peragine and Serlenga, 2008; Roemer, 2004), according to which no one should have an unfair advantage, migration is way of overcoming "differences in circumstances", in family background and place of origin.

In Italy, where study mobility is not especially marked, at least in the early 2000s (Brunello and Cappellari, 2008), students' university choices are not free, with preference given to closer universities to avoid moving costs. In such cases, inequality of opportunity leads to market failure (due to sub-optimal choices by individuals).
Undoubtedly, many factors influence spatial mobility. For example, study mobility can also be limited by the legal value of qualifications. Silvestri (2001) has carefully discussed the importance of avoiding formal value in education and differentiation between universities (specialization, course availability) in order to incentivize student mobility especially if qualification inflation (Ichino and Terlizzese, 2013) and regional economic gaps (Viesti, 2016) are making moving an "exit strategy" for those from poor areas.
However all the reasons behind migration find a common denominator if we consider that education is a private good ("rivalrous" and "excludable") with positive externalities for society as whole and on economic growth Barra and Zotti (2017).

As Acemogulu has expalined (2001):

"Often, education decisions are not taken by individuals alone, but by their families. For example, families often contribute towards schooling expenses. However, parents may be only imperfectly altruistic, that is, they may not care sufficiently about their children. In this case, they will tend to underinvest in their children's education"[14].

whether upward social mobility is correlated with an individual's geographical mobility without finding a marked link.

[13]For Italy it has been shown that moving decisions are heavily influenced by observability of wages in countries of origin and destination (Capuano, 2009) and is possible to hypothesize that this informations flow may be distorted by friendship and family ties.

[14]In the same work, studying the change in income distribution from 1970 to 1990, he finds family income to have a significant effect on university attendance figures.

Under investment can be exacerbate if students and workers are not perfectly mobile because they are strongly hindered by moving costs (Ordine and Rose, 2007) and furthermore, differences in wage levels between graduates cannot be balanced since returns on education investment are not evenly distributed between places.

The arguments discussed may lead to critiques of human capital theory (Argentin, 2010) advancing hypotheses that returns on education depend more on type of university attended and, by the match between education and labour supply than on social origin through migration:

"studies on local labour markets came to the conclusion that a considerable amount of regions are characterized by an unfavorable labour market structure. These regional disparities persisted over a long historical time period. This spatial inequality implies social inequality, because household are locally committed and migration costs are involved in leaving disadvantaged regions" (Wagner, 1989).

1.3 Social capital, migration and the labour market

As explained in the previous paragraph family background can influence investment in education and migration, with a differentiated impact from places to place. In fact, in Italy, there are also regional differences in "family structures"[15] and more generally in social capital.

Several studies (Coleman, 1988; Franzini, 2015; Granovetter, 2005) have argued that one of the channels through which the effects of family background influences labour market outcomes is the "social capital" effect, a very broad concept but which can be defined as "a tendency to develop trust relationships and extend cooperation to the whole community" with expected returns (Lin, 2000; Putnam et al., 1994).

However social capital can also generate inequality in socioeconomic achievement and quality of life (Lin, 2000). In fact, the way in which social capital endowment can depends on family ties, which in turn influence educational choices (Checchi, 2006), labour outcomes (Brunello and Checchi, 2005) and the normal functioning of the labour market (Giuliano et al., 2008) has been debated. Furthermore, the strength of this bonds varies between geographical areas, and effects on human capital distribution cannot be excluded (Alesina and Giuliano, 2010; Reher, 2004).

Social capital can influence geographical mobility because we can expect a correlation in people's behavior when they live close together. Proximity between individuals implies that they share the same sources of information and often similar individual characteristics as a result of self-selection ("exogenous social effects") and/or because they learn from one another's behavior ("endogenous social effects") (Ioannides and Datcher Loury, 2004).
The presence of marked diffrences in quality and quantity of social capital may have an adverse impact in terms of equality of opportunity in the labour market[16] but also in university choice and college enrollment.

[15]For the Southern Italian regions, Banfield (1958) has discussed the concept of "familismo amorale" or a situation in which family ties assume such great importance as to inhibit the ability of individuals to associate collectively, arguing that this is one of the causes of slow development of some regions.

[16]Argentin and Triventi (2011) have explained how informal ties, or social networks, represent a source of inequality in the school to work transition in Italy.

Showing a causal link between the role exerted by family ties and labour market outcomes is extremely difficult given its "unobservable" nature. However, study mobility flows can help in this aim. Migrants are ideally suited to testing presence of network effects since they are more susceptible to asymmetric information in the labour market and also because usually they tend to be more socially cohesive. An interesting empirical analysis has been proposed in Munshi (2001) in which the author seeks to isolate the "network effect" using data on migration patterns and labour market outcomes, based on a sample of individuals belonging to multiple origin-communities in Mexico. Through the instrumental variable approach, he found that the network effect has powerful effect on employment conditions but this effect depends on the economic condition (job and income) of the person helping in labour market success (the same concept was stressed by Holmlund (2009)).

On this point, clarifying the distinction between social capital and social network may be useful. The social capital definition proposed by Putnam (Putnam et al., 1994) identified social capital as "public good" and saw it as made up of composed by three components (Siisiainen, 2003): moral obligations, social values and social network.

The component determining "negative externalities" is the last of these since it indicates a situation in which family are levered to obtain jobs, i.e. the "informal channel" to get a job prevails over the "formal channel" (Pellizzari, 2010).
The two concepts are often used interchangeably (or in a confused way), and Im referring here to that part of social capital which is connected with migration decisions. The absence of social networks can enhance mobility in order to improve one's social condition (especially where there is a shortage of social capital and lower institutional and university quality (Scarlato, 2007)), while opportunities to benefit from social networks can disincentivize mobility.

The role of family ties and social capital in the migration model has already been examined in some studies. David et al. (2010) have explained that geographical mobility is negatively correlated with local social capital since investing in local ties is rational when workers do not expect to move to another region[17].

Some discussion on this correlation has been done for Italy and extended with student mobility path analysis. Controlling for a large set of individual and geographical covariates, for example, Labini (2008) has found that the potential for making use of family ties in the labour market decreases where the level of social capital is greater. Furthermore, he has demonstrated the extent to which social capital of the origin location influences the likelihood of using family ties to find a job and shows that this plays a greater role in the provinces where institution and university quality is low.
These results suggest the influences of geographical factors in labour market functioning and the next paragraph discusses the Italian context.

[17] They argue that different levels of social capital are causes for lower geographical mobility in Northern European countries, in constrast to South country where the social capital is low and where contacts with friends, relatives and neighbors ("informal ties") are more frequent.

1.4 Equality of opportunity, the "Bologna process" and the Italian "dualism"

The equality of opportunity concept discussed in the previous paragraph is especially significant in Italy, affected as it is by marked economic differences between regions.
This gap has persisted for some considerable time and different functioning of local labour markets due to cultural and structural factors. If ideal geographical mobility (both students and workers) was guaranteed then the negative effects resulting from these differences can be reduced. However, as discussed in the previous paragraph, migration has direct and indirect costs, dependent on family background, financial constraints and social capital. This means that regional gaps are able to influence social inquality level in a country and people, which are randomly allocated across the territory, can be subject to losses in terms of equality of opportunity.

At same time, even assuming ideal mobility, it should be considered that people are attracted to better living, working and educational conditions and a human capital clustering process ("polarization effect") but, whilst in some area this generates socio-economic development loss, other regions are not able to take advantage of the "spillover effects" discussed above.
Specifically for the Italian context other adverse effects may be created (in terms of socio-economic inequality) if migration is one way. It is well know that Italy's Southern regions, have been experiencing large scale outflow of highly educated and qualified human capital since 1990, with considerable losses in economic growth (Piras, 2005). The reasons behind this migration are various and have concerned different generations and age groups (Malanima and Daniele, 2007). Marinelli and Iammarino (2017), considering a young graduate target groups, have suggested that the Northern, more innovative and dynamics regions, are able to exploit graduate skills differently Southern regions where, the "routine public" employment has much more weight and has created a productivity and job clustering effect.
Unfortunately, this gap is present in educational opportunities too, since it seems that there is unequal distribution of resources in higher education in Italy (Viesti, 2016). A connection between educational policies and labour market outcomes cannot be excluded (Checchi and Van De Werfhorst, 2014) as well as connection between educational policies and resource clustering which impacts on inequality of opportunity and geographical mobility. For example, Peragine and Serlenga (2008) have proposed a theoretical definition of equality of opportunity in higher education and applied it to Italy, finding a strong family background effect both in academic performance and early graduate income to different extents in different place of origin[18].

Whilst this may not be the sole factor affecting Italy's regional gap, a lack of appropriate educational reform may have led to the formation of crucial factors for socioeconomic development being absent in some areas, stimulating migration (both to study and work) as alternative (and irrational) options[19].

Restricting attention to migration for study purposes and the Italian scenario, we have seen that returns on education may depend on how educational supply reacts to change in skill demand (Magni and Renda, 2010) and education quality. Contrary to what is assumed in classic human capital theory, the amount of skills acquired is of lesser significance for labour market

[18] They find a lower equality of opportunity in Southern regions, especially considering family background effect on degree marks and drop-out rates.

[19] With the "New Economic Geography" paradigm, Krugman (1991) has identified crucial socio-economic development factors that are the basis for the agglomeration economy and the same factors have been identified as push and pull factors in migration to study (Marinelli, 2011a).

outcomes, while the choice (driven by differences in quality and resource availability) of university is significant.

Many studies have focused on the effects of university quality differentiation on labour market outcomes[20].

In a microeconometric framework, students prefer to attend higher quality universities because they expect to benefit economically and are willing to move where human capital is better created and, better paid. However, if migration becomes an "exit strategy", affordable only by those capable to deal with migration costs, such differentiation between place and institution creates social inequality "resulting from the relationships between the different capabilities of different groups" (Sellar and Gale, 2011).

On the quality issue, at least for Italy, it should be stressed that the index used as proxy for quality[21] in education is summarized in national rankings (Pietro and Cutillo, 2006) which cite university choice without taking into account that good labour market outcomes may be due to differences in available resources. In light of the above arguments, it is advisable to review this index[22], discriminating between the quality deriving from by circumstances and by better skill in management resources.

Subject of study choices, additional grounds for differences in economic returns from education (Becher, 1994), are highly correlated with educational supply structure. In fact for Italy, study mobility can be justified by the absence of complete educational supply in some areas.

Several initiatives have been taken in response to this issue. The concepts of quality, subject choice and human capital distribution have certainly been influenced by one the most important European educational reforms, the "Bologna process". Set up with the aim of increasing enrollment rates in universities and reducing inequality in education (Argentin and Triventi, 2011), this can be considered a watershed in educational supply structure evolution.

The first (positive) effect shown in the literature is a rise in the enrollment rates, especially for most highly skilled students with low family backgrounds (Cappellari and Lucifora, 2009)[23].

Another positive effect is the introduction of a break in the academic path (3 years for a B.A. and 2 years for M.A.). This may have mitigated the asymmetric information inherent in human capital investment, making the decision to relocate to study less risky and thus increasing its net benefit (Cappellari and Lucifora, 2009).

However, there are also some negative effects to consider since this reform was unable to mitigate the family background effect on education or to stimulate changes in the distribution of resources in tertiary education.

On the first point, the enrollement growth rates in favor of individuals coming from lower skills or/and income distribution groups has not smoothed the differences in high school lever starting

[20]For example Di Pietro and Cutillo (2006) show a negative correlation between overeducating and institution quality while Ciriaci and Muscio (2014) show a positive university quality effect on employability. Furthermore best performance in the labour market also derives from having studied in institutions with higher scientific research rates (Cutillo and Ceccarelli, 2012; Monks, 2000).

[21]For example the pupil-teacher ratio (Brunello and Cappellari, 2008) or SAT score (Black and Smith, 2006).

[22]For a discussion on the efficiency of the quality index at international level, see Billaut et al. (2010.)

[23]According to the authors, this implies the existence of constraints (financial or cultural) affecting educational choice.

conditions. Universities made no provision to equalize pre enrollment conditions for students from disadvantaged background (Checchi, 2014), who still experience difficulties in obtaining qualifications[24].

The labour outcome effects of this lack of concern for “starting conditions” has increased with the deterioration of worker stability, (due to labour market reforms and financial crisis) and it is plausibile to assume that for the most disadvantaged investment in human capital has become more uncertain as well as family background, both through the social capital and financial resources[25] has become more relevant (Berloffa et al., 2014).

The Bologna process has thus failed to mitigate the family background effect that has always been significant in Italy[26].

Another negative effect of the Bologna process connected with educational supply structure, is the increase in university entrance fees and the proliferation of additional univeristy sites, which are extremely varied in course and available resources terms (Argentin and Triventi, 2011).
If resources are not distributed equally across countries, new universities with fewer resources (and lower quality) can lead to an efficiency loss in higher education (Viesti, 2016).

Our discussion thus far has led to the conclusion that theories explaining the labour market supply demand/balance must be reviewed and should take into account geographical differences and relative effects on spatial mobility. As explained by Argentin (2010) for Italy, the labour market-educational system relationship is neither productive nor efficient but rahter one that fosters reproduction of social stratification where “top job position” are achieved indipendently by skills and capability. If there is a risk that the returns on education depend on social origin and by place of origin, this has profound implications for the existence of a meritocracy.

Furthermore, if differences in starting condition (geographical and social) are not incorporated into the human capital theory, education does not represent an additional “tool” useful in increasing intergenerational mobility but is rather an expression of demand by families who trying to transfer labour market advantages to their children *via* migration strategies too.

1.5 Policy implication

The above arguments reflect on educational policy’s relevance in ensuring better human capital and resource distribution through spatial mobility. However it is difficult to find common ground between individual preferences and social utility since they can be incompatible.

In fact, as educational costs and benefits are supported and enjoyed by society as whole (Bowman and Myers, 1967), the decision to move to study or work has positive and negative externalities for local development and, in addition to individual utility government (local or national) preferences should also be considered.

From an individual point of view, it may be desirable to incentivize mobility and create a

[24]Cappellari and Lucifora (2009) argue that the reform has had limited effects on dropout rates.

[25]Argentin and Triventi (2011) analyzed whether the labour market flexibilization process has changed family background’s role in the school to work transition without finding marked changes. However it should be stressed that their observational period, the 1992 to 2007 period, is one of significant labour market evolution but leaves out crucial post 2007 events (the financial crisis). It might be interesting to extend the analysis to subsequent years and evaluate possible changes on the family background effect.

[26]Checchi (2003) explains how household monetary income seems to affect the private or public university choice while Bratti (2001) explains how financial constraints interact with public fundings such as scholarships.

balance between individual preferences and both educational and labour markets[27], but, at same time, the government needs to avoid already human capital poor places suffering further impoverishment (Schultz, 1982).

The two views mentioned here are not necessarily conflicting since knowledge on how migration probability varies according to individual features helps us to understands how regional development gaps can be reduced and which factors to take action on (Carnevale and Strohl, 2013)[28]. However study mobility flows of highly skilled individuals should be a priority in the formulation and evaluation of industrial policy, too.

The most troubling implication of uncontrolled mobility flows, capable of neutralizing human capital's positive effect on local development (Lucas, 1998), is the clusterization process which, as we have seen, is a feature of the Italian context. In terms of economic growth, a North-South catching up process for Italy, has been discussed by Dalamzzo and De Blasio (2003), showing that local dispersion and low levels of human capital have negative effects on the productivity of Southern areas which lag behind and proposing a solution based on direct resource allocations to this area.

The clustering process is exacerbated by "competition mechanisms" between institution, driven mainly by the mobility of high school leavears (before and after the beginning of tertiary education). In general, competition is used in order to improves educational supply quality[29] but its beneficial effects are lost if there is resource and supply "stratifiaction" between Southern and Northern universities. In fact, public funding for education seems to have triggered an adverse effect with (student) geographical mobililty becoming an alternative mechanism to direct allocation of resources universities located in disadvantaged contexts (Rizzi and Silvestri, 2001) with a social costs transposed onto household budgets.
As regards competition effects, I consider two observations to be relevant:

- competition between universities based on mobility can generate entrance selection with possible effects on student performance for those forced into a second best choice [30];
- competition between universities and the presence of low mobility costs may lead to the creation of elite universities (with the brightest students from the whole country) on one side and less prestigious universities on the other (De Fraja and Iossa, 2002).

The last point suggests that lower mobility, determined by student grants or affordable university accommodation, helps students to make their best choices but may have negative effect in terms of polarization of human capital since the less able and motivated will attend their local college and the benefits of this initiative will be enjoyed only by a select few[31].
For these reasons, measures capable of stimulating efficiency in higher education and simultaneously reducing the quality gap between universities without exploiting geographical mobility,

[27]For example, Dalmazzo and De Blasio (2003) found local human capital averages in Italy to have a positive effect on individual wages which is greater for labour markets located in the South.

[28]Carnevale and Strohl (2013) describe an interesting difference between EU countries and the US, arguing that European countries prefer to use welfare policies to adjust the labour market-citizen relationship while the US prefers to leave this goal to the private education market with questionable effects in terms of equality of opportunity.

[29]Raising university quality can be useful especially for regions with negative migration rates (Southern regions) and those with major human capital dispersion (Ciriaci, 2014).

[30]In reference to primary schools Gibbons (2006) has shown the negative effects of competition on pupil performance and that higher degrees of competition can generate polarization within and between schools.

[31]This is what is called the "locking-in effect", widely discussed in relation to employability boosting measures (Hämäläinen, 2002).

have been proposed. This kind of policy normally includes initiatives designed to connect up labour markets and university systems. Developing scientific research centers and creating the conditions for more innovative and dynamic entrepreneurship can help to reduce the clusterisation effect between regions. Policy makers can incentivize public research connected with local labour markets' entrepreneurship, training and education, in order to influence capital allocation (Ciriaci and Muscio, 2014)[32] and use policies aimed at equalizing differences between regions in transport, housing costs or, in general, on quality of life (Brezis et al., 2011; Ciriaci, 2014). Furthermore, for Italy, action on "economic external factors" sheds light on the necessity to review the current resource allocation system which rewards universities less efficiency and effectiveness than for "circumstances conditions", attracting better students and better professors on the strength of different local conditions (Ciriaci, 2014; Rizzi and Silvestri, 2001)[33].

Therefore, from a social point of view, the best policy is not necessarily incentivizing mobility and the trade-off between the two actors should always be considered. However, the existence of this effect notwithstanding, there is a common preference for policies incentivizing mobility. One of the goals of the Bologna process was harmonizing the different European university systems and, thereby, achieving a higher degree of comparability" in order to incentivize mobility, stimulate competition and increase quality (Mechtenberg and Strausz, 2008).
In Italy, were universities have been subject to enrollment competition over the past decade (Agasisti and Dal Bianco, 2007; Cattaneo et al., 2017), many initiatives have aimed to increase mobility and thus reduce institutional quality gap and, furthermore, there is a general preferences for giving resources directly to students rather than univerisities. An example is "Decreto Legge 69/2013", known as "Decreto del Fare" according to which, the Italian Government funds 1000 grants of 5000€per year to students moving from their home town to other regions[34]. However this kind of initiative is not frequent and the Italian scholarship scheme is highly fragmented as a result of a significant resource cuts in recent years (Cattaneo et al., 2017; Viesti, 2016). Firstly, in Italy there is a gap between those entitled to scholarships ("idonei") and those who actually get them. This distinction is based (at least for the first year) on financial economic situation indicators (ISEE), which can be subject to bias since they are self-declared. This leads to a loss of efficiency in resource allocation between high school leavers and, in general, higher social inequality. Furthermore, these resources designed to sustain student mobility vary between regions, typically being higher in Northern regions (Ciriaci and Nuzzi, 2012). This can generate talent allocation distortions and in resources which are likely to incentivize migration benefiting advantaged areas. A solution to this mismatch might be linking the current scholarship scheme to a different family income measurement from ISEE and creating a less expensive and more efficient "selection policy".

Other kinds of measures have been implemented to provide resources for educational facilities such as rooms, teachers and laboratories but it would seem that such "supply side policies" are not effective in improving quality and efficiency (Rizzi and Silvestri, 2001)[35].

Once again in order to promote mobility, action might target housing and rental prices. For example Mocetti and Porello (2010, B) have shown that rising housing prices (at least until the

[32] "The investment in higher education is not sufficient to improve regional development and a mix between industrial and innovation policies is needed" (Marinelli, 2011b).

[33] Pigini and Staffolani (2015) have studied the effects of policies aimed at changing educational costs, suggesting paying greater attention to regional disparities than manipulating costs and fees in education.

[34] Access to grants is based on a ranking system which uses students' secondary school grades and geographical distances between students' home towns and the chosen university.

[35] Ordine et. al (2007) have reffered to regional differences in higher education supply and discuss the effects of geographical mobility on wages. Finding positive effects on labour outcomes, they conclude that it might be more efficient to subsidize geographical mobility than to reallocate resources directly to universities.

financial crisis of 2007) have generated a slow down in geographical mobility implying than better monitoring and subsidies for students from different provinces or regions might be useful[36].

To overcome a lack of solid support for mobility and satisfying student preferences, proposals have been put forward designed to turn the current schoolarship system into a mixed system based on student loans and scholarships like those used in others European countries (Ichino and Terlizzese, 2013; Rizzi and Silvestri, 2001). However, on this point, the excessive financial responsability placed on high school leavers, should be considered, with these incurring long term debts also connected to economic fluctuations. This can generate possible negative effects on academic and labour outcomes, especially if the social network channel has some weight in the labour market (Ciriaci and Nuzzi, 2012; Franzini, 2015).

Others studies analyzing the effects of high school levers and early graduates migration (Capuano, 2009), propose paying attention to the "come-back phenomenon", i.e. those who move to study in a different region and come back to their home towns after graduation. Incentivizing early graduates coming back home after graduation (especially those coming from poor human capital areas) can in fact contribute to the socio-economic development of regions lagging behind (Mocetti et al., 2010) [37].

Additional policies may be discussed if two consideration are take into account:

- moving implies costs deriving from asymmetric labour market information (Schwartz, 1973; Sjaastad, 1962) but also from a lack of information on degree structure (internal information) that leads students to prefer to remain in their home towns before starting university and after completing their studies (Netz, 2015).

- a lower degree of social mobility in our country is related to mistaken choices and unfilled expectations from educational investments which usually promote phenomena such as "over-education" or in a worst case, unemployment (Giuliano et al., 2008).

On the first point, reliable information on what it means to study far from home (funding opportunities, housing arrangements in destination region and recognition procedures) may help to overcome this information gap and enable families and individuals to avoid geographical failing to bring the expected rewards.

A second point relates referred to the presence of a strong family background influence on educational choices (Bowles et al., 2009) especially for poor families (Giuliano et al., 2008). An information policy explaining the structure of the courses offered by universities and the difference between them is needed especially if there is intention to get it far from home. This would helps to avoid academic interruptions ("drop out") or delayed graduation ("fuori corso"), particularly marked in Italy (ANVUR, 2016).

As we can see from this discussion, measures connected with geographical mobility are highly controversial and the relative effects can be positive or negative, depending on the point of view considered. However, rather than focusing on the different actors considered, policies can be grouped according to the timeframes required for relative and possible effects. This would make

[36] The policy indications suggested by Sa et al. (2004) have the same implications since they propose, for the Netherlands, improving transport or lowering the rental cost burden in order to improve geographical mobility.

[37] This is one of the few examples in which both individual and social utility can be maximized (Vidal, 1998).

two different kinds of measure possible: short and long term policies. Reducing economic disparities between regions can be considered a long term policy, in general linked to a more equitable geographical distribution of resources, while modifying educational costs and supply structures or incentivizing geographical mobility can be considered a short term policy. The latter, which policymakers would seem to have preferred, is not the optimal solution where differences between places are so marked. Reference to studies stressing that some non-cognitive abilities and values can be strongly influenced by environment (Bowles et al., 2009; Platone, 1990) and consideration of the fact that the gap between regions also concerns the value attributed to education, work on regional gaps may be more efficient.

2

Student spatial mobility: an estimation for Italy

2.1 Introduction

Even it is well know that people move in order to rise income, make the best possible use of the human capital investment and obtain better working conditions (Machin et al., 2012), the relationship between geographical mobility and labour market outcomes cannot be defined in advance.
From a theorical point of view, since the true productivity level is not directly observable by employers, spatial mobility could act as a screening device: it can be considered a negative feature if we assume that less able decide to move (Holmlund et al., 2009), or a positive one if we assume that mobility can be considered a strong motivation proxy (Cutillo and Ceccarelli, 2012).

We expect (at least in the short run) that "movers" can be subject to wage penalties due to a lack of knowledge on the local labour market functioning and to the adpative process required to find new job opportunities but the direction of this relationship it is not definable *a priori* since others mechanisms can influence the job searching process and in turn, working conditions. The first mechanism, already discussed in the previous chapter, is the possible existence of social networks in school-work transtion, that might have even much more weight respect to regional and local labour market characteristics acting as push and/or pull migration factors (Marinelli, 2011b).

The second and more rilevant factor to consider is that a specific educational system could influences student mobility, labour mobility and in turn economic performances (Machin et al., 2012). Current literature discuss different educational system classifications, one of them is proposed by Allmendinger (1989), based on the distinction between "standardization" and "stratification" structure. In a standardize system, education maintains a degree of comparability, where quality and resources are equally distributed within country. Indeed, with a statification systems, a selection on the student having access to higher educational quality and, in the worst cases, a selection to higher education access at all, becomes possible.
Regional disparities in higher education resources may develop a human capital stratification powered by geographical mobility with relevant effect even on the local labour market functioning and specialization.

This phenomenon suggests that relevant conclusions pointed out by human capital theory (Becker, 1962) and by "signalling theory" (Spence, 1978), trying to explain differences in returns to education, looses value and furhter explanations should be found.

For Italy, where the educational system is stratified in terms of resoruces and supply and where the social network channel in school-work transition is strong and different within country (Ghignoni et al., 2017), there are empirical evidences showing that choices on where to start tertiary education has some implication on academic and working career (Ciriaci and Nuzzi, 2012) especially given that changes in the labour market functioning and in social condition have led to an higher demand for skilled workforce whose adaptability depends on spatial mobility (Faggian and McCann, 2009).
However, migration cannot be considered as an isolate event but as a dymanic phenomenon, influenced by past miration history, where the effect of differences between places on relocation decision can remains costant or can be influenced by micro and macroeconomic shocks (Kennan and Walker, 2011).

This therotical framework and some empirical evidences (Di Cintio and Grassi, 2012; Makovec, 2006), suggests that that there are different labour market outcomes according to different migration paths and consider the full migration history as an individual features with an explanatory power, can be useful to point out differences in earnings, all characteristics being equal.
Estimate by how much geographical mobility increases (or decreases) earnings is quite complex since it requires to compare economic outcomes of people who moved with people who are similar in terms of skills and human capital but did not move. Since not all similarities between groups can be take into account, investigate repeated migration is useful to clarify the role of the "unobsevarbles factors" affecting both migration and economic performances. Da Vanzo (1976) discussed widely on the utility of studying repeated migration especially since the reasons behind spatial mobility are not necessary related to economic differences between places, but also to non-economic drivers that indirectly influence working careers.
For example, individuals, after a first migration experience might return at home for disappointment in the expectations, or, the retun migrants may be influenced by non-pecuniary motivations as friendship, family ties which, however, influence even employability and income[1].

As stressed in previous works (Machin et al., 2012; Weiss, 2015), two are the main reasons why early graduates and high school levears are suitable samples on which carry out analysis aiming to measure economic effects of migration and remigration:

- more educated and younger are more prone to move since are able to reduce migration adaptive costs[2];
- moving choices are taken mainly at the end of the high school graduation or after university completion (Cutillo and Ceccarelli, 2012).

Exploit information on relocation decision before to start university gives suggestion on some channels powering social inequality often analysed only which reference to labour market functioning. For example, those who move after graduation could have been forced to remain at home after high school due to liquidiy constraints hampering the possibility to get "first best" choice in education and, in turn, with possible negative effects on working conditions. If we face

[1] According to the economic theory, non-pecuniary goods are considered as "normal goods", consumed proportionally to income, giving higher utility if consumed in origins region (Capuano, 2009; DaVanzo, 1976).

[2] Scarlato (2007), analyzing years between 1991 to 2005, points out that the "movers" are a positive selected sample of the whole population: they are more prone to move (and look for a job position suitable to own preferences), are more quailified (in terms of education) and are younger.

a situation where those with a low family background are forced to choice field of study offered by closer universities, than it might be also possible that they accept the first job avavilable with consequences on overeducation and on job satistfaction (Ciriaci, 2014).
Conversely, a good family background might incentivizes repeated migrations (even ante graduation) in places different by the origin thanks to financial support if they belive that there are higher economic returns on education in specific labour markets (Capuano, 2009; Dustmann et al., 2011), or might incentivizes to come back at home to exploit social network channel and better knowledges of local labour market (DaVanzo and Morrison, 1981).
Even if is difficult to find empirical evidence for this mechanism, do not consider it at all can be misleading. Consider past migration event add new possible hypothesis on this, helping to explain existing relationship between workplace mobility and economic output.

In addition, is interesting analyse migrations evolution in the second half of the 2000s since greater attention to repetaed migration increases when labour market conditions are unfavoreable (DaVanzo, 1976). On this point, despite is a process experienced throughout all Europe, higher flexibility has influenced Italy early than other countries. In fact, during the 2000s there were two major labour market reforms, namely “Riforma Biagi” and the “Pacchetto Treu” which have led to a wider spread of fixed-term contracts which have weakened stability workers conditions[3].

Starting by such theoretical background, this analysis aims to estimate the effect of geographical mobility on earnings after graduation, grouping the early graduates according to different migragion paths, from high school to the labour market. Two are the main hypothesis considered:

- move before to start university increase the probability to relocate after graduation[4] since some migration costs (also non-pecuniary) could be lowered if individuals already move in the past (Maier and Sprietsma, 2016; Sjaastad, 1962);
- the interaction between individual and environmental factors affects migration decision (Allmendinger, 1989).

I decide to disentangle this analysis in three different sequential steps to which correspond three different research questions and different econometric strategies, however, strictly correlated. With the first analysis I try to figure out push and pull factors influencing relocation individual decision, before and after graduation. Other than influnced by individual features, as family background, age, academic career, relocation decision can be influenced also by envoirmental factors as public trasport, quality of life and further on.
In this step I verify if the factors influencing migration have somme common grounds in the two sequential mobility decisons.
I exploit empirical evidences found in this step to estimate the final effect of workplace mobility on wage through the instrumental variable approach. Some of the enviromental and individual variables are added as control in the estimation of post graduation mobility effect on wages, affected by endogeneity as I'll explain in the next paragraphs.

In the third step, I group individuals according to different migration decisions from the end of the secondary high school to the labour market, specifying five differents migration paths and examining if there are some earnings differences between them.

[3]Furthermore there was an increase in public employment with relevant effects on workplace mobility (Mocetti et al., 2010).

[4]For Italy it has been shown that the two relocation decisions are strictly correlated (Ciriaci, 2014; Makovec, 2006).

As stressed in the previous chapter, this analysis has relevance for the policy makers since if policies incentivating the return migration are absent, human capital may be accumulated only in wealthier regions, leaving the others lagged behind (Ciriaci, 2014), especially in Italy, where those who come back after graduation are too few or the weak educational system in some regions is not able to keep on the human capital created (Ciriaci, 2009).

At same time, evidences on the convenience to move can be relevant for household paying cost of the education, and, if the case, of mobility. Even if higher average levels of human capital has positive effect on indivdual wage, the net benefit might be offsets if to higher wage are associated to higher living costs (Moretti, 2013; Rauch, 1993).
In fact, for Italy, there are empirical evidences showing how universities located in Northern regions (more attractive) could guarantee best opportunities but with major costs, with the result that choice to study in North might not be compensated in terms of economic output, at least in the short run (Brunello and Cappellari, 2008).
Here further evidences on the effect of spatial mobility on earnings are presented.

2.2 "Dualism" and resources allocation in Italy

Interregional migration in Italy acquired a new relevance in 90s and 2000s since both student and workplace mobility experienced new increasing trends (Cattaneo et al., 2017; Panichella, 2013) and explanations suggested are various.
Firstly, the public employment diffusion in the second half of the '50s in Southern regions (Franco, 2010) gave to families more economic stability and than new possibility to move in richest regions even to study and this can justify the rising graduates mobility at '90s ending. For the '2000s a relevant event to consider is the 2007 financial crisis[5]. Since working conditions are subject to worsening is plausibile assume the high school levers become more selective in human capital investment decisions and are more prone to move with expection of higher returns on education according to university attended. This assumption finds some empirical evidences since in Italy the economic crisis had its sharp effects on employment from 2009 (ISTAT, 2010), that, looking to the figure 2.1, coincides with student interregional mobility rising. Furthermore, as its turn out by figure A.1 in the appendix, the academic year 2009/2010 marks a new increase in migration from Southern to Northern regions. However, between the Southern regions, severals differences on the propensity to move are present. The figure A.2 shows the net migration rate (average) by regions from 2004/2005 to 2013/2014. It is calculated as follow:

$$\text{N.M.R}_{it} = \frac{Student\,enrolled\,in\,each\,region\;-\;Student\,residents\;enrolled\,in\,each\,regions}{Student\,enrolled\,in\,each\,region}$$

i=1,......,20.
t=$\bar{t}$=2005,......,2014

This index show if a region gains or loses human capital through student migration flows and, with exception of Val D'Aosta and Abbruzzo[6], Southern regions are those with negative

[5] Cattaneo et a. (2017) considers as further explanation the diversification in trasport modes with the entry into the transport market of new low-cost companies (*Rayanair*) and high speed trains (*Frecciarossa*, *Italo*).

[6] The reason for this outlier can be the very small size for the Val D'Aosta and the proximity to Lazio, and to University of Rome "La Sapienza" (one of Europe's bigger universities and one of the moste attractive in Italy) for Abbruzzo.

migration rate.
The same trend is confirmed looking to the figure A.3 in the appendix where difference between the net migration rate in the academic year 2004/2005 and the academic year 2013/2014 is calculated for each region[7].

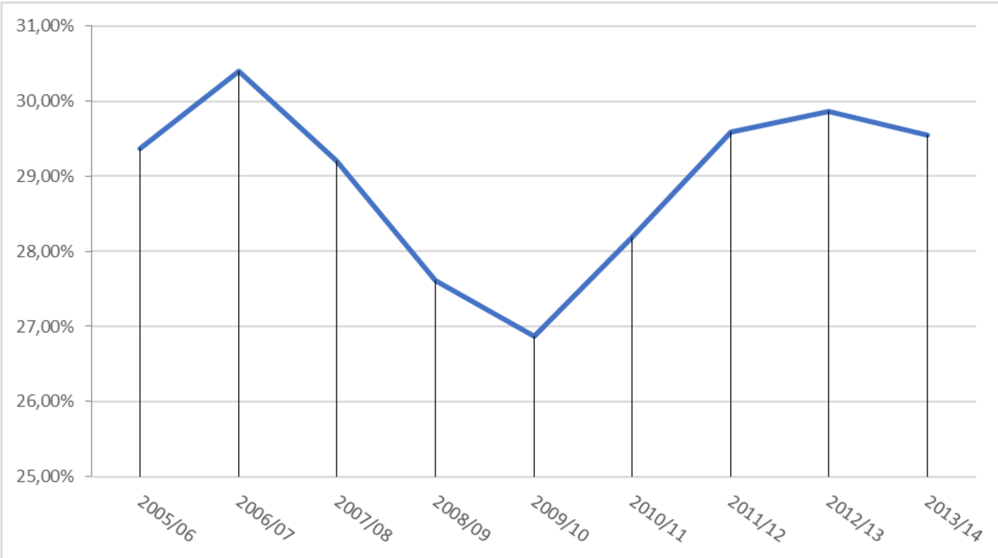


Figure 2.1: Trend in interregional students mobility (%) in the period 2005–14.
Source: own elaboration on MIUR data, section "Anagrafe nazionale degli studenti".

A further explanation for rising migration was already discussed previously. Other than regional differences in terms of labour markets, amenities and quality of life, specific educational supply features can influence both student and workplace mobility.
In Italy, tertiary education has been subject to many changes in the twenty century. After the "Second World War" there has been a strong increase in enrollment to universities, especially from those coming from low family background. The absence of finacial barriers (tuition fees) rises enrollments but, at same time, has not given relevance to implement policies aimed to redirect resources to univerities that have to face with a changed audience, composed not just by students coming from "licei" but also from vocational and technical schools. Probably this is why, until the early 2000s, we observe an increase in enrollment rates to which corresponds increase in drop out probability and delayed graduation ("fuori corso"), but not in the graduation rates (Triventi and Trivellato, 2009).
This trend reamins stable until the implementation of the "Bolonga Declaration" in the 2001-2002. Afterthat we see a decrease in the enrollment probability, stronger for student coming from Southern regions, seemingly as a consequences of adequate educational policies lack and of a simultanueous reduction in household income (De Angelis et al., 2016)[8].
An important finding regards the number of scholarships effectively assigned that drops by 82% of 2008 to 69% of 2011 (ANVUR, 2016). The last two factors have brought human capital accumulation much more dipendent by household contribution and, despite tuition fees and

[7]A very similar graph is presented in Viesti (2016). Cattaneo at al. (2017) show for the period 2002-2012 a very similar trend for in student interprovincial mobility.
[8]Even if the mean contribution for southern students is lower respect to Northern region, the average fees payed have incresed in the years 2001-2009 especially for students enrolled in this macro-area.

schoolarships vary according to individual economic condition, the percentage of those who receive public economic support sufficient to afford education costs, as the percentage of student using guaranteed public loan, is in Italy very low (OECD, 2017).

In addition, the criteria used to assign scholarships are very different between regions since interact with regional taxtions, directly modifiable at a decentralised level (Res and Viesti, 2016).

This creates huge heterogeneity in financial support available for students of different regions other than a diversification in the administrative procedures to obtain it.
In fact, the schoolarhip structure assigment is based on a fund called "Fondo integrativo per il diritto allo studio", financed through regional contribution, which seems to have had a "regressive effects" in terms of resources redistributiuon: university costs become higher in region as Molise, Campania, Calabria and lower in Northern regions that, in the period 2001-2008 were able to exploit (even due to a major courses diversification) greater financial resources.
The probability to get scholarship becomes greater in universities located in the North than in South and incentives to move where resources are higher. Furthermore we cannot exclude at all a correlation between resources available and drop-out probability (or delayed graduation), that are greater in disadvantage regions (De Angelis et al., 2016).
Differences in resources distribution among regions seem to be worsened even more after another reform implemented in 2008 ("Riforma Gelmini") that has had a general effect of decreases resources from the government and increases those coming from the private system (OECD, 2017).
Figure A.4 (appendix) shows how the amount of expenditures (public funds) in scholarships is subject to a reduction from the academic year 2009/2010, even if there is an increase starting from 2011. A very similar trend is confirmed if we consider the figure A.5 showing (in %) the amount of scholarships effectively paid on the student eligible to obtain it ("idonei").
The figure A.6 indeed, shows how much resources spent for scholarships differ between regions and is clear as Southern regions are all below the national mean.

On the migration paths just discussed, several considerations can be made. The first one is on the type of courses supplied in the Southern regions. According to a recent research (Viesti, 2016) seems that universities located in this macro-area are more specialized in a general education provided through bachelor degree (B.A.), and the lackness of advanced degrees (M.A.) may led to incentivate migration and complete studies in other regions.
The second points, is on the diversification of the educational supply provided in southern universities (even in the advanced degree), that, being low, have had the effects on lowering univeristies attractivines (Rizzica, 2013). On the issue De Angelis et al. (2016) describe accurately how, after a rapid expansion of courses available at local level in the first 2000s, by 2009 there has been a significant reduction of them partly due to a resources contraction, a trend that, by the way, seems common to all regions.

Conluding, the policies measures adopted in the last decades seems have grown the possibility that gap between regions in terms of labour market conditions is extended also in the educational system, powered by competition to get more resources in order to increase national quality ranking [9]. This effects doesn't change direction even with the increased autonomy for Italian universities, with a decentralization process which seems to have had the unique effect of a proliferation (at least in the early 2000s.) of small size university centres, less attractive respect to the bigger ones (Rizzi and Silvestri, 2001).

[9] Ciani at al. (2010), propose a quality assessment methodology for universities, discussing the relevant weight of the labour markets heterogeneity on the differences between working careers, which often are used for the quality evaluation.

Even if factors influencing student mobility are many and heterogeneous, resources distribution can have exerted some effect on this phenomenon.

2.3 Data Source

The data used in this exercise are provided by ISTAT[10] survey "Indagine sull'inserimento professionale dei laureati", a very informative data source with a great number of data about job condition and academic career. Depending on the year considered, the survey is carried out three and four years after graduation[11].
The sample is representative of the entire graduate population, from both public and private universities. Before choosing this data I considered the possibility to use alternative survies, as the one provided by "Almalaurea". As explained in the next chapter, Almalaurea is a public inter-university consortium composed (as of today) by 75 universities covering partially graduate population.

The structure of the Almalaurea survey is very similar to the one used in this analysis with the adavantage of interviewing graduates one year, three years and five years after graduation, giving than the possibilty to have repeated cross section. The strenght of Alamalura data for the specific researchs question proposed in this analysis is that allow to identify more precisely the time at which workplace mobility takes place by enriching the set of control variables excluded here since affected by reverse causality, that, as explained in the following paragraphs, is a specific form of endogeneity. Unfortunately this data are not freely available and are hardly obtainable.
ISTAT data, used in this exercise, by the way, allow the define quite precisely migration paths of early graduates, from high school[12] to the labour market.

However, being a survey, and being "movers" a specific target population, the number of observation available is quite low. Furthermore, ISTAT data are subject to the presence of missing values on relavant variables.[13]. Therefore, in order to have a larger sample, I decide to merge two survies: 2011 and 2015 referred to 2007 and 2011 graduates[14]. This allow me to increase the numbers of observations despite the survey structure change year by year[15].

After the merge the sample is composed by 90,779 observations from which I ruled out those working at time and before graduation and those engaged in postgraduate qualification, characterized by different migration behaviours[16] (Di Cintio and Grassi, 2012).
For same reasons I exclude those enrolled in medicine e defense since enrollment to such field of

[10] "Istituto Nazionale Di Statistica" is the Italian national statistical office.

[11] Before the survey carried out in 2011, tha graduates were interviewed after three years. In the last two surveys (2011 and 2015), the graduated were interviewed after four years.

[12] In order to define the origin region i decide to not consider the place of birth (additional information present in the dataset) since can be different from the high school region.

[13] Ordine and Rose (2015) using sama data but different survey (2004 and 2007), have analysed the covariates missing values distribution in order to verify if they are randomly distributed or related to some observed characteristics (they didn't find any empirical evidence supporting this thesis).

[14] Di Cintio e Grassi (2012) make the same procedure merging survies carried out in 2004 and in 2007

[15] I had to harmonize the surveis since same questions was structured differently. Furthermore happens that informations present in one of the wave are dropped in the other one.

[16] For example we can expect that those already working don't move at least until the end of the actual contract.

study is subjcet to entrance exam at national level. This implies that who is admitted is subject to a different contraints, influencing differently the choice on university location.
Finally I exclude all observations moving abroad to study or to work.
At the end of the selection, the sample size is composed by 46,892 observations[17]. However missing values on some variables allow estimation only on 5281 observations.

The table A.1 (appendix) show some descriptive statistics. Looking to the first part of the table, we see that the largest percentage of students come from southern regions (31%) and from North West (25,49%) while macro-areas losing more human capital are South and Islands since the percentage o student enrolled and working in this areas drastically goes down (respectively 14,9% and 3,84% for univrersity macro-area and 9% and 2% for working area).
The same table shows that more attractive macro-areas is the North West while center and norther east regions exhibit stability between university and working area.
The table A.1 reports also descriptive statistics for migration paths, defined as follow:

Post graduation mobilty	region of univeristy≠region of work
Ante graduation mobility	region before start university ≠ region of univeristy (transferred)

Different migration paths are identified as follow:

Stayers	• high school region = working region = university region
Come Back	• high school region = working region • university region ≠ high school region • Transferred to university region to attend
Double movers	• high school region ≠ working region • university region ≠ high school region • Transferred to university region to attend
Movers Remained	• high school region = working region • university region ≠ high school region • Transferred to university region to attend
Post graduation movers	• high school region ≠ working region • university region = high school region

From the table A.1, we can see that the highest percentage of "Stayers" is composed by those coming from Northern regions which, conversely, show the lower percentage of "Double movers". Southern regions and island show similar patterns and with higher percentage of "Moversremained" and "Post graduation movers".

Higher percentage of "Comeback" are present for Islands and North East regions.
The last part of the table show how much two migration choices are correlated: the 54% of those who move to study move also after graduation.

[17]Most of the deleted observations were composed by students who were already working at the time of graduation or who were engaged in education or training activities.

Before to continue to discuss on other descriptive statistics, some clarification on how i've specify the variable log earnings should be made. In fact, due differences among waves used, some adjustment were necesessary. Firstly, wages for self-employed workers and dependent workers are reported differently: annual salary for the first and monthly wage for employees[18]. Thus, to obtain monthly wage for self-employed workers, I divide the aggregate annual salary by 12 (months worked in one year).

This procedure has been applied just the 2011 wave since for the other one monthly income of the principal job for both self employed and dependent worker is already available.
On the functional form of the dependent variable, Di Cintio and Grassi (2012) use the logarithm of hourly salary because in this way is possible to better capture worker productivity. I decide to not use the hourly salary since Im expecting a weak short run migration impact[19].

The table A.2, A.3 and A.4 describe all the variables used, data sources and relative statistics for the full sample and for the different migration groups.

The table A.3 compare descriptive statistics for movers and stayers, distinguishing if they move after high school ("Ante graduation mobility") or after graduation completion ("Post graduation mobility"). The statistics suggests, as expected, that strong differences between stayers and movers after high school graduation are absent (the only exception is the "Autonomous" variable, showing a value clearly broder for the movers). Instead, more marked differences between stayers and movers after graduation are present. In addition to the monthly earnings, higher for movers, the descriptive statistcs suggest that those moving after graduation has better labour market outcomes since the percentage of part time worker is lower (7% against the 9% for the stayers), job specialization is higher and the percentage of those using the social network channels to find a job is lower (16% for the movers and 22% for the stayers). The table A.4 reports descriptive statistics among different migration groups and is clear that "Double Movers" and "Post graduation movers" show better performances: higher earnings, less part time job and an higher job specialization. Furthermore the variables referred to academic career ("Graduation Mark" and "On time") are higher for this two groups (especially for the "Post graduation movers").
The other two groups, "Come Back" and "Stayers", are those with less work experience[20] and the former group show even the greater percentage of autonomous worker (19%). Finally, on the family social class, the polarization between "Come Back" and "Stayers" and the others three groups is quite clear since they show lower value (especially "Stayers"). Indeed, among the last three catogories, those moving after graduation, even if have better labour markets outcomes, are even those with lower social calsses suggesting a possible empirical evidence for the "liquidity contraints" hypothesis.

[18]For dependent worker i take into account additional payments ("tredicesima and quattordicesima").

[19]Maier and Sprietsma (2016), estimating the long run effect of regional migration on labour market outcomes, use hourly salary as dependent variable (the selected individuals were 40 years old).

[20]Work experience is calculated in months after deducting by time used to find the first job. Unfortunately the data do not allow to figure out possible working interruption.

2.4 Econometric specification: what are push and pull factors influencing ante and post graduation mobility?

As anticipated, with the first step of this analysis I try to analyse factors which have some influences on the two relocation decisions, before and after graduation. As discussed in the first chapter, we can consider mobilty choice as a funcion of different factors related to the origins (X) and destination regions (Y) (Dotti et al., 2013):

$$U_{xy} = f(origin\ characteristics, destination\ characteristics, indivual\ controls)$$

x=1,......,20
y=1,......,20

To point out relationship between this factors I exploit a Recursive Bivariate Probit model (Green, 2007; Marra and Radice, 2011; Nichols, 2011) that allows to take into account correlation between ante and post graduation mobility using the first dipendent vairable ("ante graduation mobility) as a dummy variable in the second equation[21] as specified below:

$$\left.\begin{aligned} {y_1}_i^* &= x_{1i}'\alpha_1 + \varepsilon_{1i}, \\ {y_2}_i^* &= \beta y_{1i} + x_{2i}'\alpha_2 + \varepsilon_{2i}, \end{aligned}\right\} \qquad i\text{=1,......,n,} \tag{2.1}$$

where n is the sample size and ${y_1}_i^*$, ${y_2}_i^*$ are continuos latent variable which determine the observed binary outcomes y_{1i} and y_{2i} according to the following rule:

$$y_{vi} = \begin{cases} 1 & \text{if } {y_v}_i^* > 0 \\ 0 & \text{if } {y_v}_i^* < 0 \end{cases} \qquad \text{i=1,2}$$

${y_1}_i^*$ represent the decision to relocate to study after high school graduation and ${y_1}_i^*$ represent the decison to relocate to work while x_{1i}' and x_{2i}' are control variables row vectors, respectively for first and second equation[22].

The error terms $(\varepsilon_{1i}, \varepsilon_{2i})$ are assumed to be identically distributed as a bivariate normal with zero means, variance equal to one and correlation ρ, that in this framework represent the "tetrachoric" correlation between y_1 and y_2:

$$\begin{bmatrix} \begin{matrix} \varepsilon_1 \\ \varepsilon_2 \end{matrix} & |x_1 & x_2 \end{bmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 & \rho \\ \rho & 0 \end{pmatrix}\right]$$

If the correlation between the two error terms is zero than two probit models may be estimated. In fact we can consider the RBP model as natural extension of the probit model that

[21] Ciriaci (2014, A), looking to Amemya (1978) analyses ante-lauream and post-lauream migration choice with two separate probit.

[22] The control variables contained in x_1 and x_2 may be the same or different Green (2007).

allows to take into account the correlation between two dummies variables [23] (Cameron and Trivedi, 2010; Green, 2007) .

So the condition justifying the RBP model is the following:

$$corr(\varepsilon_{1i}\varepsilon_{2i}){=}\rho{\neq}0.$$

The error term in the two equations reflects the unobserved factors influencing individual utility function for each migration decision. The use of the RBP model allows for the possibility that both type of migration are influenced by the same unobserved factors. In other words, if the error terms of the two equations are correlated, unobserved factors affecting the decision to move after high school are correlated to the factor affecting decision to relocate post graduation. As discussed in the following paragraphs, this assumption allow to face with endogeneity issue affecting migration with additional econometric method. Furthermore, if correlation between two equation has been shown, the RBP model guarantees more efficient[24] respect two simple probit equations (Green, 2007; Maier and Sprietsma, 2016).

2.5 Econometric specification: is it convenient to move after graduation?

After the RPB model estimation, I try to point out if, in terms of wage, there are positive or negative returns from geographical mobility after graduation. Starting from the classical "Mincer equation" (Mincer, 1958), where post graduation mobility is an endogenus dummy variable, I exploit the model described in the previous paragraph in order to verify if it is convinient to move after graduation.

The wage equation is specified as follow:

$$ln\_w_i = \alpha + \beta y_{2i} + \sum_{i=1}^{N} X_i + \gamma_{1i}, \qquad \text{i=1,......,n} \tag{2.2}$$

The dependent variable is the logarithm of monthly wage, y_{2i}, as in the RBP model, is a dummy equal to 1 for those moving after graduation, X_i are controls added and α is the costant term.

In this framework, neglect endogeneity led to a bias in the estimation of spatial mobilty on wage. In presence of endogeneity, the β parameter will be bias and states not just the effect of workplace mobility on wage but also the effect of unobservables factors included in the error term γ_{1i} (Heckman, 1977b).
The magnitude and the direction of the bias may changes according to the existing relationship

[23] While Makovec (2006) finds a strong correlation between the two equations, Capuano (2011) finds a positive correaltion between the two equations only if regional factors are excluded from the analysis. She justifies this result arguing that relocation decision is driven only by regional factors and not from individual factors.

[24] I should obtain corrected standard errors.

between unobserved factors and the endogenous variable. Mobile graduates could be more motivated and abile and higher earnings can be justified by a plausibile positive correlation between higher skills and earnings. Conversely, as explained by Maier and Sprietsma (2016) (2016), the "Stayers", being more motivated and able, find a job close to home or university and achieving higher labour market performances.

To avoid this bias I follow the two step procedure with a non parametric identification (Dustmann et al., 1997; Heckman, 1976), expoliting the predicted value obtained by the RBP described above. Even if the endogenus dummy in the wage equation is $y2$, following Maier Maier and Sprietsma (2016), Nichols (2011) and Wooldridge (2010), considering correlation between $y2$ and $y1$, I correct for endogeneity one step before, when I estimate the predicted probability of move after the high school graduation ($y1$). In the RBP presented in fact, even the variable $y1$ is endogenous and when I add this terms in the second equation I have to take into account it.

Therefore, in the RBP model, considering ante graduation mobility as a treatment variable and post graduation mobility as outocome variable, I estimate the marginal predicted probabilty of begin mobile after graduation $\hat{P}$, used as instrumental variable for $y2$ in the wage equation through a Two Stage Least Square (Heckman, 1977a; Maier and Sprietsma, 2016):

$$\hat{P} = P(y_{2i} = 1 | Intrume\hat{n}t_j, X'_{1i}, X'_{2i})$$

$\hat{P}$ should be considered a prediction which does not include part of mobility related to unobservable factors.

The two step procedure use the inverse Mills ratio which, being a nonlinear function of the variables included in the first stage, allows to perfectly identify equation in the second stage even without exclusion restriction. However, the nonlinearity of the inverse Mills ratio is based on the indipendent variable normality assumption in the first stage (a probit model), difficult to justify. This is why is common practice use a variable in the first stage not included in the second one. In literature, this procedure is called "exclusion restriction" (Amemiya, 1985; Maddala, 1986).

If we ruled out ante graduation mobilty from this analysis, a simple two step procedure requires, in the first stage, a probit model for post graduation mobility. In this case, the exclusion restriction implies that if variables used to specify $y2_i$ and the wage equation are the same, the β will be bias since X_i (which includes the selection term λ) and $y2_i$ are collinear (Chiburis et al., 2007).
However, in this exercise, the exclusion restriction is implemented differently since I try to resolve the endogeneity problem in three steps where the instrumental variable is included in the first equation y_1 and excluded from y_2.

However, from examples shown in literature is not clear if covariates specification for 2.1 and 2.2 must be the same.
Using the same model, Maier and Sprietsma (2016) show a procedure where the instrumental variable is added in y_1 and the covariates between the equations 2.1 and 2.2 are different.

Differently to this approach, as in a standard two step procedure (Stock and Watson, 2005), is possible to use the same set of covariates for the equation in 2.1 except the instrument, added only in y_1. Even if I follow the latter option, as robusteness proof, I verify even if, depending on the alternative covariates specification in the equation 2.1 and 2.2, the estimates undergo substantial changes.

Firstly, as suggested by Nichols (2011) I present the estimations for RBP model (table 2.1) and for the Two Stage Least Square ("2sls") (table A.5, appendix)[25] The tables suggest results robusteness since the "Ante graduation mobility" effect, as the effect of the control variables added (with expectation for the variable "Family social class"), keep significance and direction in both models.

As further proof I present in the table A.6 the effect of post graduation mobility on wage calculated using a different set of covaraites for y_1 on y_2, following than the approach proposed by Maier and Sprietsma (2016)[26].
The results suggest that the effect of $\hat{P}$ on earnings remains stable regardless the coavariates specification[27].

Another iussue concerns the need to use two instrumental variable for two endogeneus dummy. As clearly stated by Wooldridge (2010) the number of instrument should be equal to the number of endogenous dummy which in this case are two: mobility ante-graduation and mobility post-graduation.

However, it is no clear if in case of error terms correlation among y_{1i} and y_{2i}, one exclusion restriction is sufficient and, even comparing the procedure used by Maier and Sprietsma (2016) and Makovec (2006), this doubt is not overcome. Even if I use just one instrumental variable, as further robusteness proof, I add an additional instrumental variable for the equation y_{2i}, the "Internal Relocation Rate" (presented in the following paragraphs) in order to very possible changes in the estimation. The Internal Relocation Rate" (I.R.R.), already used by Cutillo and Ceccarelli in the estimation of workplace mobility on wages (2012), is deinfed as the ratio between the net yearly number of migrants cancelled in the region on the total regional population as on 1 January of the year.

Even in this case, use two instrumental variable doesn't change the results[28].

Instrumental variable approach has been subject to several critics since variable exogeneity is often difficult to prove. This is why several alternative methodologies has been proposed. One of them, already applied in very similar analysis is the Propensity Score Matching (Buonanno and Pozzoli, 2009; Di Cintio and Grassi, 2012; Makovec, 2006) which is based on a very strong assumption: it is possible to resolve the endogeneity controlling for a large number of "observable" covariates contained in the dataset (Martini and Sisti, 2009)). Consistent estimation with these tecniquie requieres a considerable number of observations other than a large number of covariates (Black and Smith, 2004) and even if the second condition is satisfied, the sample size at my disposal is not quite large (especially for the sub-population analysis) for a suitable "propensity score" specification.

[25]I would like to thank Austin Nichols from Urban Institute of Washington, DC for suggestions at this stage.

[26]Different set of covaiates for the RBP model imply a different value for the marginal predicted probability to move after graduation ($\hat{P}$).

[27]The coefficient of $\hat{P}$ is very similar respect the one obtained in the table 2.3 (5% versus 4%) even if the significance level is higher with the first approach.

[28]The results are not subject to substantial changes even using two instrumental variables and changing the set of covariates in the RBP model.

In light of this issue and of the arguments set out in previous paragraphs ("dualism", human capital clustering and differences in resources allocation), leading to the assumption that the relocation decision can be influenced by external factors[29], the instrumental variable approach is used.

I suppose that some factors as human capital clustering, labour market characteristics or educational supply, having different value in the individual utility function (Dahl, 2002; Moretti, 2013), exert some influence on relocation decision.
Among such factors, I use as instrument the "Scholarships" hypothesizing that differences in resoruces assigned at the time of leaving secondary education affect the probability of being mobile after graduation only through the migration at the beginning of university. In the next paragraph I'll explain how this variable is specified.

[29]Generally it is preferable use as instrument individual variable as parents condition, presence of sibling or family income (Black and Smith, 2004). Unfortunately, I couldn't find in the dataset a suitable variable useful to this aim.

2.6 Instrumental variable, self-selection and endogeneity

As introduced previously, analyze spatial mobility effects on labour market outcomes implies to face with endogeneity, occurring when one or more than one of the covariates are related to the error term in the model. One of the common caused of endogeneity is the omitted variables problems and specifically the "self-selection".

Even if the methodological procedure to overcome endogeneity are very similar, the causes of endogenity indicate different concepts[30]. In this excercise I use different concepts of endogenity according to different research questions. Endogeneity occurs in situation where the relationship between two variable is uncorrectly identified due to the presence of unobservables factors correlated to the endogenus variable. When I estimate the returns (in terms of earnings) of the geographical mobility I assume that bias comes from this unobserved relationship.
There is self-selection when the indipendent variable is observed just for a restricted sample of the population that occurs when I compare earnings among sub-population groups with different migration paths.
All causes of endogeneity are often resolved through two step procedure where, according to this research question, in the first stage, the probability to move is calculated using one (or more) variable correlated with endogenus dummy (or with treatment) but uncorrelated with the outcome variable.
The impossibility to identify exactly a causal relationship between two variable is a recurring problem in the estimation of schooling return, labourforce participation, unionization and even in migration since there are factors influencing geographical mobility and labour market outcome which are not directly observable by researchers but must be consdier to explain difference in returns to migration (Dahl, 2002; Malamud and Wozniak, 2008; Nakosteen and Zimmer, 1980). In this fremework we can have an upwards bias (or positive self selection) if there is a positive correlation between higher educational level and migration: is possible that major earnings are justified not by migration itself but from the presence of spillover effects coming by the presence of human capital (Bartel, 1989; Nakosteen and Zimmer, 1980) or, because more able individual are prone to move in places where the returns to human capital are higher (Borjas et al., 1992; Venhorst and Cörvers, 2015).

Otherwise, even if internal migrants possess greater ability or motivation than nonmigrant (Gabriel and Schmitz, 1995), as explained previously, at least in the short run, they might have to deal with "adjustments process" due to a unclear knowledge of the local labour market, with penalty in terms of wage, employability or job position (Rodríguez-Pose and Tselios, 2009). It is still questionable the direction of the bias and the type of selection in migration since the results on the effects of geographical mobility on wage present in literature differ according to methodology used and by the observation period lenght. Furthermore, with the instrumental variable approach, the results can differ even according to the exogenous variable used.

As explained, in the last econometric framework, I start from the hypothesis that liquidity constraints and resources available influence university choice: the amount of scholarships assigned at regional level represents an opportunity to offset the lack of resources provided by family.

Analyzing push and pull factors affecting student mobility Vergolini and Zanini (2015) exaplain that the scholarships provided by region can influence mobility.

Specifically Vergolini and Zanini (2015), analyzing the role of financial aids and schoolarships

[30] For an accurate discussion see Antonakis et al. (2010).

in shaping enrollment high school levers decisions, find that resource allocation doesn't increase the number of enrollment but increases student mobility and improves the match between university supply and student preferences[31].

Following this result, I use the number of scholarships awarded (on the number of eligible candidates, i.e. "idonei") at regional level[32] and the variable is specified as follow:

$$\text{Scholarship}_{it} \quad = \quad \frac{Scholarships\ \ awarded}{number\ of\ eligible\ candidates}$$

i=1,......,20
t=$\bar{t}$=2000...2006

Since one limit of this analysis is the lack of informations on the year of enrollment at the university and since the dataset is composed by two waves, I averaged the number of schoolarships assigned (in the origin region) on different academic years, from 2000[33] to 2006[34].

This variable is presented in percentage and should represents an index of resources available *per* student, provided by regions. The main intuition is that greater are resources transferred, lower is the likelihood to move in other regions; *viceversa*, smaller is the amount of resources assigned in the origin region, major would be the propensity to relocate to study.

Being an instrument, the variable "Scholarship" should have the following characteristics (Nichols, 2011):

1. correlated with the migration at start of tertiary education;
2. the instrument must be exogenus.

Exogeneity implies that scholarships assigned influence decision to relocate to work only through ante graduation mobility.
While the first condition find empirical evidence (see table 2.1), the second one may be argued sayng that even if regions with lower resources (typically southern) can be even those who face higher human capital losses, a direct correlation between resources in higher education and workplace mobility is hardly explainable.
Before to use this variable, I consider the possibility to use other variables as instrument:

- sleeping accommodation assigned on the number of applications submitted;
- "net migration rate" (%) at regional level (student mobility, years between 2004 to 2007).

[31]This study was implemented on sample of students from one Italian province (Trento).
[32]Regional institutions ("Ente regionale per il diritto allo studio") collect data (available on University and Research Ministry site ("MIUR")) on all services provided by regions to support educational costs.
[33]First year in which MIUR data are available.
[34]I would like to thank Federica Laudisa from IRES Piemonte ("Osservatorio regionale per l'Università e per il diritto allo studio universitario") for suggestions at this stage.

The first variable is very similar to the instrument used, and even though the effect of this variable is significant I prefer to use the variable presented above since it is a most comprehensive measure of the resources available at regional level.

The “net migration rate” shows if each region gains or loses human capital through student migration flows. Since is plausibile to assume that the decision to move to study in a different regions could be influenced by informations obtained through networks (friendships or family), I expect correlation between past migration rate (from origin region) and actual relocation decision. Therefor, the first condition for a strong instrument is satisfied[35].

Unfortunately the first year available in MIUR data is the academic year 2003/2004 and I can't use it as instrument for two reasons:

- past migration helps to resolve endogeneity only if goes sufficiently backwards in time. For example when I take the net migration rate in 2006 as past migration and net migration rate in 2007 as present migration, if the actual net migration rate is endogenous there's no justification for assume that the migration rate in 2006 is exogenus since it could be correlated with some trends in the labour market present in 2007 (unobservable factors affecting relocate decision in 2006 are the same of those present in 2007);
- the exact year of enrollment is not available and it could happens that there are some individuals enrolled at university before 2004 and the instrument presented loses values for this group.

Two points just mentioned raise doubts about instrument exogeneity.

Before to continue with the discussion it should be pointed out that in this step, as in the estimation of migration premium according to migration paths, im not considering observations not enrolled at university and not active in the labour market. These groups are not randomly selected across population and self selection issue led to possible additional bias in the estimation. Since no solutions are found to overcome these limits, the results interpreation requires additional caution.

[35]Furthermore use past migration in order to endogenize present migration is the mostwidely solution (Altonji and Card, 1991; Bartel, 1989).

2.7 Econometric specification: are there migration paths more convenient than others?

After having estimates the returns from geographical mobility on wage, I investigate if it is possible to find differences on earnings among migration paths.

Looking to the RBP model described with the equation 2.1, is possible to obtain the predicted probability for four outcomes:

$$\begin{gathered}\Pr(\mathrm{y}_{1i}{=}1,\ y_{2i}{=}0 \mid x_1, x_2)\\ \Pr(\mathrm{y}_{1i}{=}0,\ y_{2i}{=}1 \mid x_1, x_2)\\ \Pr(\mathrm{y}_{1i}{=}0,\ y_{2i}{=}0 \mid x_1, x_2)\\ \Pr(\mathrm{y}_{1i}{=}1,\ y_{2i}{=}1 \mid x_1, x_2)\end{gathered}$$

Each equation identifies a subset of the study population differentiated by migration choices before and post graduation [36] and respectively:

- Movers remained (those who move to study and reamins in the same region after graduation);
- Post graduate movers;
- Stayers (those who don't move at all).

The fourth combinations of the equations in 2.3 identifies two subgroups simultaneously, namely "Double Movers" (who move twice, to study and to work) and "Comeback" (who move to study and than come back in the origin region after graduation).

In this step I follow two approach used by Makovec (2006) and Cutillo and Ceccarelli (2012)[37] with some differences. Working on same data (but on different waves), Makovec estimates the effect on earnings of attending college in Nothern versus Southern regions, than considering only a one way movement, from South to North, without distinguishing between "Comeback" and "Double movers" (due to the small numbers of observations available). Cutillo and Ceccarelli (2012) use an Oaxaca-Blinder decomposition to compare earnings among movers and non movers after graduation, without take into account previous migration paths.

Here I use the Oaxaca-Blinder decomposition (Oaxaca and Ransom, 1994) to calculate earning's differences between groups identified with equation 2.3, taking always like a reference group the Stayers[38].

[36] Faggian (2009) identifies same groups.

[37] I thank Andrea Cutillo from ISTAT for valuable advices provided at this stage.

[38] Use the Stayers as reference group is standard practice. Furthermore the Stayers is the largest subgroup in the sample as shown in table A.1.

The Oaxaca-Blinder decomposition is specified as follow:

$$\underbrace{\bar{Y}_M - \bar{Y}_N}_{\substack{\text{Earnings difference}\\ \text{between Movers}\\ \text{and Stayers}}} = \underbrace{(\bar{X}'_M - \bar{X}'_N)\hat{\beta}_N}_{\text{Endowment effect}} + \underbrace{\bar{X}'_M(\hat{\beta}_N - \hat{\beta}_M)}_{\text{Migration premium}} + \underbrace{(\hat{\gamma}_M \bar{\lambda}_M - \hat{\gamma}_N \bar{\lambda}_N)}_{\text{Selectivity term}} \tag{2.3}$$

The decomposition is implemented as a sum of two terms: endowement effect and coefficient effect. The endowment effect quantifies differences on outcome varaiable explained by observed characteristics while the coefficient effect explains how observed characteristic are valued and compensated by the market.

The presence of self-selection implies that, to get an unbiased estimation of spatial mobility on wage, for every groups I calculate the inverse Mills ratio used as a covariate in the Oaxaca Blinder decomposition (Jann et al., 2008), implemented as many are the comparisons [39].

However this step is a little bit complex since, for two of the groups identified in 2.3, I have to consider simultaneously more than one selection related to mobility. For the "Post graduate movers" I can simply consider selectivity bias deriving by post graduation mobility, while for the "Moversremained" I consider only self-selection deriving by ante graduation mobility.

For two differents migration choices, two inverse Mills ratios (calculated with two differents probit), are estimated and used in the "corrected" Oaxaca-Blinder decomposition.

Contrary, for "Double movers" and "Come Back", since they move twice, I calculate two inverse Mills ratios, one for the first migration decision (ante graduation mobility) and one for the remigration decision (post graduation mobility), added simultaneously in the decomposition (Iammarino et al., 2017).
Even if identified by same equation, the last two groups are different and costs and benefits of migration and remigration can be considered differently (Tunali, 1986).

The two selection equations for "Double movers" and "Come Back" are specified with different instrumental variables: endogeneity of ante graduation mobility is resolved using the variable "Scholarship", used in the previous step, while for post graduation mobility I use the "Internal relocation rate" introduced in the previous paragraph. Using data on Italian interreggional residence transfer, I pick up the hypothesis discussed previously: the propensity to migrate from one region to another is a function of the number of people who have previously migrated from the same region (Cutillo and Ceccarelli, 2012).

The "Internal Relocation Rate" (I.R.R.) is deinfed as follows:

$$I.R.R._{it} = \frac{Cancelled\,in\;Region_{it}}{Regional\,population\,at\,1\;January} \qquad \text{i=1,......,20.}$$

$$\text{t}=\bar{t}\text{=1995,......,2006.}$$

[39]Di Cintio and Grassi (2012) estimate the effect of the regional mobility on the wage for five trajectories of mobility (study movers, work movers, early movers, late movers, back movers) using a Propensity Score matching.

I.R.R. is assigned to the region where individual attend to university and we expect that bigger is this value, bigger is the probability to relocate after graduation[40].
I calculated the average regional rate from 1995[41] to 2006, express in ‰.

The variable just described suffer of some limitations. The first one is about the "composition". Propensity to move varies by educational level (Shryock Jr and Nam, 1965) which is not specified in ISTAT data as well as the reason behind mobility[42].
The second limitation is the impossibility to identify origin and destination region.

Alternatively to the Oaxaca-Blinder decomposition, the migration premium for "Double movers" and "Come Back" can be estimated following the approach proposed by Tunali (1986), which estimates the effect of geographical mobility on earnigns take into account migration and remigration decision in a Bivariate Probit model (not recursive).

In presence of remigration process, as in this exercise, Tunali proposes to use a three steps procedure that adapted to this framework are specified as follow:

$$\begin{aligned} y_{1i}^* &= x'_{1i}\alpha_1 + Schoalrship + \varepsilon_{1i}, \\ y_{2i}^* &= x'_{2i}\alpha_2 + I.R.R. + \varepsilon_{2i}, \\ ln\_w_i &= \alpha + x'_{1i}\beta + x'_{2i}\gamma + \lambda_1 + \lambda_2 + \upsilon_{1i} \end{aligned}$$

where λ_1 and λ_2 are the invers Mills ratios calculated with two Probit models for two selection equations y_{1i} and y_{2i}. Migration and remigration are specified with the following rules:

Stay	if $y_{1i} = 0$ and $y_{2i} = 0$
move once	if $y_{1i} = 1$ and $y_{2i} = 0$ or $y_{1i} = 0$ and $y_{2i} = 1$
move more than once	if,$y_{1i} = 1$ and $y_{2i} = 1$.

and "Double movers" and "Come back" are identified with the following equation:

$$M = \begin{cases} 1 & \text{if } y_{1i}^* > 0 \text{ and } y_{2i}^* > 0 \text{ ("Double movers" and "Come Back")} \\ 0 & \text{Otherwise} \qquad\qquad\qquad \text{("Stayers")} \end{cases}$$

[40]Even if not shown in the Oaxaca-Blinder decomposition results, the direction of the effect of I.R.R on y_2 is positive and highly singnificant.
[41]The first year available on the ISTAT website for the regional residence cancellation. The data are available in the ISTAT website for demographic information, http://demo.istat.it.
[42]The same issue will be treated in the next chapter.

This structure is similar to a Bivariate Probit model where M_i is given by the product of y_{1i} and y_{2i}. Than I can write the probability of a positive outcome as follow:

$$\Pr(\mathrm{M}_i{=}1) = \Pr(y_{1i} = 1, y_{2i} = 1) = F(\mathrm{x}_{1i}\alpha_1,\, x_{2i}\alpha_2,\, \rho)$$

where F is cumulative distribution function.
The difference with the Bivariate Probit model is that all the observations where ($y_{1i} = 1$ and $y_{2i} = 0$) or ($y_{1i} = 0$ and $y_{2i} = 1$) are identified through M_i.
This model is estimable through a "Bivariate Probit model with partial observability" (Poirier, 1980), where joint outcomes take the form of a dichotomous observable variable (Tunali, 1986). STATA allows to estimate Poirier's model and the inverse Mills ratio used to correct the double selection for "Double movers" and "Come back".

However I didn't used this model for several reasons.
The model propesed by Porier is not recursive, this means that the first dummy indicating ante graduation mobility is not added as control in the post graduation mobility equation. Since I have not found in literature any empirical example adaptable to this analysis that use a RBP model with partial observability I avoided to use it, even for the small sample size discussed. In fact, as my knowledge, in order to estimate a RBP model and obtain the maximum likelihood estimation an adequate number of observations is required especially for a Poirier specification.

This limits are confirmed since i've tried to estimate Poirier model model without reaching model convergence, even using few controls for the two selection equations.

2.8 Empirical results for the Recursive Bivariate Probit model

The table 2.1 reports the results for RBP model[43]. First observation is on "goodness of fit": the model fits the data well (χ^2=2344.87; p < 0.000) and most parameters are statistically significant. Furthermore the LR test (χ^2=42.10) suggests that the disturbances error for the two equations are significantly correlated and the main hypothesis justifying the use of the RBP model is respected [44]. In fact the estimated correlation 0.407, is far away from zero and is statistically significant (p < 0.000).

In the ante graduation mobility equation I find a significant value of the "Net Migration rate" with a sign in line with the expectation: bigger is the net migration rate in the origin region, less is the probability to move after high school.
The "Scholarship" is significant and the coefficient direction suggests that the number of scholarships awarded in the region before enrollment are negative correlated with probability to move after high school, even if the coefficient is quite low (-4%). The last result is in line with Pigini and Staffolani (2015) which show that the resources available at regional level act as attractivenes measure for the high school leavers. Cattaneo (2017) finds very similar result but, differently from here, he assigns the value of the variable "Scholarship" to the origin province (before to start tertiary education)[45].
On the university size of the region before enrollment, it is possible to note that value are positive but only "mega" university size seems have influence on relocation decision (reference categorie: small). If we assume that students prefer to enroll in univerisity with larger number of courses (Pigini and Staffolani, 2015), we can expect that bigger are universities in the region of origin, less is the probability to move. However it is also possible, as this result confirms, that the student might prefer small size universities since these may offer higher teachear standard or a more efficient placement service (Bacci et al., 2008).
The variable "University size" in the right side of the table 2.1 referes to the size of the university attended and show an opposite effect (even if non significant) on relocation probability after graduation: greater is the size, lower the probability to move after graduation.

The occupational rate, that allows to control for the heterogeneity between local labour markets (Sá et al., 2006)[46], is based on ISTAT historical time series[47] is assigned to the region before enrollment for the equation y_1 and to the university region for the equation y_2.
The coefficient is significant and higher but the sign show a counterintuitive result, especially if read considering the variable "High school area": an higher occupational rate is associated with a greater probability to move before graduation.
This can be explained saying that the economic factors have less relevance in the relocation decision before graduation where, indeed, the "consumption reason" for migration (amenities, quality of life etc.) might have higher weight.

[43]For a variable structure description see table A.2 in the appendix.

[44]Otherwise two different probit model would be used.

[45]In order to verify the consistency of the variable, I've tried to assign this value to the region where people attend to university getting anyway similar results in terms of significance and direction.

[46]I have to stress that as explained by Etzo (2011) the unemployment rate is itself endogenous and may be simultaneously determined with migration.

[47]The ISTAT web site provides time series for the occupational rate at regional level from 2004 to 2017. Here I take an average of different years depending on the equation considered (2004 to 2008 for the first equation and 2009 to 2014 for the second equation). Data are available at the following link: http://dati.istat.it/

The variable "Transport quality"[48] is a satisfcation index on transport means provided annually by the ISTAT. To cover observational period, I consider an average of data collected in different years, selected according to the equation considered: years from 2003 to 2007 for y_1 and years from 2008 to 2012 for y_2. The index is based on the most importants means of transport: bus, train and pullman (turistic, regional)[49].

Trasport is one of index used to rank provinces quality of life, annualy update by the main national newspapers ("IlSole24ore" and "LaRepubblica") and among different contextual variables available may exerts a particular relevance in relocation decision. In fact, previous results (Demarinis, Iaquinta, Leogrande, and Viola, Demarinis et al.; Etzo, 2011) show that interregional migration flows are favored by the presence of good trasports both at origin and destination[50] and the same result is confirmed here: the coefficient is significant (even if the magnitude is low) for the first equation suggesting that more satisfaction on transport quality discourage ante graduation mobility.

In contrast to previous results which showed a propensity to move greater for female (Faggian and McCann, 2009), the results highlight that female are less mobile, especially after graduation (5% less than male).

Even if non significant, to higher high school marks are associated negative moving likelihood. Conversely,for post graduation mobility, those with better academic performance (especially those with a degree mark higher than 106) are those with an higher probability to relocate. In line with previous empirical findings for Italy (Bacci et al., 2008; Impicciatore and Tuorto, 2011), this result support the hypothesis of a positive self-selection (those who are more motivated or skilled are more prone to move)[51].
On the family background, (variable "Family social class") I find interest results. Others empirical analysis show how family income and liquidity constraints are relevant factors affecting decision to relocate after high school graduation (Kratz et al., 2011; Lupi and Ordine, 2009). Even if the coefficient is significant only for the last class, I find very similar results since to an higher social class is associated greater probability to relocate ante graduation, in line with descriptive statistics presented in the table A.3.
For y_2 I find opposite results even in comparison to previous litearture findings. In fact, while Ciriaci and Nuzzi (2012), using same data, but differents waves, support the thesis that probability to relocate after graduation is higher not for most skilled students but for those wiht more economic support, the table 2.1 shows an opposite result. However, the latter should be read with caution since the social class index, here made up as the most prestigious professional position between father and mother, in addition to being an approximation for the family economic condition, is arbitrary .

However, if we suppose that individuals move in order to improve own social condition and obtain better match in the labour market or if we suppose that family support (economic and psychological) exerts its greater influence more in university choice than in post graduation mobility, we might also expect greater propensity to move after graduation for those with low family

[48] I thank Roberto Fantozzi from ISTAT for the help provided in the data selection.

[49] Croce and Ghignoni (2015), use as transport quality proxy (congestion) the accidents per 1000 cars in the local labour market.

[50] As stressed by Cattaneo et al.(2017), the recent increase in competition, lowering prices, has facilitated regional as provincial journeys.

[51] Furthermore, even without achieving significant results, for equation y_1 and as proxy for individual ability, I add a dummy variable indicating if the student have obtained the title on schedule ("On time").

background.

Since as stated by Faggian et al. (2007) not necessarily prestigious profession are associated with higher education, I decide to keep separate the parental education effect.

The results suggest that the higher educational level is strongly correlated with ante graduation mobility. For example having at least one parent with a B.A or M.A. increase the probability to move by 20% points. This results may also be explained considering that most of psychological costs are due to cultural gap between origin and destination (Brezis et al., 2011), and these can be reduced if we assume positive correlation between family support and family educational level.

In the first equation, I add as a control, the macro-area where the people obtained high school graduation ("High school area") while, for the second equation, I use as a control the university macro-area. In line with expectation and previous findings (Ciriaci, 2009; Di Cintio and Grassi, 2012), Southern regions and Islands are those showing higher propensity to move before graduation.

Less clear are the results for the post graduation mobility since differences between macro-areas are not so marked and only northern region show significant correlation[52]. Literature suggests several hypotheses on reasons behind such differentiating paths by macro-area. For example, for Italy, Etzo (2011) shows that northern migrants (coming from richer regions) place greater weight on site-specific amenities as climate or quality of life and is plausibile assume that according to the macro-area of origin, individuals respond differently to differences between places.

On the type of high school graduation, I find that those coming from vocational school are less prone to move before graduation (baseline categories is lyceum)[53] while, for the field of study I find a significant coefficient only for economics, which is negative correlated with post graduation mobility. However, differently from what is suggested by empirical evidences, is plausibile expect that quantitatve fileds show less mobility since, as argued by Kratz (2011), should guarantee greater probability to find a jobs in university region.

As living cost measure I use data provided by national newspaper "Il sole 24Ore" which carries out (annualy) reviews of housing costs[54] and monthly rental costs (by provinces).

As for the occupational rate and the trasport quality, this is an average on three different year (2003, 2007 and 2011) and the value is assigned in to province before enrollment for the first equation, "Housing cost (origin)" and to the province where people attend to university, "Housing cost (university province)". The reason why different years are selected is that using two waves (graduates in 2007 and graduates in 2011), individuals can decide to move in a very wide temporal range[55].

However, the living cost measure used is rather rough and the results should be read carefully[56]. Furthermore the variable structure is different among y_1 and y_2. For 2003 only rental prices are available while for the 2007 "IlSole24" survey provides global housing costs. The average on

[52]I've tried to substitute the university macro-area with high school macro-area in y_2, obtaining that those coming from South and Island are more prone to move even after graduation.

[53]Makovec (2006) shows that have attended to lyceum increases ante graduation probability to move, with a greater extent for northern students.

[54]Cost per square meter in euro.

[55]Since even for graduates in 2007 relocation after high school is considered, the time frame goes (presumably) from 2003 to 2011.

[56]A more comprehensive measure, other than considers the exact amount paied for a rent, should take into account even the location (near o far to unviersity) since differences in terms of accessibility give more information on individual socioeconomic condition.

two years is necessary and to overcome limits poses by different data structure, the index must be defined as a difference form the national mean (rental price for 2003 and housing cost for 2007)[57]. Than, the variables used have a different value even if is plausibile to suppose that at higher rental costs can be associate to higher housing costs[58].

Table 2.1 show a negative correlation between housing costs and the two relocation decisions, even if the coefficients magnitude are very low. It is possible to suppose that to higher living costs correspond higher occupational opportunities which disincentive mobility. However, as empirical evidences suggest (Etzo, 2011), if we suppose that higher disposable income, allowing to deal with transaction cost, is associated to higher living costs, even a positive correlation with mobility can be justified, especially for first move decisions. Unfortunately, the working of this "inderect channel" is difficult to disentangle without more accurate data.

Again on the estimation of the "contextual variables" effects, clearer relationships can emerge if defined as difference between origin and destination region (Rabe and Taylor, 2012), as indeed it was done in other works which try to estimate the effect of differences in housing prices on labourmobility (Cannari et al., 2000; Mocetti et al., 2010).

However, in this analysis expressing all contextual variables as difference between origin and destination, implies that is not possible to assign the relative value to those who don't move. To overcome this problem a try a different specification calculating the difference between the variable assigned to the orgin region and the national mean for mobility to study, and the differences between the variable value assigned to the university region and the national mean for the post graduation mobility. However, probably because regions showing mean values under the national mean are always southern regions, collinearity led to exclude such variable from the analysis.

The right side of the table 2.1 shows that mobility ante graduation is a good predictor for post graduation mobility: having moved to study increases relocation probability after graduation by 18%[59].

Respect to the equation y_1 I introduce as additional control the age at time of graduation. Even if the original dataset provides only age in classes, I find (wiht all coefficients strongly significant), in line with previous results (Ciriaci, 2014; Kratz et al., 2011) that is negatively correlated to migration probability.
This results, concurrently with results obtained on the graduation mark and on the dummy "On time", suggest a movers positive selection, *i.e.* are those completing to study early and with higher graduation mark that move after graduation.
This hypothesis is also supported by the dummy "Network" if we assume that the social network is a signal of lower skills and/or motivation.

The set of dummy variables indicating post-lauream specialitation (completed) show very different results. At first, i've added a unique dummy, comprising all the type of specializations, but, to disentagle different effects, I decide to keep them separate. Those who completed a

[57]This is why negative values are possible (see table A.2 in the appendix).
[58]Pigini and Staffolani (2015) use secondary school graduates survey (2004) provided by ISTAT and to measure the housing costs effect on enrollment decision they exploit the 2003 "IlSole24" survey dividing rental costs by 5, under the assumption that 20 square meters correspond to an average acceptable size for a room.
[59]Ciriaci and Nuzzi (2012) find that the effect of mobility ante graduation increase the probability to move after graduation by 77%.

Phd are less likely to move post graduation[60] while who continue with Master or stage ("in firms") show higher propensity to move. Finally those who have concluded a training for liberal profession (variable "Training") show a lower moving probability.

For the dummy "Married" (at time of inteview), the direction of the effects is in line with the expectation (Kratz et al., 2011) and is negative correlated with mobility after graduation even if the coefficient is not significant and the magnitude is low[61].

The second last dummy on the right side of the table 2.1 show that those who have gradauted in a private university show less probability to move by 10%. Finally, since Im considering two waves, two year dummy are added. The coefficients are highly significant and even the magnitude is quite large. This support the hypothesis of a rising migration propensity after 2009 (see figure 2.1)

2.9 Empirical results for the wage equation

Comparable results for the estimation of the equation 2.2 can be found in three empirical works by Makovec (2006), Cutillo and Ceccarelli (2012) and Maier and Sprietsma (2016).

Considering only mobility from southern to northern Italian regions, Makovec estimates the eranings returns of attending to a North University versus a South one.
Using a two steps procedure ("endogenous switching regression model") finds that those who move early earn more than both those who do not move at all and those who move later (after graduation). Furthermore, with the Oaxaca-Blinder decomposition, shows that those who move are those with better "endowment" (positive selection).
As instrumental variable for y_2 uses the presence of children while, for y_1 he uses 4 instrumental variables, mainly referred to differences in educational supply: a dummy indicating whether the student was living in a main city ("capoluogo"), a dummy capturing whether a university was recently founded in the origin province, the total number of undergraduate courses supplied by universities located in each province before enrollment, and, finally, a dummy capturing whether it was present a polytechnic in the high school province.

Cutillo and Ceccarelli (2012), looking to differences in wage only after graduation[62] with a switching regression model find a relavant gap between migrants and non migrants: move after graduation increase wage by 10%. They find also a positive self-selection arguing that also if migrants start from a lower wage (due to a bad knowledge of the local labour market), may still get higher wage thanks to greater ability and motivation.

Even Maier and Sprietsma (2016), using the same model presented in this exercise, find a positive wage returns to regional mobility for the first job [63].

The results presented in this paragraph confirm the literature findings. Firstly, from the F-value of excluded instrument we can conclude that the predicted mobility after graduation derived from the RBP model (equation 2.1) is strongly correlated with actual regional mobility and that the instrument is strong.

[60] However I don't know if the Phd is completed in the region where individuals get the M.A. or if it started in a different region.

[61] This can be due to the low number married individuals. See table A.2 for descriptive statistics.

[62] They didn't consider ante migration mobility and differents migration paths.

[63] Differently from here they use longitudinal data and the log hourly wage as dependent variable.

The first regression for the wage equation (table 2.2) is estimated without take into account endogeneity while the table 2.3 show results for the wage equation estimated with endogeneity correction.
The effect of the post graduation mobility is strongly significant in the first table and remains very similar in the second one: interregional migration after graduation is associated to greater earnings (even if the value is low and varies between 4% and 5%). The table 2.3 reports even all control variables used. As stressed by Mocetti (2013), higher housing costs in the working province are associated to higher earnings (even if the coefficient magnitude is not particularly high) and, furthermore, in line with expectations, to higher job specializations are associated higher wages. The parent education doesn't have effect on wage while higher family social classe is strongly correlated with higher earnings.

As expected those engaged in part-time job earn much less than full time worker (around 50%) while, considering different working area, those located in western regions mantain a wage gain respect to the others macro-area, especially South and Islands.
As stressed previously, attend to a private universities, generally smaller than public ones and then able to provide better placement services, disincentivizes mobility post graduation (even if the coeffiecient is not significant).

In line with previous empirical findings (Makovec, 2006; Oaxaca, 1973), quantitative field (engineering and economics) give higher wage returns than math and physic (scientific is the reference category) while women earn less by 8.6% point .

The last consideration is on the experience, a continuos variables (see table A.2) giving the months intercurrent between the first job and the time of interview. Even if months used to find the first job are considered (and ruled out), this is a very rough measure for the accumulated experience since doesn't take into account possible job breaks or job change[64]. However, I find a positive correlation with earnings, but low, being observations at the beginning of their professional career.

[64]Unfortnualy is not available any additional information helping to measure accurately working experience.

Table 2.1: **Recursive Bivariate Probit: marginal effects**

Ante graduation mobility	Marginal Effect	Post graduation mobility	Marginal Effect
Net Migration Rate	-0.412***	Ante graduation mobility	0.186***
Scholarships	-0.040**	Housing cost (university province)	-0.00004***
University size (high school area): medium	0.308	Female	-0.0532***
University size (high school area): big	0.378	Family social class: medium	-0.00853
University size (high school area): mega	0.387*	Family social class: high	-0.020
Occupational rate 2004 2008 (%)	0.775***	University macroarea: North East	0.088***
Trasport quality 2002-2007	0.019***	University macroarea: Center	0.0956***
Female	-0.0005	University macroarea: South	0.094
High school mark: medium	0.005	University macroarea:Islands	0.078
High school mark: high	-0.008	Engineering	0.00240
Family social class: medium	0.013	Economics	-0.0474**
Family social class: high	0.055**	Social	-0.0352
Poli. high school area	-0.028	Humanities	-0.0161
High school macroarea: North East	0.064	Physical educ.	-0.0206
High school macroarea: Center	0.241***	Family study title: middle School	0.00437
High school macroarea: South	0.437***	Family study title: high school	0.0610
High school macroarea: Islands	0.540***	Family study title: graduated	0.0437
High school track: psico. Art.	-0.020	Family study title: post gradut.	0.0868*
High school track: vocational	-0.085***	Transport quality 2008 - 2012	-0.00343***
Family study title: middle School	0.043	Occupational rate 2009 2014 (%)	-1.331***
Family study title: high school	0.086*	Age: more than 23-24	-0.046*
Family study title: graduated	0.200***	Age: more than 25-29	-0.062**
Family study title: post gradut.	0.152***	Age: more than	-0.094***
Housing cost (origin)	-0.0002***	University size: medium	0.024
Year (2015)	0.203***	University size: big	-0.029
		University size: mega	-0.043
		Network	-0.0787***
		On time	0.002
		Grad.Mark: 91-100	0.047**
		Grad.Mark: 101-105	0.050**
		Grad.Mark 106-110	0.087***
		Grad.Mark 110 lode	0.059**
		Ereasmus	0.067***
		Phd	-0.127**
		Specialization	0.027
		Scholarship (work)	0.049*
		Master	0.137***
		Stage	0.073***

Continued on next page

Table 2.1 – continued from previous page

Ante graduation mobility	Marginal Effect	Post graduation mobility	Marginal Effect
		Others spec.	-0.014
		Training	-0.059***
		Training (educ)	0.054*
		Polytechnic	-0.007
		Married	-0.007
		Private	-0.101**
		Year (2015)	0.209***
N	5281		
	Coeff	**Stand.errors**	P>z
/athrho	0.432	0.066	0.000
ρ	0.407	0.055	
Wald test of rho=0		chi2(1) = 42.10	Prob > chi2 = 0.000
$\chi^2 = 2344.87$			p < 0.000

(dy/dx) is for discrete change of dummy variable from 0 to 1
* p<0.10, ** p<0.05, *** p<0.010
Cluster standard errors

Table 2.3: **Regression with instrument**

Dependent variable: Monthly earnings (log)

	Coeff.	**Stand.errors**
Post graduation mobility	0.053**	(0.023)
Housing cost (working area)	0.001**	(0.000)
Job specialization: middle	0.079	(0.076)
Job specialization: low-middle	0.072	(0.075)
Job specialization: high	0.079	(0.075)
Family study title: middle school	0.030	(0.028)
Family study title: high school	0.026	(0.028)
Family study title: graduated	0.031	(0.036)
Family study title: post gradut.	0.034	(0.031)
Part-time	-0.509***	(0.026)
Private university	0.032	(0.028)
High school mark	0.007	(0.008)
Family social Class: medium	0.044***	(0.013)
Family social Class: high	0.041**	(0.016)
Field of study: engineering	0.055***	(0.015)
Field of study: economics	0.027	(0.016)
Field of study: social	-0.069***	(0.020)
Field of study: humanities	-0.140***	(0.020)
Field of study: physical education	-0.088*	(0.052)
Female	-0.086***	(0.012)
Age: 23-24	0.010	(0.019)
Age: 25-29	0.036	(0.024)
Age: more than 30	0.021	(0.036)
Graduation mark: 91-100	0.004	(0.019)
Graduation mark: 101-105	0.023	(0.019)
Graduation mark: 106-110	0.013	(0.022)
Graduation mark: 110 Lode	0.056***	(0.021)
Working area: North East	-0.032**	(0.013)
Working area: Center	-0.073***	(0.016)
Working area: South	-0.087***	(0.022)
Working area: Islands	-0.175***	(0.058)
Network	-0.011	(0.015)
On time	0.030**	(0.012)
Phd	-0.036	(0.049)
Specialization	0.001	(0.028)
Master	-0.002	(0.021)
Scholarship (Work)	0.015	(0.033)
Stage	0.033***	(0.011)
Other spec.	-0.025	(0.019)
Training	-0.082***	(0.017)
Training (educ)	-0.003	(0.027)
Experience	0.004***	(0.000)
B.A.	-0.022	(0.017)
Self-employed	-0.587***	(0.037)
Married	0.016	(0.014)
Year 2015	-0.071***	(0.014)
_cons	7.015***	(0.091)
N	5281	

F test of excluded instruments:
F(1, 5280) = 1378.52
Prob > F = 0.0000

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

2.10 Empirical results for the Oaxaca-Blinder decomposition

Mains empirical findings comparable on the results achieved with the Oaxaca Blinder decomposition are proposed by Makovec (2006) and Di Cinitio and Grassi (2012).
The latter, using same data (waves 2004 and 2007 for graduated in 2001 and 2004), applies a Propensity Score Matching to compare labour market outcomes for the migration paths identified in 2.3[65] and the results found are the follows:

- the "Comeback" show little benefits (in terms of wage) respect to others group;
- those showing greater benefits are those who move after graduation.

Furthermore, thanks to a considerable amount of observations, they divide the sample according to the macro-area of origin and applying the same methodology, finds that graduates coming from southern regions have good performances if the find a job in norhtern regions.

As explained, the propensity score matching starts from the strong assumption that is possible to resolve endogeneity only through information provided by the dataset (Martini and Sisti, 2009). However, even if useful to balance observed covariates between groups, the Propensity Score method doesn't allow to overcome the omitted variable bias discussed above, *i.e.* doesn't allow balance between unobservable characteristichs. Furthermore, to have a good specification of the propensity score (which is the probability of being treated), only pre treatment variable should be included (Caliendo and Kopeinig, 2008; Garrido et al., 2014; Jones, 2007; Winkelmayer and Kurth, 2004) and, since with data available is not possible to ruled out exactly when the individual moves (treatment), a good covariates specification is hardly achievable[66].

With a similar research question, Makovec (2006) use both Oaxaca-Blinder decomposition and Propensity score in order to verify if it is convenient to move from south to north regions to study and work.

In the decomposition exercise, he finds that differences in exptected earnings are always significants for the three population subgroups (which corresponds here to "Movers remained", "Post graduation movers" and "Stayers"): attending college in Northern (and find a job there) versus Southern regions give more earnings respect to who move after graduation and respect to "Stayers"[67]. The propensity score method confirms the results of the first decomposition.

Since are not present in literature empirical findings focused on "Double Movers" labour market outcomes I try to close this gap comparing them with "Come back" and "Stayers".

The tables 2.5 and 2.6 reports wage differences (respect to "Stayers") for the last groups mentioned.

The unadjusted procedure (fourth line of the tables) show a positive gap (8%) for "Double Movers" and a negative one (10%) for "Come back". However, applying the adjusted procedure (eighth line of the tables), the estimation are subject to greater changes since for the "Double

[65]They implement 7 comparisons considering different treament and control groups.
[66]An esaustive desription of the causal model and of the use of the propensity score is suggested by Nichols (2007).
[67]As in this excercise, this is the groups with higher number of observations.

Movers" the gains on the Stayers become of 16% ("downard bias") while for the "Come back" the results completely turn over in terms of coefficient magnitudine and direction.

In both comparison, the endowmente effect ("explained part") is significant. This parameter can be interpreted as the mean increase in the stayer's wage if they had the same characteristchs of the compared group, *i.e.* the explained part represents the difference in earnings due to different characteristichs for individuals belonging to different groups.

Indeed, the coefficient terms (unexplained part or "migration premium") quantify the change in the relative groups when I apply the "Stayers" coefficient for the entire sample (Jann et al., 2008) and can be interpreted as the "labour market discrimination", *i.e.* how the labour market evaluates mobility.
In others words, the unexplained part is the migration disparity in wage that would remain even if "Double Movers" or "Come back" had the mean levels of the "Stayers" measured characteristics (Sen, 2014).
However, in the both comparisons, the coefficient for the unexplained part is not significant, suggesting that the differences in earnings among the two group are due to differences in observables characteristics.

As further proof for the presence of selection bias, I add as a covariate in the wage equation the inverse Mills ratios, assessing their significance. If the inverse mills ratio coefficient (which represents the covariance between the errors in the wage and the migration equation), is significant the adjusted procedure finds empirical justification (Tucker, 2009).
For the "Come back", the selection term is positive for post graduation mobility and negative for ante graduation mobility while, for "Double Movers", I find opposite results. However, in both equations, they are never significant.

Following the selection term interpretation suggested by Cutillo and Ceccarelli (2012), a negative coefficient for the inverse Mills ratio indicates that there are unobserved factors increasing the probability of selection and decrease ("downward bias") the score on the dependent variable. When the coefficient is positive, than there are unobserved factors increasing both the probability of selection and the score on the dependent variable ("upward bias"). The direction of the bias is confirmed by selectivity term sign (downward bias for the Double Movers and an upward bias for the Come Back), but, as explained, lack of significance for the unexplained part and for the inverse mills ratio suggests that are the observable variables explaining earnings differences between groups.
The others two tables (2.7 and 2.8) compare "Stayers" with those who move after graduation ("Post graduation movers") and with the "Movers Remained". Those moving after graduation exploit a wage premium on the "Stayers" by 11% points while those moving before graduation and working in the same region where they attend to university show lower eranings by 5%. The adjusted procedure confirms the results even if in the table 2.8 earnigs differences between "Stayers" and "Movers Remained" becomes not significant. A slightly differences regards the unexplained part for those who move after graduation that is the unique one significant (even if, in a preliminary regression I find that the inverse Millls ratio is not significant and positive). Indeed, for the second comparison (table 2.8) I find that the inverse Mills ratio is significant and positive, suggesting than an upward bias, confirmed comparing adjusted and unadjusted coefficients.

From this results appears that some differences between the migration paths considered exist. In general there are eranings gains from mobility but they differ according to mobility pattern after graduation. Those who come back at home after graduation or decide to remain in the region where they attend to university show lower earings while those who move two times (before and after graduation) or only after graduation show higher earnings. Between the last two groups, looking to unadjusted procedure, are those who move after graduation that have greater benefits from mobility. Higher earnings for "Post graduation movers" is confirmed implementing the Oaxaca Blinder decompostion (without correction since in this case it not possible to calculate the inverse mills ratio) between this group and the "Double movers": "Post graduation movers" show a wage premium on the "Dobule movers" of 3%.

From the table 2.4 is clear how the results are subject to marked changes when the adjusted procedure is applied, especially for "Come Back" and "Dobule movers". As additional tests i've implemented the Oaxaca decomposition changing the set of covariates used in the selection equations (y_1 and y_2) findings that a slightly change in the covariates used in the first step to calculate the inverse Mills ratio, produce very differnts results[68]. Reasons for a low results robusteness can be found or in the small sample size or in the incorrect specification of the two steps procedure used to overcome self-selection. However disentagle the two effects is hardly achievable with data available and further researchs are necessary. My suggestion is to interpret the results with caution and, by the way, is arguably to give more reliability to the andjusted procedure, which appear to be more stable and consistent even with descriptive statistcs (table A.4).

[68]Even in this case some differences between comparison appear and the results presented in tables 2.7 and 2.8 seem more stable.

Table 2.4: **Oaxaca-Blinder decomposition**

Table 2.5: **Stayers Vs. Double-movers**

n1=2384 n2=596		
	Coeff.	Stand.errors
Overall		
Stayers	7.172***	(0.008)
Double-movers	7.252***	(0.017)
Difference	-0.0807***	(0.019)
Adjusted		
Stayers	7.172***	(0.008)
Double movers	7.265***	(0.083)
Difference	-0.166**	(0.083)
Explained	-0.0354***	(0.015)
Unexplained	-0.1309	(0.082)
N 2980		

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Table 2.6: **Stayers Vs. Comeback**

n1=2384 n2=563		
	Coeff.	Stand.errors
Overall		
Stayers	7.170***	(0.008)
Come Back	7.069***	(0.022)
Difference	0.103***	(0.024)
Adjusted		
Stayers	7.170***	(0.006)
Come Back	7.201***	(0.050)
Difference	-0.0315	(0.049)
Explained	0.112***	(0.016)
Unexplained	-0.144	(0.128)
N 2947		

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Table 2.7: **Stayers Vs. Post graduation movers**

n1=2384 n2=757		
	Coeff.	Stand.errors
Overall		
Stayers	7.172***	(0.008)
Post grad. mover.	7.286***	(0.015)
Difference	-0.114***	(0.017)
Adjusted		
Stayers	7.172***	(0.008)
Post grad. mover.	7.296***	(0.032)
Difference	-0.125***	(0.033)
Explained	-0.0699***	(0.013)
Unexplained	-0.0558*	(0.031)
N 3141		

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Table 2.8: **Stayers Vs. Movers-remained**

n1=2384 n2=981		
	Coeff.	Stand.errors
Overall		
Stayers	7.171***	(0.008)
Movers remained	7.115***	(0.020)
Difference	0.056***	(0.026)
Adjusted		
Stayers	7.171***	(0.008)
Movers remained	7.125***	(0.177)
Difference	0.046	(0.177)
Explained	0.0158	(0.017)
Unexplained	0.0305	(0.176)
N 3365		

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

2.11 Conclusion, limits and further research

The analysis carried out suggests a positive effect of spatial mobility on earnings with some differences according to different migration paths, specially due to post graduation migration choices. While “Come back” and “Moversremained” show losses in earnings, “Double Movers” and “Post graduation movers” show a wage premium on “Stayers”. Looking for a job on a national scale seems compensates direct and inderects cost of migration which, from the table A.1, are being dealt with by southern regions. As already hypothesized by Di Cinto and Grassi (2012) the results appear to confirm that, in spite of lower resources, Southern universities prepare graduates performing well in different labour markets. However, to draw such conclusion, further decomposition should be implemented. If, as shown in the descriptive statistics of this analysis, Italy is still facing with a “brain drain” phenomenon, to keep human capital in southern regions, innovations in educational supplies, accompanied by a parallel evolution of local labour markets, must be implemented. If the low educational level continues to characterizes workforce composition, north-south gap can be hardly reduced and educational policies, which must be supported by adequate resources, may have less effects if new professions with high human capital are not included as further possibilty of local development.

However, as stressed several times in this chapter the result interpretation should proceed carefully. Firstly all the estimation should be read take into account an additional self-selection since the sample is composed by graduates already employed. Than the relationship between unemployment and migration, which has a considerable weight in migration literature (Hämäläinen, 2002; Pekkala and Tervo, 2002; Pissarides and Wadsworth, 1989) is not considered in this analysis.
Furthermore, additional bias can arise from selectivity in education since those enrolled to university are not randomly selected among high school graduated.

A second observation must be made on the time frame considered (4 years after graduation). Even if higher earning variance among early graduates can be found, the return on education at beginning of working career tend to not differs significantly within country and long run analysis may be preferred (Ciani and Mariani, 2014). On this point, several works explain the relevance of using longitudinal data to estimate the migration effect on labour market outcomes (Hilmer, 2000) given that the migration effects could reflects temporary situation or a transition phase in the labour market making more difficult to identify a casual link with economic performances (Argentin, 2010). However, even if some alternative datasets[69] would allow the analysis to be extended over the long term, the degree of precision with which mobility is defined, it is subject to a considerable reduction. As best of my knowledge, ISTAT and Almalaurea surveis are the unique data sources with specific information on relocation decision.
A solution can be to evaluate the spatial mobility effect on the occupational status (contract, job specialization and career breaks) or different measure of performances[70].

Other limitation regards the data used that although suitable to research questions discussed, do not allow to define the exact moment of migration. As explained in the next chapter in fact, the “timing” of mobility is essential to estimate returns to spatial mobility, epsecially in short run analysis. Furthemore the timing of mobility helps to overcome the “reverse causality” between

[69]Some waves of the Bank of Italy survey on household income and wealth make possible to identify origin region, university and working region.

[70]Ghignoni and Croce (2015) investigate the effect of spatial mobility on educational mismatch showing a negative effect of migration distance for university graduates while Marinelli (2011) finds that migrants (“non returners”) are more satisfied on job tasks, economic treatment, and stability and security.

unemployment and migration.

Finally, the analysis may be further extended starting from following point:

- since I have used the definition of regional migration, commuters, which has different behaviour and charactetistics (Mocetti et al., 2010) are not analysed[71];
- despite rising interest for the relative consequences on Italian labour market(Mocetti and Porello, 2010), interantional migration is not considered.

[71]Ciriaci (2014, A) show that graduates who studied in university located at regional (or macro-area) borders are more likely to migrate after having completed their university career.

Table 2.2: **Regression without instrument**

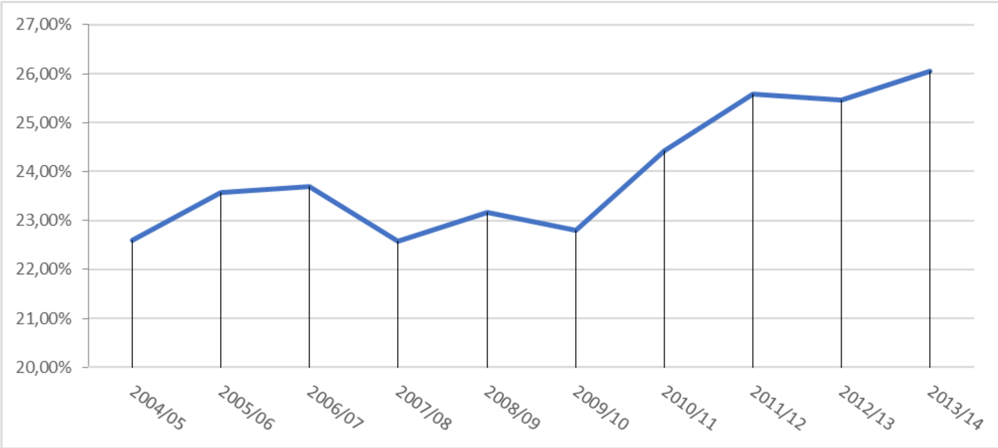
Monthly earnings (log)	**Coeff.**	**Stand.errors**
Post graduation mobility	0.048***	(0.012)
Housing cost (working area)	0.000**	(0.000)
Job specialization: middle	0.080	(0.076)
Job specialization: low-middle	0.073	(0.076)
Job specialization: high	0.080	(0.075)
Family study title: middle school	0.029	(0.028)
Family study title: high school	0.026	(0.028)
Family study title: graduated	0.031	(0.036)
Family study title: post gradut.	0.034	(0.031)
Part-time	-0.509***	(0.026)
Private university	0.031	(0.028)
High school mark	0.007	(0.008)
Family social class: medium	0.044***	(0.013)
Family social class: High	0.040**	(0.016)
Field of study: engineering	0.055***	(0.015)
Field of study: economics	0.027	(0.016)
Field of study: social	-0.069***	(0.020)
Field of study: humanities	-0.140***	(0.021)
Field of study: physical Education	-0.088*	(0.053)
Female	-0.086***	(0.012)
Age: 23-24	0.010	(0.019)
Age: 25-29	0.036	(0.024)
Age: more than 30	0.021	(0.036)
Graduation mark: 91-100	0.005	(0.019)
Graduation mark: 101-105	0.023	(0.020)
Graduation mark: 106-110	0.014	(0.022)
Graduation mark: 110 Lode	0.057***	(0.021)
Working area: North East	-0.032**	(0.013)
Working area: Center	-0.073***	(0.016)
Working area: South	-0.086***	(0.022)
Working area: Islands	-0.174***	(0.058)
Network	-0.011	(0.015)
On time	0.030**	(0.012)
Phd	-0.037	(0.049)
Specialization	0.001	(0.028)
Master	0.016	(0.033)
Scholarship (Work)	-0.002	(0.021)
Stage	0.034***	(0.011)
Other spec.	-0.025	(0.020)
Training	-0.082***	(0.017)
Training (educ)	-0.003	(0.027)
Experience	0.004***	(0.000)
B.A.	-0.022	(0.017)
Self-employed	-0.587***	(0.037)
Married	0.016	(0.014)
Year 2015	-0.069***	(0.012)
_cons	7.016***	(0.091)
N 5281		

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Appendix A

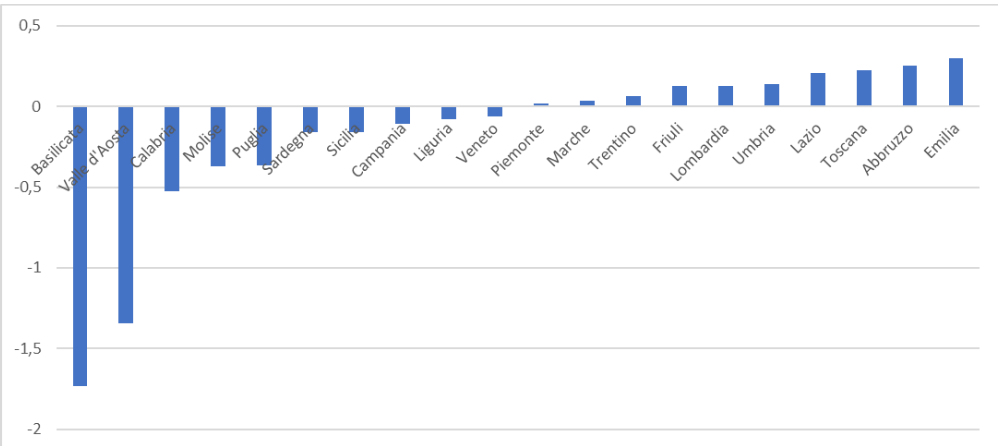
Appendix

Figure A.1



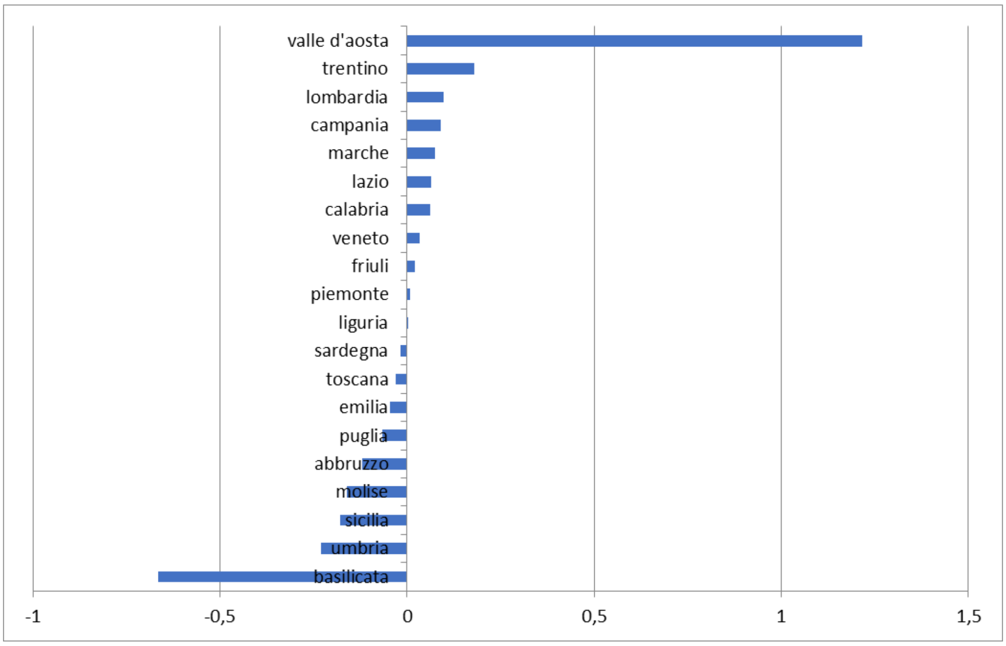
Trend in interregional student mobility (%) in the period 2005–14 from southern to northern region.
Source: own elaboration on MIUR data, section "Anagrafe nazionale degli studenti"
*Southern regions include: Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia.

Figure A.2



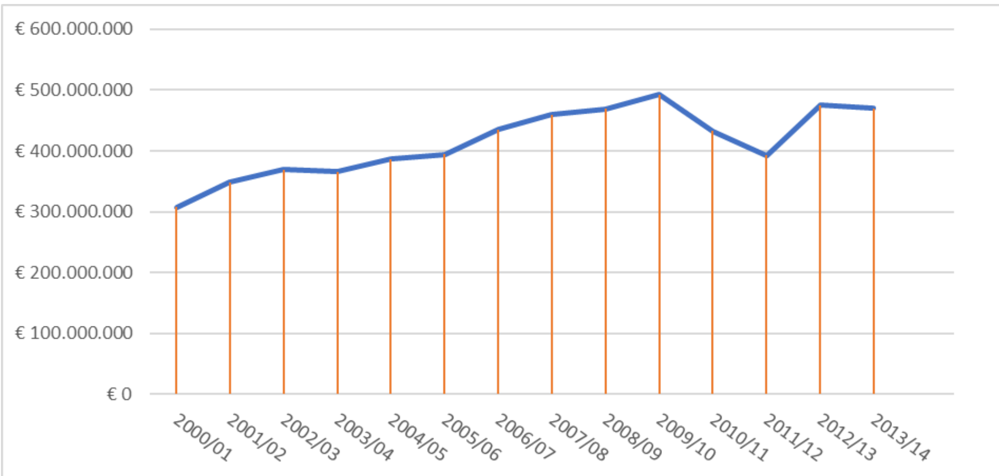
Net migration rate for all the Italian regions (%); average on ten academic years (2005–14).The elaboration exlcuede on-line universities
Source: own elaboration on MIUR data, section "Anagrafe nazionale degli studenti".

Figure A.3



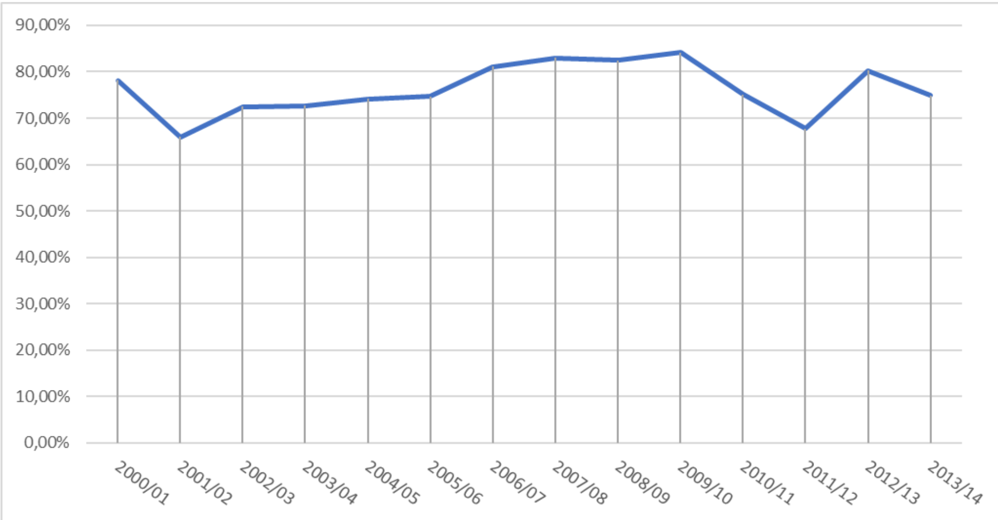
Difference between net migration rates in the academic year 2004/2005 and 2013/2014 for all Italian regions.
The elaboration exlcuede on-line universities
Source: own elaboration on MIUR data, section “Anagrafe nazionale degli studenti”.

Figure A.4



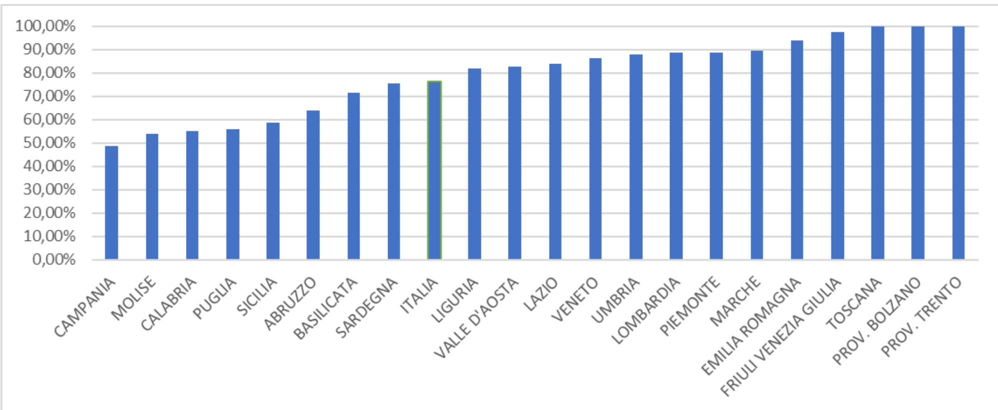
Annual expenditure (absolute value) in scholarships by all Italian regions.
Source: own elaboration on MIUR data.

Figure A.5



Scholarships paid on the number of eligible students (%)
Source: own elaboration on MIUR data.

Figure A.6



Scholarships paid on the number of eligible students (%) for each region. Average on academic years between 2001 to 2014
Source: own elaboration on MIUR data.

Table A.1: **Descriptive statiscts: full sample**

	High school macro-area	University macro-area	Working macro-area			
North West	25,49	32,34	41,64			
North East	20,34	26,30	26,23			
Center	14,58	22,61	20,77			
South	31,11	14,90	9,05			
Islands	8,48	3,84	2,31			
Total	**5281**	**5281**	**5281**			
High school macro-area	**Comeback**	**Stayers**	**Double movers**	**Moversremained**	**Post graduation movers**	
North West	14,92	42,70	6,38	9,99	14,27	
North East	34,46	26,8	7,05	9,99	13,34	
Center	13,14	16,36	13,76	10,70	15,72	
South	24,51	11,03	58,56	54,84	46,90	
Islands	12,97	3,11	14,25	14,48	9,77	
Absolute values	**563**	**2384**	**596**	**981**	**757**	
High school macro-area	**Comeback**	**Stayers**	**Double movers**	**Moversremained**	**Post graduation movers**	**Absolute values**
North West	6,24	75,63	2,82	7,29	8,02	**1346**
North Est	18,06	59,50	3,91	9,12	9,41	**1074**
Center	9,61	50,65	10,65	13,64	15,45	**770**
South	8,40	16,01	21,24	32,74	21,61	**1643**
Island	16,29	16,52	18,97	31,70	16,52	**448**
Ante graduation mobility	**Post graduation mobility**					
	Stayes	**Movers**				
Stayes	75,90	24,10				
Movers	45,84	54,16				

Table A.2: **Variable description**

Variable	Description	Source	N.obs.	Mean	S.dev.	Min.	Max.
Net Migration Rate	Net migration rate for each region; year 2004-2007	MIUR data, section: "Angrafe nazionale degli studenti"	5281	-0,078	0,358	-1,768	0,360
Housing cost (origin)	Housing cost and rental prices in the origin province (average between two years: 2003 and 2007)	"Il Sole24ore" survey	5281	51,825	424,30	-764 (a)	953
Scholarships	Scholarships paid on the number of eligible students (%, average from 2001 to to 2006) in the high school region	MIUR data	2970	0,747	0,188	0,469	1
Max University size origin region	University size (in terms of student enrolled by year) in the origin region	MIUR data	5281	3,572	0,680	1	4
University size (high school area): small	up to 10 000 students	-	18	0,003	0,058		
University size (high school area): medium	10 000–15 000 students	-	540	0,102	0,303		
University size (high school area): big	15 000–40 000 students	-	1307	0,247	0,431		
University size (high school area): mega	more that 40 000 students	-	3416	0,646	0,477		
Occupational rate 2004 2008 (%)	Regional occupational rate in the origin region (average between years 2004-2008)	ISTAT data	2970	0,698	0,142	0,483	0,838
Trasports quality 2002 2007	Transport satisfaction in the orgin region; average on three different trasport modes: train, bus and pulman. Average on different years: from 2002 to 2007	ISTAT data	5281	51,62	6,734	40,94	71,11
Female	-	ISTAT graduates survey	5281	0,503	0,500	0	1
High school mark	Discete variable divided in three classes: from 60 (minimum) to 75, from 76 to 90 and from 91 to 100 cum laude	ISTAT graduates survey	5281	2,190	0,786	1	3
High school mark: low (60 to 75)	-		1041	0,197	0,397		
High school mark: medium (75 to 90)	-		1668	0,315	0,464		

High school mark: high (90 to 100 cum laude)	-		2572	0,487	0,499		
Family social class	Most prestigious professional position among father and mother	ISTAT graduates survey	5281	2,165	0,803	1	3
Family social class: low	-	-	1337	0,253	0,434		
Family social class: medium	-	-	1733	0,328	0,469		
Family social class: high	-	-	2211	0,418	0,493		
Poli. high school area	Dummy for the presence of a polytechnic in the origin region	"Repubblica" survey	5281	0,382	0,486	0	1
High school macroarea	Discrete variable indicating the macroarea where student takes high school diploma	ISTAT graduates survey	5281	2,768	1,349	1	5
North West	-	-	1346	0,254	0,435		
North East	-	-	1074	0,203	0,402		
Center	-	-	770	0,145	0,352		
South	-	-	1643	0,311	0,462		
Islands	-	-	448	0,084	0,278		
High school track	-	ISTAT graduates survey	5281	1,700	0,896	1	3
Licei	-	-	3148	0,596	0,490		
Psyco-Art	-	-	568	0,107	0,309		
Vocational	-	-	1565	0,296	0,456		
Field of study		ISTAT graduates survey	5281	2,872	1,481	1	6
Scientific (math and physic)	-	-	969	0,183	0,387		
Engineering	-	-	1687	0,319	0,466		
Economics	-	-	982	0,185	0,389		
Social	-	-	521	0,098	0,298		
Humanities	-	-	1031	0,195	0,396		
Physical education	-	-	91	0,0172	0,130		
Family study title	Higher education level among parents	ISTAT graduates survey	5281	3,276	1,137	1	5
Elementary/nothing	-	-	189	0,035	0,185		
Middle school	-	-	994	0,188	0,390		
High school	-	-	2591	0,490	0,499		
Graduated	-	-	185	0,035	0,183		
Post graduated	-	-	1322	0,250	0,433		

Transport quality 2008 2012	Transport satisfaction in the orgin region; average on three different trasport modes: train, bus and pulman. Average on different years: from 2008 to 2012	ISTAT data	5281	57,293	10,23	41,871	73,723
Occupational rate 2009 2014 (%)	Regional occupational rate in the origin region (average betwee years 2009-2014)	ISTAT data	5281	0,696	0,121	0,401	0,793
Age at graduation	-	ISTAT graduates survey	5281	2,649	0,721	1	4
Age 22 or less	-	-	416	0,078	0,269		
Age 23 24	-	-	1375	0,260	0,438		
Age 25 29	-	-	3135	0,593	0,491		
Age 30 or more	-	-	335	0,067	0,250		
Size University attended	-	MIUR data	5281	2,922	0,836	1	4
University size: small	-		202	0,0382	0,191		
University size: medium	-		1460	0,276	0,447		
University size: high	-		2167	0,410	0,491		
University size: mega	-		1452	0,274	0,446		
Network	Social network to get the first job	ISTAT data	5281	0,207	0,405	0	1
On time	Graduation on time	ISTAT data	5281	0,538	0,499	0	1
Graduation Mark	Degree mark is divided in five categories: from 66, minimum value found to 110 cum laude,	ISTAT data	5281	3,082	1,447	1	5
Mark less than 91	-	-	971	0,183	0,387		
Mark 91 100	-	-	1101	0,208	0,406		
Mark 101 105	-	-	1044	0,197	0,398		
Mark 106 110	-	-	853	0,161	0,368		
Mark 110 lode	-	-	1312	0,248	0,432		
Erasmus	Erasmus experience	ISTAT data	5281	0,117	0,321	0	1
Phd	Get a Phd;1=concluded 0=interrupted or not started	ISTAT data	5281	0,018	0,132	0	1
Specialization	Post laurea specialization; 1=concluded 0=interrupted or not started	ISTAT data	5281	0,041	0,197	0	1
Scholarship (work)	Grant for a work 1=concluded; 0=interrupted or not started	ISTAT data	5281	0,062	0,241	0	1
Master	1=concluded; 0=interrupted or not started	ISTAT data	5281	0,038	0,191	0	1

Stage	Stage in a firm; 1=concluded 0=interrupted or not started	ISTAT data	5281	0,316	0,465	0	1
Other spec.	1=concluded; 0=interrupted or not started	ISTAT data	5281	0,124	0,329	0	1
Apprenticeships	1=concluded; 0=interrupted or not started	ISTAT data	5281	0,182	0,386	0	1
Training (education)	1=concluded: 0=interrupted or not started	ISTAT data	5281	0,062	0,24	0	1
Polytechnic	University attended was a polytechnic	ISTAT data and “Repubblica” survey	5281	0,093	0,29	0	1
Married	-	ISTAT data	5281	0,194	0,396	0	1
Private university	Attended to a private university	ISTAT data and “Repubblica” survey	5281	0,068	0,251	0	1
Internal Relocation Rate (I.R.R.)	The ratio between the yeraly number of cancellation for transfer residence in another region and the regional population as on 1 January (‰)		5281	0,005	0,001	0,003	0,010
Post graduation movers	Dummy indicating if the observation move in another region after graduation	ISTAT graduates survey	5281	0,362	0,481	0	1
Ante graduation movers	Dummy indicating if the observation move in another region after high school	ISTAT graduates survey	5281	0,405	0,490	0	1
Monthly earnings (logarithm)		ISTAT graduates survey	5281	7,177	0,488	3,689	8,294
Housing cost (working area)	Housing cost in the working province (rental price; average between 2007 and 2011)	“Il Sole24ore” survey	5281	3324,0	1167,90	1175	5150
Housing cost (university province)	Housing cost in university province (rental price; average between 2007 and 2011)	“Il Sole24ore” survey	5281	3302,0	1124,88	1450	5150
Job specialisation	Worker specialisation (ATECO 2007, two digits)	ISTAT graduates survey	5281	3,155	0,895	1	4
Low specialisation			30	0,005	0,075		
Low-middle specialisation			1679	0,317	0,465		
Medium specialisation			1017	0,192	0,394		
High specialisation			2555	0,483	0,499		
Part time			5281	0,086	0,281	0	1
Working area		ISTAT graduates survey	5281	2,042	1,092	1	5
Working area: North East			2199	0,416	0,493		
Working area: North West			1385	0,262	0,439		
Working area: Center			1097	0,207	0,405		
Working area: South			478	0,090	0,286		

Working area: Islands			122	0,023	0,150		
Experience	Working experience (months)	ISTAT graduates survey	5281	38,664	15,282	2	54
B.A.		ISTAT graduates survey	5281	1,311	0,463	1	2
Self-employed		ISTAT graduates survey	5281	0,11	0,313	0	1
University macroarea		ISTAT graduates survey	5281	2,316	1,179	1	5
University macroarea: North East			1708	0,323	0,467		
University macroarea: North West			1389	0,263	0,44		
University macroarea: Center			1194	0,226	0,418		
University macroarea: South			787	0,149	0,356		
University macroarea: Islands			203	0,038	0,192		
Year 2015	Dummy for the wave 2015		5281	0,580	0,493	0	1

(a)The presence of negative value is explained in the section 2.8.

Table A.3: **Descriptive statistics: Stayers vs. Movers**

	Ante graduation mobility						Post graduation mobility					
	Stayers			Movers			Stayers			Movers		
	Count	Mean	St.dev.	Count	Mean	St.dev.	Count	Mean	St.dev.	Count	Mean	St.dev.
Monthly earnings (log)	3141	7,202	0,416	2140	7,141	0,575	3365	7,156	0,496	1916	7,214	0,471
Housing cost (working area)	3141	3231,230	1117,037	2140	3460,308	1226,390	3365	3270,604	1110,137	1916	3417,938	1257,792
Job specializatiion	3141	3,114	0,897	2140	3,214	0,888	3365	3,114	0,899	1916	3,226	0,882
Part-time	3141	0,083	0,277	2140	0,091	0,287	3365	0,090	0,287	1916	0,079	0,270
Private university	3141	0,042	0,201	2140	0,105	0,307	3365	0,077	0,266	1916	0,052	0,221
Family social class	3141	2,074	0,801	2140	2,299	0,786	3365	2,147	0,802	1916	2,199	0,804
Field of study	3141	2,838	1,471	2140	2,921	1,494	3365	2,906	1,476	1916	2,811	1,488
Female	3141	0,504	0,500	2140	0,503	0,500	3365	0,522	0,500	1916	0,471	0,499
Age	3141	2,630	0,727	2140	2,678	0,711	3365	2,629	0,729	1916	2,686	0,705
Graduation mark	3141	3,097	1,438	2140	3,060	1,459	3365	3,011	1,445	1916	3,208	1,442
Working area	3141	1,969	1,075	2140	2,149	1,108	3365	2,018	1,058	1916	2,083	1,148
Network	3141	0,210	0,408	2140	0,202	0,401	3365	0,229	0,420	1916	0,169	0,375
On time	3141	0,526	0,499	2140	0,557	0,497	3365	0,544	0,498	1916	0,529	0,499
Phd	3141	0,017	0,130	2140	0,019	0,135	3365	0,021	0,145	1916	0,011	0,107
Specialization	3141	0,037	0,189	2140	0,046	0,209	3365	0,036	0,187	1916	0,048	0,214
Scholarship (Work)	3141	0,054	0,227	2140	0,073	0,260	3365	0,053	0,224	1916	0,078	0,268
Master	3141	0,028	0,166	2140	0,052	0,223	3365	0,025	0,157	1916	0,061	0,239
Stage	3141	0,294	0,456	2140	0,349	0,477	3365	0,290	0,454	1916	0,363	0,481
Other spec.	3141	0,114	0,318	2140	0,138	0,345	3365	0,121	0,326	1916	0,128	0,335
Training	3141	0,159	0,365	2140	0,215	0,411	3365	0,181	0,385	1916	0,182	0,386
Training (educ)	3141	0,062	0,242	2140	0,060	0,238	3365	0,059	0,235	1916	0,067	0,250
Experience	3141	37,964	15,719	2140	39,692	14,559	3365	38,762	15,499	1916	38,492	14,896
B.A.	3141	1,357	0,479	2140	1,243	0,429	3365	1,333	0,471	1916	1,272	0,445
Autonomous	3141	0,086	0,280	2140	0,146	0,353	3365	0,114	0,318	1916	0,104	0,306
Scholarships	3141	0,801	0,172	2140	0,670	0,184	3365	0,783	0,177	1916	0,687	0,191
Married	3141	0,227	0,419	2140	0,145	0,353	3365	0,213	0,410	1916	0,161	0,367
Year	3141	0,469	0,499	2140	0,744	0,436	3365	0,500	0,500	1916	0,723	0,448
High school mark	3141	2,262	0,781	2140	2,330	0,763	3365	2,276	0,782	1916	2,315	0,762

Table A.4: **Descriptive statistics by mobility path**

	Comeback			Stayers			Double movers			Moversremained			Post graduation movers		
	Count	Mean	St.dev.	Count	Mean	St.dev.	Count	Mean	St.dev.	Count	Mean	St.dev.	Count	Mean	St.dev.
Monthly earnings (log)	563	7,069	0,542	2418	7,173	0,414	596	7,252	0,440	981	7,115	0,651	757	7,292	0,410
Housing cost (working area)	563	2477,293	892,740	2384	3050,177	1032,018	596	3819,435	1174,272	981	3806,279	1111,369	757	3801,413	1181,710
Job specialization	563	3,101	0,902	2384	3,056	0,902	596	3,255	0,884	981	3,255	0,878	757	3,296	0,857
Part time	563	0,133	0,340	2384	0,092	0,289	596	0,057	0,232	981	0,087	0,281	757	0,057	0,232
Private university	563	0,052	0,221	2384	0,046	0,210	596	0,081	0,272	981	0,151	0,358	757	0,029	0,168
Family social class	563	2,123	0,785	2384	2,046	0,792	596	2,314	0,785	981	2,391	0,772	757	2,165	0,823
Field of study	563	3,004	1,638	2384	2,918	1,501	596	2,914	1,481	981	2,877	1,414	757	2,587	1,342
Female	563	0,522	0,500	2384	0,526	0,499	596	0,471	0,500	981	0,511	0,500	757	0,433	0,496
Age	563	2,714	0,668	2384	2,613	0,734	596	2,661	0,740	981	2,667	0,717	757	2,684	0,703
Graduation mark	563	3,139	1,356	2384	3,026	1,416	596	3,128	1,461	981	2,973	1,512	757	3,322	1,483
Working area	563	2,812	1,260	2384	2,031	1,110	596	1,790	0,962	981	1,986	0,921	757	1,771	0,933
Network	563	0,218	0,414	2384	0,234	0,423	596	0,163	0,369	981	0,216	0,412	757	0,137	0,344
On time	563	0,510	0,500	2384	0,522	0,500	596	0,537	0,499	981	0,596	0,491	757	0,538	0,499
Phd	563	0,012	0,111	2384	0,017	0,130	596	0,003	0,058	981	0,032	0,175	757	0,017	0,130
Specialization	563	0,036	0,185	2384	0,031	0,172	596	0,049	0,215	981	0,050	0,218	757	0,057	0,232
Scholarship (Work)	563	0,064	0,245	2384	0,047	0,213	596	0,092	0,290	981	0,066	0,249	757	0,077	0,266
Master	563	0,046	0,210	2384	0,019	0,138	596	0,079	0,270	981	0,040	0,195	757	0,057	0,232
Stage	563	0,281	0,450	2384	0,266	0,442	596	0,413	0,493	981	0,349	0,477	757	0,384	0,487
Other spec.	563	0,140	0,348	2384	0,115	0,320	596	0,139	0,347	981	0,136	0,343	757	0,111	0,314
Training	563	0,224	0,417	2384	0,160	0,367	596	0,180	0,384	981	0,232	0,423	757	0,153	0,360
Training (educ)	563	0,101	0,302	2384	0,063	0,244	596	0,044	0,204	981	0,047	0,212	757	0,059	0,237
Experience	563	36,158	15,773	2384	37,497	16,057	596	39,502	14,287	981	41,835	13,574	757	39,433	14,516
B.A.	563	1,275	0,447	2384	1,380	0,486	596	1,255	0,436	981	1,216	0,412	757	1,284	0,451
Autonomous	563	0,187	0,390	2384	0,095	0,294	596	0,087	0,282	981	0,159	0,366	757	0,057	0,232
Scholarships	563	0,766	0,175	2384	0,840	0,141	596	0,622	0,168	981	0,643	0,177	757	0,678	0,199
Married	563	0,229	0,421	2384	0,254	0,435	596	0,119	0,324	981	0,113	0,317	757	0,143	0,350
Year	563	0,405	0,491	2384	0,346	0,476	596	0,852	0,355	981	0,874	0,332	757	0,857	0,350
High school mark	563	2,158	0,779	2384	2,219	0,790	596	2,359	0,753	981	2,413	0,745	757	2,396	0,739

Table A.5: **Second stage of the 2SLS estimation: the effect of ante graduation mobility on post graduation mobility**

Dependent variable: Post graduation mobility		
	Coeff.	**Stand.errors**
Ante graduation mobility	0.117***	(0.030)
Family social class: medium	-0.016	(0.016)
Family social class: high	-0.031*	(0.018)
Female	-0.048***	(0.013)
University macroarea: North East	0.088***	(0.022)
University macroarea: Center	0.120***	(0.025)
University macroarea: South	0.144**	(0.059)
University macroarea: Islands	0.136*	(0.071)
Field of study: engineering	-0.008	(0.019)
Field of study: economics	-0.064***	(0.020)
Field of study: social	-0.023	(0.025)
Field of study: humanities	-0.025	(0.020)
Field of study: physical educ.	0.007	(0.045)
Transport quality 2008 - 2012	-0.003***	(0.001)
Occupational rate 2009 2014 (%)	-0.734***	(0.178)
Age: 23-24	-0.039*	(0.023)
Age: 25-29	-0.045*	(0.023)
Age: more than 30	-0.079**	(0.033)
Univ. size: medium	0.008	(0.043)
Univ. size: high	-0.011	(0.046)
Univ. size: mega	-0.058	(0.048)
Family study title: middle school	-0.009	(0.032)
Family study title: high school	0.036	(0.031)
Family study title: graduated	0.015	(0.045)
Family study title: post gradut.	0.056	(0.035)
Network	-0.067***	(0.014)
On time	-0.000	(0.014)
Grad.Mark: 91-100	0.044**	(0.019)
Grad.Mark: 101-105	0.051**	(0.020)
Grad.Mark: 106-110	0.073***	(0.021)
Grad.Mark: 110 lode	0.052***	(0.020)
Ereasmus	0.077***	(0.020)
Phd	-0.122***	(0.046)
Specialization	0.025	(0.031)
Scholarship (Work)	0.043*	(0.025)
Master	0.137***	(0.033)
Stage	0.059***	(0.013)
Others spec.	-0.006	(0.018)
Training	-0.044***	(0.016)
Training (educ)	0.041	(0.025)
Polytechnic	-0.022	(0.024)
Housing cost (univer. prov.)	-0.000***	(0.000)
Married	-0.010	(0.015)
Private university	-0.060	(0.037)
Year: 2015	0.169***	(0.015)
_cons	1.005***	(0.164)
N 5281		
F test of excluded instruments:		
F(1, 5280) = 1425.54		
Prob > F = 0.0000		

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Table A.6: **Wage regression corrected trough with a different specification of the RPB model**

Dependent variable: Monthly earnings (log)		
	Coeff.	**Stand.errors**
Post graduation mobility	0.040*	(0.024)
Housing cost (working area)	0.000**	(0.000)
Job specialization: middle	0.081	(0.076)
Job specialization: low-middle	0.074	(0.075)
Job specialization: high	0.081	(0.075)
Family study title: middle school	0.029	(0.028)
Family study title: high school	0.026	(0.028)
Family study title: graduated	0.032	(0.036)
Family study title: post gradut.	0.035	(0.031)
Part-time	-0.510***	(0.026)
Private	0.031	(0.028)
High school mark	0.007	(0.008)
Family social class: medium	0.043***	(0.013)
Family social class: high	0.040**	(0.016)
Engineering	0.055***	(0.015)
Economics	0.026	(0.016)
Social	-0.069***	(0.020)
Humanities	-0.141***	(0.020)
Physical Education	-0.088*	(0.052)
Female	-0.086***	(0.012)
Age: 23-24	0.010	(0.019)
Age: 25-29	0.036	(0.024)
Age: more than 30	0.022	(0.036)
Graduation mark: 91-100	0.005	(0.019)
Graduation mark: 101-105	0.024	(0.020)
Graduation mark: 106-110	0.015	(0.022)
Graduation mark: 110 Lode	0.058***	(0.022)
Working area: Nord East	-0.032**	(0.013)
Working area: Center	-0.073***	(0.016)
Working area: South	-0.086***	(0.022)
Working area: Islands	-0.172***	(0.058)
Network	-0.012	(0.015)
On-time	0.029**	(0.012)
Phd	-0.039	(0.049)
Specialization	0.001	(0.028)
Master	-0.002	(0.021)
Scholarship (Work)	0.017	(0.033)
Stage	0.034***	(0.011)
Other spec.	-0.025	(0.019)
Training	-0.082***	(0.017)
Training (educ)	-0.003	(0.027)
Experience	0.004***	(0.000)
B.A.	-0.023	(0.017)
Self-employed	-0.588***	(0.037)
Married	0.016	(0.014)
Year 2015	-0.068***	(0.014)
_cons	7.018***	(0.091)
N 2251		
F test of excluded instruments: **F(1, 5280) = 1317.17** **Prob > F = 0.0000**		
Cluster Standard errors in brackets *** p<0.10, ** p<0.05, *** p<0.010**		

3

Migration and "job level": an estimation using an Ordered Probit model

3.1 Introduction and research issue

Workplace mobility has been considered a tool with which to rebalance labour market differences in terms of unemployment and the skills required in them and even a way to obtain better opportunities in terms of job specialization, wages and type of contract (Middeldorp et al., 2016). As well as being included as an additional issue in any study of effectiveness and efficiency of the university system, it might give suggestions in the evaluation of the early graduates' working careers, job quality, satisfaction and "job level" (Bacci et al., 2008), characterized, at least for Italy, by greater contractual instability and mobility between job and places (Argentin and Triventi, 2011). Where the workings of the labour market vary, intensifying the spatial search effort may be a good strategy for the purposes of obtaining a better job-match, coherent with an individual's academic career and expectations.

Interest in the effects of workforce mobility is not new and its relevance to macroeconomic and microeconomic policies has been widely discussed (DaVanzo, 1981; Pissarides and Wadsworth, 1989). Many of the empirical findings have been limited by a data structure which generates, especially, difficulties identifying the exact moment when people move and why (is it after or before finding job). This also explains why any interpretation of the effects of workplace mobility on wages (or other outcomes) should be read carefully. In fact, migration analysis usually infers employment status before or at the time of migration with data on labour outcomes referring to the period before migration (Mitchell, 2008). The same problem occurs in the evaluation of factors affecting migration decisions, which should relate to earlier periods if interpretations are to be correct (Mocetti et al., 2010).

Equally important is the choice of which variables are to be used to evaluate migration effect. Most studies considered wages the most significant outcome to consider, but, as we saw in the previous chapter, job position, contract and job specialization can also be consider, especially if administrative data are available.
In fact, definitions of employment status and working conditions based on survey data are often

generic and do not consider periods of labour inactivity between contracts that may have negative effects on working careers (Argentin and Triventi, 2011).

In the previous chapter I illustrated the effect of interregional mobility on wages taking into account the endogeneity of migration. The results suggest that moving has a positive (though small) impact on the early stages of a career. In this chapter I will introduce an empirical exercise whose aim is to:

- evaluate the effects of workplace migration on a different labour market outcome;
- overcome the limits referred to above: timing of mobility and possible survey data bias.

Using information collected directly by the Italian Ministry of Labor and Social Policy, adequately integrated with data provided by the "La Sapienza" University of Rome and the "Almalaurea" database, I'll try to answer the following questions: does workplace mobility lead to a good "job level" in the labour market four years after graduation? What are the main drivers of relocation after graduation? Other than observable factors such as field of study, age and degree mark are there other unobservable factors affecting the likelihood of relocation and labour market outcomes?

Before beginning with my empirical methodology, I will discuss research motivations and some relevant results ruled out by previous empiriacal works in the next section.

3.2 Reasons behind workplace mobility

As explained in the first chapter, the flexibilization of the labour market in presence of significant disparities between places may increases internal migration flows. Even if changes in labour market conditions are greater for the unemployed than for the other individuals (Westerlund, 1998), different functioning of local labour markets can prompt even those who are already employed to move to improve their working conditions.
Certainly the reasons behind changes to young graduates' employment opportunities over the last decade are varied and complex. Complementary factors such as infrastructure costs, unemployment rates, local bargaining (even at firm level) and family background may have affected both employment opportunities and working conditions differently and a clear distinction between them is very difficult to achieve (Parenti and Tealdi, 2015).
A range of empirical works has attempted to analyze correlations between job changes and migration decisions. Haussen (2016) has analyzed migration decision determinants for first jobs and the relationship between graduate job and location changes after labour market entry (five years after graduation). He has shown that the majority of university graduates change job more than once in the five years after graduation and that changes are strongly linked to interregional migration [1].

Using a longitudinal Italian dataset Bacci et alt. (2008)[2], have investigated which type of degree courses are associated with a high level of mobility for occupational reasons and what the individual characteristics influencing mobility (post-graduate studies, marriage, having at least one graduate parent, having children, age at graduation, job satisfaction or being a working student) are. This analysis produced interesting results. The degree courses with the highest

[1] He found that over five years, 40% of graduates left their university region with variation across regions
[2] The analysis draws upon the ALMALAUREA database on year 2000, 2001 and 2002 graduates.

rates of mobility for occupational reasons are those with a considerable mobility "predisposition" (international and diplomatic relations, translation and interpreting, institutions and financial markets) and the likelihood of moving after gradutaion is strictly related to previous migration since movers are more likely to study in a region other than their home region[3].
As regards the effects of job changes and workplace mobility on labour market outcomes, there is general agreement on the positive effects exerted on early graduates' career paths.
Venhorst and Corvers (2015) used a sample of early graduates from the Netherlands, with an OLS, controlling for different observed personal and regional characteristics, have shown that job mobility has a positive effect on wage level and on job-match[4].
Taking into account a twofold selection of migration and industry change, Abreu, Faggian and McCann (2014) have shown a positive workplace mobility effect, and a negative one related to changing both location and industry.

Starting with the assumption that job change can reinforce models explaining why earnings increase with tenure, Topel (1992) has shown that in ten years after graduation, employees have changed jobs an average of seven times and one third of their wage growth was attributable to this factor. Furthermore, he argues that job duration correlates with wages, and wage growth is associated with searching process (looking for a job on a national or international scale).

Van Ham (2001), has shown that workplace mobility is instrumental in career advancement especially for those who accept long distances jobs: workers who accept long distance jobs show greater career adavancement after job change as compared with those opting for jobs close to home[5].

The real innovation of the work referred to here is its introduction of the concept of job level into career advancement measured comparing job levels obtained with previous employment[6] with job levels defined by assigning skill levels to work on the basis of National Statistical Office classifications.
Very similar resutls were obtained by Mitchell (2008) who argued that positive workplace mobility effects do exist (occupation and activity sector changes), but these are strongly related to "skill level": the low skilled (also less mobile) experience diminished workplace mobility benefits, other things being equal.

In the current literature, migration is seen as an investment, enabling specific human capital to be acquired and this may explain why those who move earn more. The role of specific human capital is comparable to the "tenure effect", which is generally used to explain earnings variance. Middeldrop (2016), for example, has shown that the tenure effect (on wages) varied in accordance to different mobility paths: it is higher for those who move several times (which even those obtaining higher percentages of full time contracts in 5 years) and lower for stayers[7].
Hensen et al. (2009) suggets that accumulated human capital is maximized by permanent full time contracts, and contract types are associated with specific mobility path.

[3]He find also that those who graduates in universities located in centre-north regions are found to be less prone to mobility than those who attend to university located in Southern regions, while, graduates employed in central or Northern regions typically display a considerably higher tendency to mobility than those who found job in the South.

[4]However, controlling for the endogeneity of migration through the instrumental variable approach, they finds an insignificant effect of mobility on wage and gives this interpretation: local and economic characteristic has effect on wage and not the mobility itself.

[5]The same authors, talking about spatial accessibility, stresses how the increase in quality and means of transport in the last decade has grown commuting tolerance increasing predisposition to mobility.

[6]They estimate the effect of the workplace mobility on the difference in the job level.

[7]He also stressed that the positive effect of mobility on wages is significant for early ("Movers remained" in the previous chapter) but not late movers ("Mobility post study" in the previous chapter) or commuters.

Furthermore, he also points out that failure to account for different types of mobility and their timing may underestimate the effect of spatial mobility on labour market outcomes.

A further factor considered in career progression analysis is the number of temporary contracts preceding a permanent contract. The dissemination of permanent contracts has been a feature of the response of almost all European countries to high unemployment. In Italy, too, where good worker protection laws existed prior to reforms, these types of contracts, aiming to ensure both a better match in the labour market and worker stabilization[8], have spread ever since.

However if temporary and short term contracts allow more flexibility for firms, permanent contracts generate greater benefits since, assuming that training opportunities are correlated with contract duration, they lead to greater capital accumulation, with positive effects for both firms and workers. Other than by internal reforms, the likelihood of getting a permanent job has undoubtedly been influenced by the 2007 crisis (Berloffa et al., 2014; Lilla et al., 2012)[9] which increased instability strictly correlated with higher wage volatility (Staffolani and Lilla, 2009). On this point, Lilla and Staffolani (2012) have discussed the entry market conditions of young entrants using Ministry of Labour and Social policy data ("Comunicazioni obbligatorie") for the 2008-2010 period. Through a survival model, they sought to understand whether there are individual characteristics affecting the likelihood of obtaining an open ended contract and whether some contracts are more likely to turn in permanent [10]. They also found that experience helps people to obtain a permanent contract and those who have spent many years in education experience greater difficulties finding a permanent job (although their fixed contracts are more likely to be made permanent).

The last evidence suggested by the authors relates to Italian geographic differences: they show that the use of temporary contracts may differ between geographical areas and found that firms located in North-East and Central Italy are more inclined to use temporary contracts. This suggests not only the need for heterogeneity between local labour markets to be considered, but also that this heterogeneity may act as a push factor in migration models.

3.3 "Timing" of mobility

In the first chapter I discussed the issue of migration within the "Signalling" theory framework, identifying migration as a screening device. As Middeldorp has stressed (2016), in estimating spatial mobility on labour market outcomes, requires including information on the timing of mobility (when it takes place) in order to calculate whether readiness to take a job in a different province or region helps people to obtain better employment conditions. Furthermore, even if the reverse causality between spatial mobility and labour market outcomes is not completely overturned (Gibbons and Telhaj, 2011), this information gives us some suggestions on the causes of migration and distinguishes between voluntary and mandatory choices.

In fact, the assumption that looking for a job in a different place may indicate greater effort and motivation cannot be ruled out, while those who try to find a job locally, without moving,

[8] Picchio (2008), shows that temporary position, rather than unemployment, increases the probability of getting a regular job in the short run.

[9] Berloffa et al. (2014) show that greater contractual instability in the Italian labour market has led to an increased family role in the school to work transition.

[10] They use employment contracts as a unit of analysis and consider the unemployed too; furthermore they consider all workers and not just graduates.

may be "forced to stay" (and probably forced to accept jobs which do not correspond to their expectations) or, are willing to wait for a suitable job without moving (and are probably influenced by "non-pecuniary" motives such as social networks and family ties).
This assumption implies that the returns on migration may vary not only according to the migration paths discussed previously, but also by time as stressed by Kratz (2013)[11].

3.4 Data sources

This work began with a project[12] developed by "La Sapienza" University in Rome in conjunction with Italian Ministry of Labor and Social policy[13] aiming to connect two administrative databases: "Infostud", an archive containing information on graduates of this university, and the Ministry of Labor and Social Policy's "Comunicazioni obbligatorie", a database containing the beginning and end of every work contract for all Italian workers. In fact, in accordance with legislative decree 30/10/2007, starting on 1 March 2008, all employers are obliged to notify the Labor Ministry of the start, extension, transformation and end of every contract[14].

The first of these two databases (Infostud) contains both personal information (such as gender, province of birth and residence) and data on education (from high school graduation to university graduation marks). The information present in this database is very detailed, enabling field of study, marks in each examination and time used to complete studies to be examined.
The "Comunicazioni obbligatorie" database is divided in two parts (Attivazioni and Cessazioni)[15] the combination of which reports the following information[16]:

- contract start date (presumed and effective);
- contract end date (presumed and effective);
- number of contracts activated after graduation;
- number of contracts activated before graduation;
- duration of contract;
- type of contract;
- job qualification and level;

[11]He estimates the returns on regional migration through a fixed effect model (on longitudinal data) controlling for the number of years after migration and finding that higher returns are visible three years after migration.

[12]PRIN: Programmi di Ricerca di Interesse Nazionale; bando anno 2010-2011. Area 11. Successo formativo, inclusione e coesione sociale: strategie innovative, ICT e modelli valutativi. Coordinatore scientifico nazionale: G. Domenici. Coordinatore unità locale Sapienza: P. Lucisano (http://prin.cineca.it).

[13]The data are taken from the archive "Comunicazioni Obbligatorie".

[14]Unfortunately, information on the "transformation" of employment contracts, which tell us whether and when contracts are made permanent is not available for the data used.

[15]The difference between the two matrixes is that the first reports information related to the contract activation phase while the second reports information on the contract cessation phase. Some of the information reported in the two databases overlaps.

[16]The variables reported are only part of those available. For a list of variables used in this analysis see table B.5 while for a full list of the variables provided by Infostud and Comunicazioni obbligatorie see Lucisano and Magni (2016).

- activity sector;
- nation of birth;
- employer identification number;
- workplace location ("Comuni");
- citizenship.

Great care was required in dataset construction since the information sources vary in structure.

Firstly, the Infostud database observations are not uniquely identified and have different identification numbers in the presence of more than one qualification (B.A. or M.A.). In order to avoid considering the same observation twice, the chronological approach used in Alleva (2012, 2015) can be used. However, in this case, where just two cohorts were considered this problem should not arise since gaining two qualifications in the same year or less than two is not standard practice[17].

Even more significant is "contract repetition for the same individual", a problem also highlighted by Alleva (20152, 2015). In fact, for the same observation I have as many rows as there are contracts activated in the observational period. Furthermore, for every worker, it is common to find more than one contract activated, simultaneously, an issue that makes it difficult calculate real days worked.
Since my unit of analysis are workers (rather than contracts) I had to synthesize all available informations in a single row to obtain a matrix without repetition where, for each row I have one worker with all academic and working information.

Despite the great and comprehensive range of variables available, information on family background (parents' qualification), which, as already explained in previous chapters, are relevant factors to take into account in migration studies, is lacking. To fill this gap I will use data coming from "Almalaurea questionnaire"[18], available for La Sapienza since 2011. This survey has collected data on both academic career and family background, some of which overlaps with Infostud data[19]. In contrast to ISTAT surveys used in the second chapter, the Almalaurea questionnaire, is performed four times: before graduation, one year after graduation, three years after graduation and five years later[20]. The repetition of the questionnaires over time allows longitudinal data to be collected which is also useful in transition studies. However some limitations prevented me from in depth exploitation of the survey's "panel nature". First of all, whilst the Almalaurea questionnaire is provided by the university, the information in it is not directly available since it is directly trasmitted to Almalaurea. This requires a waiting period before it is put back (to university).

Further problems are the presence of missing values. In fact the three and five year period questionnaires are not compulsory and are subject to this problem.

[17] A few observations in which a single individual obtained more than one qualification in one or two years do exist. In such cases I considered the first qualification obtained if they are of same level (two M.A.s for example) and the higher qualification where they are different.

[18] "Alamalurea" is an inter-university consortium made up (at present) of 73 universities accounting for about 90% of Italian graduates (with the exception of those coming from private universities).

[19] Since Infostud is an administrative database I consider this data as principal source, and, as further proof, I use the Almalaurea database to compare the consistency and possible errors in the data reported.

[20] Another difference is that the first Almalaurea questionnaire is compulsory and the data referred to above is available for all graduates and not just for a random sample.

The time lag mentioned limited the data at my disposal and the following table shows the questionnaires available for the different cohorts of Sapienza graduates:

Year of graduation	Available Almalaurea questionnaire
2011	All
2012	One and three years after graduation
2013	One and three years after graduation
2014	One year after graduation
2015	Only pre-graduation questionnaire

Since estimating the effects of migration one year after graduation may lead to biased results (it may happen that too few graduates are employed one year on) and since the information contained in the questionnaire carried out five years later is available only for 2011 graduates[21], I had to select 2011 and 2012 graduates alone[22] (B.A. and M.A.) and the Almalaurea questionnaire carried out three years after graduation. Therefore, even if the original matrix has a panel structure, where the same observation is followed from 2008 to 2016, the implementation of the Almalaurea database forced me to take just two cohorts, where the data used are treated as pooled cross section[23]. Whilist, as in the previous chapter, the use of longitudinal is advisable, in this case it was not possible[24].

The decision to use Almalaurea data implies the use of contracts activated up to the end of the third year only although all academic and working career data is available for every graduate of La Sapienza University in Rome up to 30/9/2016 (latest updated data available). For example, for 2011 graduates, I have considered all contracts activated until 31/12/2014 and, for each one of these, I have calculated several summary variables such as the number of contracts activated, mean duration, number of employers and so on. This operation has been done for all quantitative variables while for qualitative variables (for example region of work) I have registered the last value for the last contract activated before 31/12/2014 alone[25].

A further limitation to take into account is that the final dataset contains no information on the self-employed or those who register no contracts in the reference period. Three assumption can be made:

- they might be active in the "black economy";
- they might be self-employed;
- they might be "Not (engaged) in Education, Employment or Training" (NEET)[26].

[21]Furthermore the response rate after 5 years is lower than the others.

[22]I cannot consider 2013 graduates since data from the Italian labourministry is updated up to 30/9/2016.

[23]In the panel data we follow the same individuals over time while in the pooled cross section repetition of the same observation in more than one year is purely accidental (Wooldridge, 2010). Here I am using the same technique usable for a cross section analysis, which is equally efficient with the data structure described above, too (Thill, 1995).

[24]For example the relationship between dependent and independent variables may be affected by temporal and cross-sectional components which are easier to identify with panel data (Podestà, 2002).

[25]For the two cohorts of graduates I have not considered those changing region of work after 31/12/2014 (for 2011 graduates) and 31/12/2015 (for 2012 graduates).

[26]This group also includes those who continue to study but these are identifiable thanks to information provided by Infostud.

Identifying the "true" unemployed is impossible with Comunicazioni obbligatorie but this can be overcome using the "Almalaurea" questionnaire which reports labourstatus (employed or unemployed)[27].
This may be a way of distinguishing between self-employed and those forced into the black economy, on one hand, and those who are inactive, on the other[28]. However, in this exercise I have only considered those already in the labour market (I decided to drop those with no active contracts in the reference period), leaving aside the relationship between mobility and unemployment.

After the adjustment discussed above, graduates cohort sample size is as follow:

Year of graduation	**N**	**Freq.** %
2011	13.394	18,41%
2012	14.199	19,52%
2013	14.395	19,79%
2014	15.361	21,12%
2015	15.400	21,17%
Total	**72.749**	

The number of observations is subject to an additional reduction due to the presence of missing values on key variables. Furthermore, as in the second chapter, I decided to drop those enrolled in medicine[29] those on other courses (M.A., Phd or other B.As and M.As) and those who were working at the time of and prior to graduation. After this selection, for the year 2011 and 2012 I have at my disposal 3549 observations, 1534 for the first and 2015 for the second. As shown in the next table, the percentage of movers after graduation in the two cohorts is quite stable.

	Stayers		**Movers**	
Year	**N.obs**	**Freq.**	**N.obs**	**Freq.**
2011	1311	85,46%	1720	81,17%
2012	223	14,54%	295	14,64%
	1605		2119	

The table B.7 in the appendix shows that greater part of student outside Lazio coming from Campania (10,5%) and Calabria (5,2%) (even if we are not sure that the region of birth is exactly the same where student take high school graduation.) while, after the first job, the place where they move are in Emilia Romagna (11,2%) and Lombardia (32,4%).
Looking to the table B.10, where statistics for stayers and movers are reported, is clear that those who move has an higher job level, higher graduation mark, higher full time contracts and have actived a greater number of contracts three years after graduation.

3.5 Definition of "workplace mobility" and job level

Here I have defined mobility to work as a dummy with value 1 where region workplace after three years is different from the original job.

[27]However information on employed/unemployed status is self-declared and thus potentially subject to bias.
[28]Another solution may be using other administrative data as those provided by I.N.P.S ("Istituto Nazionale della Previdenza sociale")
[29]Defense (military Academy) is not offered at La Sapienza.

I have not considered different mobility paths and the remigration process, as in the previous chapter, since it proved impossible to identify high school area even if individuals who moved to study can be identified thanks to a variable from the Almalaurea survey which specifies whether or not students rent rooms in order to attend university.
However I do have only information on birth region, and being the assumption that coincides with region prior to enrollment, a very strong assumption, I have preferred not to consider study mobility at all[30].
For similar reasons I have not defined mobility as a change of residence since regions of work frequently do not coincide with individual residence (Mocetti et al., 2010). Furthermore in the definition of workplace mobility, I have not considered movement within university regions (Lazio in this case). In fact, as in the previous chapter, the mover groups does not include those who changed municipality ("Comuni" or provinces) after the first job[31].

Another difference from the second chapter, where workplace mobility was defined as the movement between university region and first job is that, here I have considered mobility after transition in labour market was completed in order to reduce bias coming from reverse causality, arising when it is not possible to distinguish whether individuals have moved due to unemployment (but are looking for work in region they studied in) or are looking for a job on a regional or national scale.
As I argued above this makes a difference to estimates of the migration premium.

Taking into account that from the first migration to the end of the observation period, there may have been other remigration processes (not considered here), my interpretation of the "workplace mobility" dummy is the following: has been at least one migration after the first job and up to three years after graduation?

As dependent variable I follow the concept of "job level" defined by Van Ham (2001) as the job position to which corresponds "the amount of theoretical or practical schooling needed to perform the task adequately and needed working experience (or training time)"[32].
As Venhorst and Corves have explained (2015), the "job level" is a much broader concept that captures the effects of spatial mobility on the labour market better than wages [33]. The differences in labour market functioning may imply not simply differences in earnings (adjustable in Italy through second-rate or firm level baragaining) but also in the dissemination of certain types of contract or in sector specilization according to working area.

Therefore, the dependent variable synthesizes three categories of information: type of contract, job qualification and a variable given by the ratio between days effectively worked and the number of days between graduation day and the last day in the observational period (31/12/2014 for 2011 graduates and 31/12/2015 for 2012 graduates)[34].

[30]Venhorst and Corvers (2015) justify the same choice, hypothesizing that relations with area of birth could have modified over time and are stronger by the age of 16.

[31]The region of work is derived by aggregating municipalities by regions. I have not used provinces as aggregation units since, starting from 2011, they have been subject to many modifications. From the same year municipalities have also been subject to modification (some of these have been cancelled) and to avoid mistakes I have not considered individuals coming from and working in one of these.

[32]He defined five job levels according to different job specialization degrees (tabella su come ho definito il job level dai dati istat)

[33]The data on wages is available in the Almalaurea questionnaire but divided into classes and, furthermore, characterized by the presence of many missing values for the reasons explained above.

[34]A very similar approach is used in Alleva et al. (2015) where, via a logit model, the authors seek to estimate factors affecting the job level specified taking into account type of contract, duration and job specialization. Specifically, the dependent variable is divided into "contratto ottimale" (permanent contract, higher

The variable is specified as follows;

$$Potential = \frac{Net\,worked\,day_i}{Maximum\,days\,of\,employability_i} \qquad \text{i=1,......,N.}$$

The last component ("Potential") of the dependent variable should express a measure of how many days workers were employed and how many potential employment days there were. As we saw above, the presence of overlapping contracts is a problem which is compounded by the presence of "one day contracts"[35] and a great deal of care has been paid to consider only the net working days.

The Comunicazioni obbligatorie dataset reports types of contracts which are differentiated into many categories (around 60) and I decided to reduce these to two: permanent and temporary contracts. In addition, whilst distinguishing apprenticeship contracts from temporary contracts would be preferable, making this distinction implied sixteen categories for the dependent variable and some of these are empty. For this reason I decided to use the first specification with twelve categories[36].

As far as job qualifications are concerned, this component is based on the classification adopted by ISTAT[37] in 2011 (see table B.5 in the appendix).

Initially i grouped qualifications into three categories: high, medium and low specialization and low specialization but given the low number of observations for the last level I decided to merge medium and low specialization [38].

The last consideration is on the variable timing of mobility. This framework has been built starting from the first contract. I calculated the days between the first contract activated by the individual and the first contract obtained in a different workplace (where this occurred). This variable assumes values other than zero for those who move at least once in the observation period and zero values for those who do not move at all (see table B.10 in the appendix).

specialization and duration of at least 8 months) and "contratto quasi ottimale" (higher specialization and duration of at least 8 months).

[35] Alleva et al (2012) show that the same individual can have hundreds of contracts in the same year and many of these last one day.

[36] Whilst in reducing many categories the Ordered Probit model generates a loss of information, this choice makes sense when numbers of observations for each categories are very low (Greene and Hensher, 2010).

[37] CP2011

[38] This classification is modeled following the report: "Fraboni R. and Sabbadini L.L. (eds.) 2014, Generazioni a confronto. Come cambiano i percorsi verso la vita adulta. Istat, Roma"; pg. 85.

The categories for the dependent variable are specified as follows:

Table 3.1: **Job level specifications**

Dependent variable: categories	**Type of contract**	**Job qualification**	**Days worked / Working days** (%)
1	Temporary	Medium-Low specialization	x<75%
2	Temporary	High specialization	x<75%
3	Permanent	Medium-Low specialization	x<75%
4	Permanent	High specialization	x<75%
5	Temporary	Medium-Low specialization	75%<x<25%
6	Temporary	High specialization	75%<x<25%
7	Permanent	Medium-Low specialization	75%<x<25%
8	Permanent	High specialization	75%<x<25%
9	Temporary	Medium-Low specialization	x>75%
10	Temporary	High specialization	x>75%
11	Permanent	Medium-Low specialization	x>75%
12	Permanent	High specialization	x>75%

3.6 Econometric specification

The empirical strategy used accounts for the possibility that unobservable factors affecting migration decisions will also affect the outcome variables. The model is thean made up of two stages. In the first stage I have estimated migration probability through a Probit model and, in the second one I have used an Ordered Probit model to calculate the effects of workplace mobility on various labour market levels.

The methodology takes up a recent work by Iammarino and Marinelli (2017) using an Ordered Probit model to estimate the effect of workplace mobility on over-education. The authors used a two-step procedure and without using any "exclusion restrictions" to overcome migration endogeneity, found that interregional mobility increases employability and the likelihood of a better labour market match[39]. Other than considering the endogenous relationship between migration and "job level", as in the precious chapter, also self-selection into employment should be take in to account. However, I have not considered the second issue since here, too, it proved impossible to identify a good instrumental variable for the employment selection equation[40]. Self-selection into employment can bias our results if the likelihood of obtaining a certain "job level" is different for employed and unemployed workers respectively. This could limit the relevance of the

[39] Devillanova (2013) reached a conflicting result for the effect of interregional mobility on over-education: accounting for migration endogeneity and including job characteristics as control, he found a positive interregional mobility effect on the likelihood of over-education. Although it is not verifiable in the theoretical framework adopted, one explanation mentioned is that since human capital is not portable (not a perfect substitute), migrants are more likely to be over-educated.

[40] Devillanova (2013) use family member numbers as tools for self-selection in employment and critique Van Ham (2003) who use age as an exclusion restriction since this variable impacts both on employment and over-education (dependent variable).

estimate presented and an extension of this work would be to resolve this.

The econometric specification proposed uses a latent regression model (Green, 2007) where the outcome equation is specified as follows:

$$Y_i^* = X_i'\beta + M_i + \varepsilon_i \tag{3.1}$$

M_i represents the endogenous dummy variable (here workplace mobility), X_i' a vector of explanatory variables and ε_i is the random error term, assumed normally distributed across observatinos, which has mean equal to zero and variance eqaul to one.
The unobservable latent dependent variable Y_i^* is related to an observed ordered discrete variable Y_i:

$$Y_i^* = \begin{cases} 0 & if & Y_i^* & \leq & 0 & & \\ 1 & if & 0 & < & Y_i^* & \leq & \mu_1 \\ 2 & if & \mu_1 & < & Y_i^* & \leq & \mu_2 \\ . & & & & & & \\ . & & & & & & \\ . & & & & & & \\ J & if & \mu_{J-1} & \leq & Y_i^* & & \end{cases}$$

where μ's are unknown parameters to be estimated with β. From is model we obtain the probability for different ordered outcomes:

$$\begin{cases} \Pr(y=0 \mid x) & = & \Phi(x'\beta) \\ \Pr(y=1 \mid x) & = & \Phi(\mu_1 - x'\beta) - \Phi(-x'\beta) \\ \Pr(y=2 \mid x) & = & \Phi(\mu_2 - x'\beta) - \Phi(\mu_1 - x'\beta) \\ \quad . & & \\ \quad . & & \\ \Pr(y=J \mid x) & = & 1 - \Phi(\mu_{J-1} - x'\beta) \end{cases}$$

The relevant part of this model is represented by the marginal effects and their coefficient interpretation is the following: each increment of a unit in the independent variable increases/decreases the probability of selecting alternative j by a certain percentage. Formally, these are expressed as follows:

$$\begin{cases} \frac{\partial \Pr(y=0|x)}{\partial x} & = & \phi(x'\beta)\beta, \\ \frac{\partial \Pr(y=1|x)}{\partial x} & = & [-\phi(x'\beta)\beta - \phi(\mu - x'\beta)]\beta, \\ \frac{\partial \Pr(y=J|x)}{\partial x} & = & \phi(\mu - x'\beta)]\beta, \end{cases}$$

Here Φ represents the standard normal cumulative density function. Since this model can be considered an extension of the univariate Probit model, optimization is obtained with the maximum likelihood estimation.

The 12 classes identified with table 3.1, must be ordered, mutually exclusive and exhaustive[41]. Within the random utility function framework, every class is associated with a different utility function and a higher class is associated with higher utility (Greene and Hensher, 2010).

As in the second chapter, I assumed that migration is related to labour market condition and to observable and unobservable individual characteristics (Picchio, 2008). Mobile graduates are more able and motivated (or have more financial resources) and better labour market outcomes could be partly explained by selectivity and not by migration itself (Wiers-Jenssen, 2011).
To overcome this problem I used the top step "Heckman procedure". In the first step I calculated the likelihood of migration and derived inverse Mills, adding it as a covariate to the Ordered Probit model.
The selection equation is as follows:

$$\mathrm{M}_i = X_i'\alpha + \mathrm{P.R.}_{\cdot i2002} + \eta_i \tag{3.2}$$

M is a dummy variable indicating migration, X_i' a the set of covariates affecting both migration decisions and job levels, and $P.R._{\cdot i2002}$ is the instrument variable that should be correlated with migration probability but not with outcome variable. As usual, the error term has a normal distribution.

The inverse Mills ratio (the ratio of the probability density function to the cumulative distribution function of a distribution) is calculated as follows[42]:

$$\lambda_i = \frac{\phi(X_i'\alpha)}{\Phi(Z_i'\alpha)}$$

The problem in using the inverse Mills ratio is the collinearity between the correction term and other regressors in the outcome equation (Bushway et al., 2007). In fact, even if the model's assumption of non-linearity may be sufficient to avoid the use of the instrumental variable, I would add $P.R._{\cdot i2002}$, which does not enter the set of covariate X_i' used in the Ordered Probit model. The next section describes the instrument used.

[41] It is standard practice to order classes from worst to best (Boes, 2013).

[42] Since the inverse Mills ratio is derived from normal distribution, it is advisable to use an Ordered Probit model and not a logit model. In fact, while in the logit model errors are assumed to follow standard logistics distribution, in the Probit model the error term follows normal distribution.

3.7 Instrument and exclusion restriction

As stressed previously, past migration affects the actual likelihood of moving and not simply on the basis of the results in terms of labour market outcomes and education. In fact, empirical work has argued that previous migration is relevant to the second generation of immigrants and the results in terms of wage and educational outcomes are related to changes in concentration of immigrants in the chosen location (Borjas, 1992; Goodwin-White, 2012).

One of the main channels by which past migration influences newer migration is the local labour market information flow that facilitates the catching up process, reducing the disadvantage deriving from being "non-native" (Cutillo and Ceccarelli, 2012). Taking into account that one of the determinants in location choice is the percentage of an individual's ethnic group that is working in the same area (Bartel, 1989), I have assumed that relocation decisions after graduation are influenced by the percentage of people who relocate and the fact that some of these come from the same region of origin[43].

For these reasons I have taken the internal migration rate between regions in 2002, the first year available. This data are provided by ISTAT and refers to registration and deregistration (of Italian and foreign individuals) numbered in local authority birth records[44].

The index ("Past Relocation in 2002") used as instrument is structured as follows:

$$P.R._{\cdot j2002} = \frac{Region_{ij}}{Total\,number\,of\,invidual\,transferred\,from\,region_i}$$

i=1,......,20 (Origin[45])

j=1,......,20 (Destination)

The index is expressed in percentage terms and given by the ratio between of total number of individuals coming from the region i and transferred to region j on the total number of individuals transferred from region i in 2002.
Table B.1 (appendix) shows the value of the index, by region of birth and destination. The higher value corresponds to the cell where region of birth and destination are the same, suggesting that the lion's share of mobility occurs within the same region[46].

I have sought to disentangle this "composition effect" using a different instrumental variable derived from data already used in a previous work (Piras, 2005).
The instrument proposed has the same structure as its predecessor but is based on the graduate migration flow (between regions), from 1990 to 1999.

[43]Bartel (1989) has suggested that economic conditions have relatively limited effects on destination choice and immigrants are mainly attracted by a large concentration of earlier immigrants.

[44]Documents and data are downloadable from the following website:
http://dati.istat.it/Index.aspx?DataSetCode=DCIS_MIGRAZIONILang=

[46]Interregional mobility rates are in fact derived from mobility between Italian town council areas.

The alternative instrument ("Past Graduates relocation") is made up as follows:

$$P.G.R._{ijt} = \frac{Region_{ijt}}{Total\,number\,of\,individuals\,transferred\,from\,region_{it}}$$

i=1,......,20 (Origin[47])

j=1,......,20 (Destination)

t=$\bar{t}$=1990,......,1999.

The index is expressed in percentages and show how many graduates coming from region i went to region j (transfer residence).

The two instrument presented are very similar except in the compostion: in the second there are only graduates (with no distinction between M.A.s and B.A. or specification reasons for movement). Testing a further instrument helped me to understand the composition effect better, even though the motivation behind it is the same as explained above. Using alernative instrument, the results were very similar both for selection and outcome equations but, as shown in table B.8 (appendix), the correlation between past relocation and current workplace mobility becomes non significant and I decided to opt for the first instrument presented.

Scholarly arguments on the right variable to use in interregional mobility vary and often conflict. With a linear probability model, Devillanova (2013) tried to estimate the effect of migration on over-education and used 'housing tenure' as instrumental variable, a variable which should affect the likelihood of moving but not the independent variable (over-education)[48]. Devillanova also discussed the problems potentially coming from using regional variables as tools for migration, supporting the idea that local variables cannot capture the individual unobservable characteristics which are at the origin of the endogeneity problem.
In a very similar work in which she tried to rule out determinants of study and work migration through a bivariate Probit model, Capuano (2009) also supported the thesis by which regional variables are not suitable as exclusion restrictions in both equations.

Internationally speaking, Venhorst and Corvers (2015) investigated the impact of interregional mobility on job-match quality using two dummies as instrumental variables: one indicating whether a graduate lives in the central economic region of the Netherlands at age sixteen, and one indicating whether the graduate had one or more parents born outside the Netherlands. The latter is an individual characteristic while the second is based on motivation closely related to the one argued for here. In fact, living in a rich region at the age of 16 affects search behavior, positively if we assume that there is a correlation between coming from a rich region and available information, negatively if we assume that there are better employment opportunities in rich regions.
Furthermore they also introduced a third variable, "Spatial mobility before the onset of study", which is a similar variable to that used in this exercise. Every individual's migration path (in terms of distance) is compared to the same migration path of very similar individuals (same graduation cohort, same home region, same field of study)[49].
The example cited above and the absence in the dataset of an individual variable suitable to overcoming endogeneity, led me to choose the instrument described above.

[48]However, housing tenure can be correlated with income and with actual profession and this casts doubt on this choice.

[49]This is the ratio of the distance moved by graduate i to the average distance traversed by his or her peer group, excluding graduate i.

3.8 Empirical results for the Probit model

Table 3.2 reports the marginal effects for the Probit model. The ISEE code (Equivalent Economic Situation Indicator) is the assessment tool for the household's economic situation used to apply tariff reductions and/or contributions for educational services. I have used it as a proxy for disposable household income. I split this continuous variable into five categories (from worst to better conditions) and used the first category as a reference category. As we have seen, the second category alone is significant and shows that "belonging to wealthier families" decreases the likelihood of moving by 2,6%. The other classes are not significant but show the same trend.

Differences in the ISEE code result may be due to significant differences in the number of observations between the first two modalities and the last (see table B.5). Furthermore, it should be considered that it is standard practice especially for those with self-employed parents, not to declare their true economic condition. In fact, Alleva has stressed (2015), the ISEE code is self-declared and thus subject to some bias which reduces the trustworthiness of the results.
The "post graduate specialization" dummy inidicates if individuals have completed an M.A., a Phd and any other kind of activity (non-academic) and, as we can see, it is not significant[50].

There is no information in the dataset which distinguishes between public or self-employed work but it is possible to derive this distinction from the ISTAT code on job qualification which specifies the public or private nature of almost all professions (see table B.6 in the appendix). This distinction is relevant in this analysis. In fact, those employed in the public sector show different migration likelihoods since their area of work is decided by government or regional administrations (Devillanova, 2013).
I have used the same variable both in the Probit and Ordered Probit models but their structures are different.
In the Probit model, I considered public employment for first contracts, thus prior to migration, and sought to answer this question: does being a public employee affect migration decisions negatively or positively? On the other hand, in the Ordered Probit model, I considered the "public sector employees" variable as a control in order to verify whether workplace mobility maintained its effect even when the distinction between public and private employees was taken into account[51]. However, since for some professions this distinction cannot be deduced, I was unable to calculate all the individuals effectively working in the public sector with absolute certainty.
As shown in the Probit model, the variable is significant and positive (5%), in line with Devillanova's findings (2013), where public employees showed higher rates of mobility. For the "parent self-employed", which is a dummy indicating the presence of at least one parent working independently, I used the same methodology (I cross-referenced information from different questions). Here, the distinction between public and self-employed is much clearer and thus these results are more reliable.
However this variable, as parents' social class and educational level[52], does not show significant effects. This result may be justified by an assumption that families with higher education and social class might attach greater value to human capital investment (Impicciatore and Tuorto, 2011), than, to relocation for study and I would not expect a direct influence on workplace mobility.

[50] In contrast to the previous chapter here it proved impossible to distinguish between specialization types but only whether these were complete, interrupted or underway.

[51] In this case, job qualifications were observed at the end of the observed period and the distinction between public or private was made on the basis of the last contract activated.

[52] The two variables have the same structure as those used in the second chapter except for the educational level where I have added a category indicating whether both parents are graduates (the reference category).

The results confirm a negative (but non significant) relationship between age at graduation and migration since young graduates are more prone to move after their first job (Parenti and Tealdi, 2015)[53]. Graduates in chemistry, pharmaceuticals, social sciences and humanities are more mobile than scientific graduates (maths). Some of these results correspond with Bacci et al (2008) who used Almalaurea data to investigate the fields of study associated with greater mobility rates. He stressed that some degree courses lead to a natural predisposition to mobility: political science, art, translation and interpreting[54]. As regards Economics graduates I was expecting a positive correlation with mobility to work since the empirical work cited above shows that in general, more technical fields show a greater propensity to mobility[55].

The relevance of the subject of study control is also highlighted by other empirical work focusing on different countries. Abreu, Faggian and McCann (2014) used longitudinal microdata on 5,000 recent UK graduates who finished their studies in 2002/03, showing that business graduates are more flexible in their migration strategies and earn higher salaries (this suggests adding this covariate in outcome equations too).

Those with M.A.s show greater mobility than those with B.A.s. This may be explained in terms of an increased level of specialization making national-scale competition possible while B.A. graduates have more general competences and are easier to replace in other local labour markets. In according that expected regards, positive migration selection in graduation mark is shown (Ciriaci, 2009), even if the coefficients magnitude are very low.

Controlling for region of birth generated no significant result and this may be due to the specific sample selected (newly graduated students in Rome) or, as explained above, to possible differences between region of birth and home region before enrollment at university.

The last variable reported in table 3.2 shows the marginal effects of the instrumental variable. The coefficient is highly meaningful and the effect negative: the relocation rate from region i to the region j in 2002 is negative correlated with the present relocation rate. If we start from Borjas's hypothesis (Borjas, 1992), this is a counterintuitive result since I would have expected that individuals to be attracted to place where individuals had moved previously. It is difficult to identify the reasons behind these results but some hypotheses may be suggested.
The first relates to the composition effect which I have already discussed. The composition effect is based on possible changes in labour market functioning (especially technological progress[56]) which has changed geographical labourdemand. In fact, while the main direction of migration remains the same (from the South to the Central-Northern regions), the composition in terms of age and education may be substantially different (Etzo, 2011; Mocetti et al., 2010)[57] .

However, as I have explained, I sought to isolate this effect using past relocation rates of graduates from 1990 to 1999, and obtained very similar results (see table B.8 in the appendix) in terms of direction (but not significance) of the effect on the endogenous dummy and thus can exclude this argument as a possible justification for this result.

[53] Bacci et al. (2008) arrived at an opposite result, interpreting it as a consequence of delayed entry in the labour market by those individuals with a post-graduate qualification (which are those with a greater mobility rate).

[54] Here, translation and interpreting are grouped together with humanities.

[55] Some results may be different due to different field of study classification or grouping.

[56] An interesting reflection on the effect of technological change on the Italian labour market has been proposed by Staglianò (2016).

[57] Etzo explains how this change influenced the role of family networks on migrations paths too.

Another possible explanation of this result may be related to a change in the relationship between native internal mobility and immigration in Italy, which is discussed in Porello and Mocetti (2010, B). These two authors found that immigration is positively associated with inflows of highly educated local people and it is possible that the clustering of foreigners in the North-Central regions might have met a job demand that was satisfied in the past by those from the Southern regions. If this reasoning is baseless then we might expect that low skills decrease migration propensity and high skills increase migration propensity with some effects in terms of composition.[58].
A last possible reason for the results obtained may be the "saturation effect". Past migration may have been induced by some activity sector which saturated over the years and this may have obliged present graduates to choose other destinations in their job searches. The three hypotheses proposed are intertwined and, showing their empirical validity would be very difficult here. These are simply speculative answers that may be used as avenues to be explored in subsequent research.

3.9 Empirical results for the Ordered Probit model

Table 3.7 shows the probability forecast for each outcome given that the rest of the variables are at their mean values[59].
The values are all significant and the probabilities are much greater for the first outcome. For example in the first table we can see that the predicted probability of being in the first class is 22% given that all predictors are set to their mean values while the probability of being included in the ninth class is 10%. This is a plausible result since I have considered individuals three years after graduation, at the first stage of their professional careers, when employment instability is usual.
However, other than the "short term effect", a possible explanation for this result may be that the classes of the independent variable are clustered in terms of number of observations and some categories have many more observations than others. As shown in table B.5 (appendix) the lion's share of the observations is distributed in the first (24%), fifth (22%) and ninth (9%) class. This could lead to higher predicted probabilities for classes with high numbers of observations.

This could led to get higher predicted probability for the classes with the high number of observations.
Tables 3.3 and 3.4 show the Ordered Probit model results, respectively with and without correction for endogeneity. Leaving aside interpretation for the control variable coefficients, in the uncorrected Ordered Probit model (table 3.3), the endogenous dummy is highly significant, with a positive coefficient (18,8%). Looking at the corrected estimation for endogeneity (table 3.4), the effect of migration on job levels is lower (11,6%) than that estimated previously. This means that unobservable characteristics (other than "being a migrant") increase the likelihood of achieving a good job level. Furthermore the correction term λ is positive and significant and thus the two step correction finds empirical justification. In fact, adding the selectivity term, which in this case indicates the likelihood that an individual might decide to relocate after their first job over the cumulative probability of an individual's decision, as additional control, helps to control for unobservable factors present in the error term influencing the decision to move and job levels.

[58]This could also have induced the low skilled to change destination and turn their attention to international labour markets.
[59]The numbers in brackets are the outcomes, ordered from worst to best job level.

The direction and significance of the selection term suggests that there is a positive reward (than an "upward bias") from unobservable factors affecting migration propensity or, as explained in section 2.10, there are unobserved factors increasing both the probability of selection and increasing the dependent variable score.

The same table shows the cut off parameter μ, which is needed for the computation but there is no direct interpretation. However, it serves to show the extent to which the differences between the ordered categories are sharply delineated. Where these differences are not clear, the cut-off point (and its relative significance) is more widely dispersed[60] (Greene and Hensher, 2010). In tables 3.3 and 3.4 a polarization between the first threshold parameters and the last, clearly defining the direction of the effects of workplace mobility on job level, is visible.

Since reporting the marginal effect of all predicted outcomes would burden results representation, within class showing a negative and positive relationship between spatial mobility and job levels (see table 3.7), I have selected those with the highest numbers of observations and reported marginal effects for these two predicted outcomes alone. As explained above, the classes to select (see table B.5 in the appendix) are the first for the classes where there is a negative relationship between workplace mobility and job level, and the ninth where I found a negative relationship.

Tables 3.5 and 3.6 show the marginal effects of the classes selected. The most natural way to interpret ordered response models (and discrete probability models in general) is to determine how a marginal change in one regressor changes the distribution of the outcome variable. For the dummy explanatory variables, the marginal effects of an Ordered Probit model denote a change in probability for the outcomes when a specific characteristic is present (female=1) versus when it is not (female=0). In the case of discrete variables, the marginal effects show the difference in predicted probabilities for each category relative to the reference ones.
For continuous variables the marginal effect indicates change in the dependent variable for small independent variable changes ("instantaneous rate of change") (Torres-Reyna, 2014). For example if one covariate increases by very small amount (e.g. 0.001), then P(Y=1) would increase by the estimated percentage.

Considering table 3.6 where the effect of workplace mobility on job levels is positive. Firstly I found a negative relationship between post graduate specialization and job level and between public employment and job level. It is plausible to assume that those with higher human capital (thus in this case those who complete a post-graduate activity) are subject to more contractual instability (which could be offset by higher wages) while I was expecting (in the short run) the opposite result for public employees. A possible reason might be a more widespread use of temporary contracts in the public sector or it is possible that career progression in the public sector is slower than in the private sector.

On the family background effect I found opposite results between social class and educational level: while higher educational levels are associated with better results in the labour market, higher social class is associated with lower job levels. The results obtained for this variable are the opposite of those found in the previous chapter (where higher social classes are associated with higher earnings) but the independent variable used in this analysis is different and the concept of job level defined here is much more similar to a performance concept. In fact, whilst it is possible that those with better family backgrounds earn more, it is also possible that such

[60]For example, if the dependent variable was an opinion and the preferences were dispersed, than the cut-off parameters would be less significant.

individuals wait longer for the "best job" and thus start work later[61]. Furthermore, this result may be biased by self-employed workers, absent in the sample analyzed.

As usual I added controls for field of study finding that quantitative subjects are associated with higher job levels as compared to humanities, psychology and architecture. On the strength of the data available, I also controlled for numbers of contracts activated up to the end of the observational period ("number of contracts" variable). This variable is positively associated with higher job levels (the coefficient is small but highly significant) confirming that a large number of contracts activated contributes to obtaining better employment conditions (Lilla et al., 2012; Picchio, 2008).

The effect of workplace mobility remains strongly significant even when I controlled for age of first contract which seems to impact on job level: first contracts are later and employment conditions are worse. This accords with previous results and with the "tenure effect", where experience and specific human capital accumulation pay over time[62].
I added the activity sector as control (Ateco classification, 2007). Firstly I used three categories (agriculture, industry and services) but those employed in the first were very few and thus I decided to merge agriculture and industry into a single sector (here the reference group). The last relevant control added was the timing of mobility ("timing" variable). As I have stressed several times in this dissertation, this represents relevant information to consider in estimating workplace mobility.

This variable can be called the "delaying effect" and suggests that after their first jobs, those who decide to move early (and are thus available for new jobs in a different regions) tend to achieve higher job levels, though magnitude coefficient is very low.
As expected, comparing this results with table 3.5 where I estimate the marginal effects for first job level (the worst employment condition in this framework), the direction of workplace mobility is the opposite (-6%) as the effect of the control variables discussed above.

Finally, table 3.8 reports the marginal effects for the two variables of interest, selectivity term and endogenous variable. The coefficients are almost all significant but for the migration dummy values are very low (from 0,3% to 6%). A clear turnaround in the sixth category, which is also the median category, is extremely interesting. The change concerns the direction for the endogenous dummy and this helps to confirm the positive effect of workplace mobility on employment conditions. The strongest effects are shown for the categories with the greatest number of observations (1st and 9th).

[61] On this point, Bratti and Staffolani (2001) have found that higher social class is associated with worse academic career performance. They also argue that those with better family backgrounds are able to achieve better employment conditions thanks to the social network effect discussed in the first chapter.

[62] Result confirmed by the number of contracts effect.

Table 3.2: **Probit model: marginal effects**

Dependent variable: workplace mobility		
	Coeff.	**Stand.errors**
ISEE code:8 to 14	-0.026**	(0.012)
ISEE code:15 to 21	-0.033	(0.029)
ISEE code:22 to 27	-0.004	(0.032)
ISEE code:28 to 34	-0.010	(0.031)
Post graduate specialization	0.007	(0.012)
Public sector employees	0.052*	(0.029)
Parent self employed	0.009	(0.014)
Parent social class: medium	-0.00002	(0.012)
Parent social class: low	0.017	(0.026)
Parent educational level: higher	0.005	(0.023)
Parent educational level: medium	-0.002	(0.026)
Parent educational level: low	-0.001	(0.031)
Age at graduation: >26	-0.003	(0.009)
Age at graduation: >30	-0.033	(0.026)
Chemistry/pharmacy	0.052***	(0.0192)
Engineering	0.025	(0.019)
Architecture	0.011	(0.025)
Economics	-0.005	(0.028)
Politics/social science	0.072***	(0.022)
Law	-0.017	(0.075)
Literature	0.062***	(0.018)
Psychology	0.059**	(0.025)
M.A.	0.041***	(0.012)
Grad. Mark 104	-0.017*	(0.009)
Grad. Mark 105-109	0.009	(0.014)
Grad. Mark 110 cum laude	0.004	(0.018)
Male	0.008	(0.013)
Erasmus	0.019**	(0.009)
Macro-area of birth: North East	0.037	(0.065)
Macro-area of birth: Center	0.005	(0.057)
Macro-area of birth: South	-0.023	(0.056)
Macro-area of birth: Islands	0.067	(0.056)
Past relocation 2002	-0.373***	(0.154)
Year	0.012	(0.011)
N	3724	

(dy/dx) is for discrete change in dummy variable
Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Table 3.3: **Ordered probit without correction**

Dependent variable: job level	**Coef.**	**Stand. errors**
ISEE code	-0.007	(0.016)
Post graduate specialization	-0.186***	(0.054)
Parent self employed	-0.066	(0.047)
Public sector employees	-0.197***	(0.068)
Parent social class	-0.061**	(0.029)
Parent educational level	0.069***	(0.013)
Age at graduation	0.353***	(0.029)
Field	-0.076***	(0.006)
M.A.	0.550***	(0.058)
Graduation mark	-0.032***	(0.012)
Male	0.173***	(0.051)
Number of contracts	0.004***	(0.0008)
Erasmus	-0.122***	(0.033)
Last working area	0.006	(0.020)
Macro-area of birth	-0.107**	(0.046)
Age first contract (classes)	-0.543***	(0.033)
Full time	0.257***	(0.0341)
Activity sector: services	0.041	(0.030)
Timing mobility	-0.0001***	(0.00003)
Workplace mobility	0.188***	(0.044)
Year	0.130***	(0.023)
cut1	-1.306***	(0.183)
cut2	-1.023***	(0.185)
cut3	-0.900***	(0.181)
cut4	-0.873***	(0.180)
cut5	-0.231	(0.183)
cut6	-0.0106	(0.184)
cut7	0.253	(0.183)
cut8	0.329*	(0.180)
cut9	0.789***	(0.190)
cut10	1.115***	(0.195)
cut11	1.782***	(0.192)
N 3549		

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Table 3.4: **Ordered probit with correction**

Dependent variable: job level		
	Coef.	**Stand. errors**
ISEE code	-0.013	(0.015)
Post graduate specialization	-0.184***	(0.057)
Parent self employed	-0.062	(0.049)
Public sector employees	-0.195***	(0.065)
Parent social class	-0.058*	(0.030)
Parent educational level	0.065***	(0.013)
Age at graduation	0.349***	(0.030)
Field	-0.074***	(0.006)
M.A.	0.569***	(0.056)
Graduation mark	-0.030**	(0.011)
Male	0.177***	(0.052)
Number of contracts	0.004***	(0.0008)
Erasmus	-0.111***	(0.032)
Last Working area	-0.019	(0.020)
Macro-area of birth	-0.077*	(0.042)
Age first contract (classes)	-0.543***	(0.033)
Full time	0.257***	(0.033)
Activity sector: services	0.044	(0.029)
Timing mobility	-0.0001***	(0.00004)
λ	0.230***	(0.042)
Workplace mobility	0.116**	(0.047)
Year	0.133***	(0.023)
cut1	-1.055***	(0.247)
cut2	-0.771***	(0.252)
cut3	-0.649***	(0.245)
cut4	-0.622**	(0.244)
cut5	0.0215	(0.248)
cut6	0.242	(0.254)
cut7	0.506**	(0.252)
cut8	0.582**	(0.246)
cut9	1.043***	(0.254)
cut10	1.368***	(0.265)
cut11	2.036***	(0.257)
N 3549		

Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Table 3.5: **Predicted probability for outcome 1: marginal effects**

Dependent variable: job level	**Coeff.**	**Stand. errors**
ISEE code: 8 to 14	0.002	(0.007)
ISEE code: 15 to 21	0.019	(0.018)
ISEE code: 22 to 27	0.063**	(0.027)
ISEE code: 28 to 34	-0.0003	(0.032)
Post graduate specialization	0.067***	(0.023)
Public sector employees	0.018	(0.014)
Parent self employed	0.042**	(0.018)
Parent social class: medium	0.016***	(0.005)
Parent social class: low	0.041**	(0.019)
Parent educational level: higher	-0.028**	(0.014)
Parent educational level: medium	-0.035***	(0.012)
Parent educational level: low	-0.064***	(0.012)
Age at graduation: >26	-0.110***	(0.008)
Age at graduation: >30	-0.165***	(0.013)
Chemistry/pharmacy	-0.008	(0.013)
Engineering	-0.096***	(0.010)
Architecture	0.169***	(0.026)
Economics	-0.023	(0.015)
Politics/Social science	0.096***	(0.016)
Law	0.025	(0.059)
Literature	0.156***	(0.012)
Psychology	0.088***	(0.011)
M.A.	-0.138***	(0.011)
Grad. Mark 104	0.002	(0.013)
Grad. Mark 105-109	0.006	(0.011)
Grad. Mark 110 cum laude	0.018	(0.011)
Number contracts	-0.021*	(0.011)
Male	-0.0009***	(0.0001)
Erasmus	0.021*	(0.011)
Macro-area of birth: North Est	-0.021	(0.062)
Macro-area of birth: Center	-0.031	(0.020)
Macro-area of birth: South	0.001	(0.022)
Macro-area of birth: Island	0.091***	(0.035)
Last Working area: North East	0.076***	(0.014)
Last Working area: Center	-0.008	(0.010)
Last Working area: South	0.032	(0.027)
Last Working area: Islands	-0.075	(0.048)
Age first contract (classes) (26 to 30)	0.135***	(0.016)
Age first contract (classes) (greater 30)	0.268***	(0.021)
Full time	-0.055***	(0.007)
Activity sector: services	-0.023***	(0.008)
Timing mobility	0.00003**	(0.00001)
λ	-0.019**	(0.007)
Workplace mobility	-0.060***	(0.012)
Year	-0.034***	(0.006)
N 3549		

Cluster Standard errors in brackets
*** p<0.10 ** p<0.05 *** p<0.010**

Table 3.6: **Predicted probability for outcome 9: marginal effects**

	Coeff.	**Stand. errors**
ISEE code: 8 to 14	-0.001	(0.002)
ISEE code: 15 to 21	-0.007	(0.007)
ISEE code: 22 to 27	-0.022***	(0.008)
ISEE code: 28 to 34	0.0001	(0.012)
Post graduate specialization	-0.024***	(0.007)
Public sector employees	-0.015**	(0.006)
Parent self employed	-0.007	(0.005)
Parent social class: medium	-0.006***	(0.002)
Parent social class: low	-0.015**	(0.006)
Parent educational level: higher	0.010**	(0.005)
Parent educational level: medium	0.013***	(0.004)
Parent educational level: low	0.025***	(0.004)
Age at graduation: >26	0.042***	(0.003)
Age at graduation: >30	0.070***	(0.007)
Chemistry/pharmacy	0.003	(0.006)
Engineering	0.050***	(0.004)
Architecture	-0.056***	(0.008)
Economics	0.011	(0.007)
Politics/Social science	-0.036***	(0.006)
Law	-0.010	(0.024)
Literature	-0.053***	(0.005)
Psychological	-0.033***	(0.004)
M.A.	0.052***	(0.003)
Grad. Mark 104	-0.0009	(0.005)
Grad. Mark 105-109	-0.002	(0.004)
Grad. Mark 110 cum laude	-0.007	(0.004)
Male	0.008*	(0.004)
Number contracts	0.0003***	(0.00007)
Erasmus	-0.008**	(0.004)
Macro-area of birth: North East	0.008	(0.024)
Macro-area of birth: Center	0.012	(0.007)
Macro-area of birth: South	-0.0004	(0.008)
Macro-area of birth: Islands	-0.028***	(0.010)
Last working area: North East	-0.026***	(0.004)
Last working area: Center	0.003	(0.004)
Last working area: South	-0.012	(0.009)
Last working area: Islands	0.034	(0.023)
Age first contract (classes) (26 to 30)	-0.059***	(0.007)
Age first contract (classes) (greater 30)	-0.096***	(0.007)
Full time	0.021***	(0.002)
Activity sector: Services	0.009***	(0.003)
Timing mobility	-0.00001**	(0.000005)
λ	0.007**	(0.003)
Workplace mobility	0.025***	(0.005)
Year	0.013***	(0.002)
N	3549	

Cluster Standard errors in brackets
*** p<0.10 ** p<0.05 *** p<0.010**

Table 3.7: **Predicted probability for the outcomes**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pr(Y =i)	0.220***	0.092***	0.092***	0.010***	0.252***	0.080***	0.084***	0.021***	0.101***	0.043***	0.039***	0.010***
	(25.44)	(18.95)	(18.95)	(10.28)	(46.91)	(13.13)	(37.05)	(6.50)	(19.52)	(13.50)	(17.93)	(8.10)
N	3549	3549	3549	3549	3549	3549	3549	3549	3549	3549	3549	3549

t statistics in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.8: **Marginal effects for the inverse Mills ratio and the endogenous variable**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Work. mob.	-0.060***	-0.010***	-0.003***	-0.0006***	-0.001	0.005***	0.009***	0.003***	0.025***	0.013***	0.018***	0.009***
	(-5.59)	(-5.11)	(-5.36)	(-3.82)	(-0.87)	(4.66)	(5.67)	(5.01)	(5.52)	(4.77)	(6.01)	(3.99)
λ	-0.019**	-0.005*	-0.001**	-0.0003*	-0.0005	0.002*	0.004*	0.001***	0.007**	0.006*	0.009*	0.004*
	(-2.50)	(-2.29)	(-2.84)	(-2.25)	(-0.76)	(2.32)	(2.52)	(3.37)	(2.41)	(2.22)	(2.54)	(2.28)
N	3549	3549	3549	3549	3549	3549	3549	3549	3549	3549	3549	3549

Cluster standard errors in brackets

***** $p < 0.05$, ****** $p < 0.01$, ******* $p < 0.001$

3.10 Limits and further research

The dataset built into this exercise enabled me to overcome some problems in the estimation of the return from workplace mobility, especially those referred to the timing of mobility.
However some limitations persist. The first one relates to the lenght of the observation period, probably too short for an in-depth understanding of the relationship between migration and labour market outcome. This suggests to extending this analysis on the long run.

Other limitations regard the definition of public employer which may be subject to bias for the reason explained above.

The dataset created has great potential and can be used to carry out policy suggestions on the school to work transition issue.
With reference to the research question addressed in this empirical work, this analysis can be extended by analyzing migration decision and simultaneous changes of employer or sector of activity in order to get a better measure of the return on workplace mobility. In fact, it has been shown that if this changes, it may alter the relationship between workplace mobility and employment condition (Hunt, 2004).
Usefully complementing the dataset with additional information, is possible to carry out studies on the coherence between subject of study and job qualification in order to investigate the labour market balance between demand and supply (over-education, job quality and the duration model).

It might also be interesting to study the relationship between educational supply and the productivity system in greater depth together exploiting the territoriality of the data collected. Understanding which types of graduates are absorbed into the local labour market can be useful for the purposes of adapting study courses to labour market subject to ongoing changes. Finally, the dataset can be supplemented with other source data (for example INPS data) to include self-employed workers unfortunately not considered in this analysis.

A general observation needs to be made on the restricted sample since i use just graduates from "Sapienza", that, despite the fact it's one of the bigger University in Europe, doesn't provide a rappresentative sample of the entire population. However, since in the estimation of the return from regional migration it is important to consider group as homogenus as possibile (Venhorst and Cörvers, 2015)[63], we should not see this as analysis weakness because use such data allow to eliminate part of heterogeneity coming from having graduates in very different Universities and labour markets.
Even if the results generalization can be subject to some limits, analysis based on different adminstrative data source are quite rare for Italy and the methodologies proposed in this chapter might be a good starting point to implement big data collection for public policies evaluations.

[63]Sestito and Viviani (2016) have also tried to estimate the effect of two labour market policies using data on just one Italian region (Veneto). They explain that using microdata on a single Italian region has the benefit of the estimates not being affected by spurious local labour market trends.

Appendix B

Appendix

Table B.1: **Past relocation in 2002 by region of birth and destination**

Region of birth//Region of destination	Piemonte	Valle d'Aosta	Liguria	Lombardia	Trentino	Veneto	Friuli	Emilia Romagna	Toscana	Umbria	Marche	Lazio
Piemonte	78,80%	0,39%	2,88%	4,72%	0,15%	1,05%	0,32%	1,41%	0,88%	0,16%	0,35%	1,12%
Valle D'Aosta	8,47%	71,81%	1,52%	2,78%	0,12%	1,35%	1,67%	2,38%	1,30%	0,02%	0,32%	1,35%
Liguria	9,41%	0,23%	65,98%	6,72%	0,32%	1,12%	0,35%	2,34%	4,67%	0,20%	0,42%	1,65%
Lombardia	2,27%	0,05%	1,16%	82,21%	0,29%	1,45%	0,33%	2,17%	1,06%	0,16%	0,44%	1,13%
Trentino	0,69%	0,02%	0,36%	3,62%	79,83%	4,61%	0,83%	1,78%	1,06%	0,15%	0,42%	1,43%
Veneto	0,69%	0,02%	0,33%	3,36%	0,75%	83,54%	2,16%	1,99%	1,23%	0,16%	0,28%	1,08%
Friuli	0,91%	0,05%	0,49%	2,89%	0,50%	6,87%	77,84%	1,32%	0,80%	0,14%	0,36%	1,72%
Emilia Romagna	0,91%	0,06%	0,61%	4,47%	0,29%	2,09%	0,38%	76,51%	1,41%	0,25%	1,43%	1,47%
Umbria	1,30%	0,03%	0,52%	3,13%	0,34%	1,46%	0,31%	2,63%	5,54%	62,07%	2,89%	10,34%
Marche	0,71%	0,06%	0,36%	2,94%	0,31%	2,03%	0,33%	5,73%	1,23%	1,04%	71,94%	3,19%
Lazio	1,34%	0,06%	0,57%	4,03%	0,41%	2,14%	0,81%	2,22%	2,73%	2,03%	1,51%	69,44%
Abruzzo	1,10%	0,02%	0,35%	3,70%	0,36%	1,57%	0,52%	3,20%	1,28%	0,64%	3,79%	8,19%
Molise	1,99%	0,11%	0,49%	5,83%	0,70%	1,08%	0,13%	5,51%	1,76%	0,83%	2,46%	9,90%
Campania	1,96%	0,05%	0,53%	6,37%	0,38%	2,36%	1,01%	6,64%	3,64%	0,98%	1,63%	5,16%
Puglia	3,37%	0,08%	0,74%	10,69%	0,92%	4,26%	1,43%	9,09%	2,51%	0,59%	3,09%	4,30%
Basilicata	4,76%	0,08%	0,87%	9,71%	0,53%	2,10%	0,71%	8,31%	4,95%	0,86%	1,48%	5,80%
Calabria	6,17%	0,46%	1,92%	14,60%	0,68%	2,98%	0,75%	6,27%	3,99%	1,09%	0,93%	7,37%
Sicilia	3,95%	0,09%	1,13%	10,32%	0,51%	3,75%	1,26%	5,64%	3,59%	0,46%	1,10%	2,90%
Sardegna	3,54%	0,24%	1,51%	6,88%	0,64%	3,18%	0,99%	3,62%	2,77%	0,48%	0,77%	3,74%
Toscana	50,41%	0,53%	0,02%	1,48%	0,11%	0,53%	0,13%	1,13%	39,43%	0,55%	0,26%	1,49%

Own elaboration on ISTAT data

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Region of birth//Region of destination	Abruzzo	Molise	Campania	Basilicata	Calabria	Sicilia	Sardegna	Puglia
Piemonte	0,28%	0,10%	1,41%	0,20%	1,41%	2,19%	0,92%	1,28%
Valle D'Aosta	0,27%	0,02%	0,86%	0,27%	2,60%	1,35%	0,88%	0,64%
Liguria	0,27%	0,04%	1,20%	0,12%	1,21%	1,54%	1,27%	0,94%
Lombardia	0,32%	0,08%	1,47%	0,18%	1,25%	1,87%	0,78%	1,32%
Trentino	0,27%	0,06%	1,03%	0,09%	0,73%	1,29%	0,45%	1,29%
Veneto	0,24%	0,04%	1,04%	0,07%	0,47%	1,24%	0,43%	0,90%
Friuli	0,35%	0,08%	1,65%	0,07%	0,44%	1,64%	0,50%	1,38%
Emilia Romagna	0,49%	0,13%	3,12%	0,21%	1,14%	2,15%	0,65%	2,23%
Umbria	0,76%	0,15%	3,37%	0,23%	1,52%	1,37%	0,67%	1,37%
Marche	2,29%	0,24%	2,36%	0,19%	0,42%	1,48%	0,29%	2,88%
Lazio	2,19%	0,48%	3,55%	0,27%	1,76%	1,56%	1,30%	1,59%
Abruzzo	68,39%	1,02%	2,20%	0,13%	0,34%	0,57%	0,36%	2,26%
Molise	7,57%	48,36%	7,36%	0,38%	0,21%	0,49%	0,55%	4,28%
ùCampania	0,72%	0,57%	64,96%	0,47%	0,76%	0,65%	0,33%	0,83%
Puglia	1,60%	0,61%	1,86%	0,96%	0,78%	0,97%	0,40%	51,74%
Basilicata	1,06%	0,38%	7,35%	37,70%	2,88%	1,09%	0,21%	9,18%
Calabria	0,48%	0,20%	2,24%	0,54%	44,53%	2,73%	0,37%	1,72%
Sicilia	0,31%	0,07%	0,92%	0,09%	0,94%	61,80%	0,36%	0,81%
Sardegna	0,27%	0,08%	1,02%	0,03%	0,58%	0,99%	68,21%	0,46%
Toscana	0,14%	0,04%	1,35%	0,44%	0,12%	0,42%	0,97%	0,44%

Table B.3: **Past (graduates) relocation 1990-1999 by region of birth and destination**

Region of birth//Region of destination	Abruzzo	Basilicata	Calabria	Campania	Emilia Romagna	Friuili	Lazio	Liguria	Lombardia	Marche	Molise	Piemonte
Abruzzo	61,94%	0,27%	0,90%	1,85%	5,55%	0,55%	7,26%	0,39%	4,84%	3,79%	1,54%	1,73%
Basilicata	1,20%	37,79%	2,86%	9,89%	5,58%	0,81%	5,66%	0,89%	7,45%	1,00%	0,18%	3,74%
Calabria	0,68%	0,69%	46,98%	2,47%	5,43%	0,57%	6,35%	1,86%	10,96%	0,71%	0,23%	6,04%
Campania	0,88%	1,11%	1,24%	69,75%	2,92%	0,64%	5,57%	0,62%	5,36%	0,65%	0,65%	1,98%
Emilia Romagna	0,94%	0,24%	1,62%	1,10%	72,94%	0,93%	1,20%	0,91%	6,00%	1,97%	0,14%	1,30%
Friuili	0,39%	0,15%	0,82%	0,92%	3,25%	69,81%	1,66%	0,69%	3,91%	0,77%	0,08%	1,26%
Lazio	3,38%	0,79%	6,25%	3,85%	2,72%	1,02%	52,47%	1,06%	4,78%	1,87%	1,18%	2,22%
Liguria	0,38%	0,18%	3,10%	0,88%	3,35%	0,80%	1,79%	55,64%	9,97%	0,50%	0,03%	10,69%
Lombardia	0,52%	0,20%	2,09%	1,40%	3,25%	0,61%	1,30%	2,01%	75,01%	0,73%	0,11%	3,29%
Marche	2,83%	0,11%	0,71%	0,82%	9,21%	0,81%	3,04%	0,33%	4,40%	65,98%	0,25%	1,28%
Molise	7,90%	0,62%	1,21%	6,29%	5,97%	0,52%	10,69%	0,34%	5,49%	2,16%	43,35%	2,15%
Piemonte	0,49%	0,24%	2,84%	1,32%	1,99%	0,74%	1,64%	3,41%	6,67%	0,54%	0,12%	71,28%
Puglia	2,07%	1,75%	1,30%	2,23%	8,19%	1,00%	4,32%	0,78%	9,01%	1,64%	0,51%	3,38%
Sardegna	0,34%	0,08%	0,66%	0,89%	1,99%	0,51%	3,01%	0,92%	3,30%	0,48%	0,06%	1,57%
Sicilia	0,28%	0,13%	1,57%	0,80%	2,37%	0,81%	2,54%	0,61%	6,99%	0,35%	0,06%	3,04%
Toscana	0,43%	0,26%	2,23%	1,31%	2,74%	0,58%	2,54%	2,14%	3,86%	0,66%	0,15%	1,44%
Trentino	0,78%	0,10%	0,68%	0,98%	4,54%	1,39%	0,85%	0,63%	5,02%	0,84%	0,03%	1,11%
Umbria	1,41%	0,30%	3,66%	1,68%	3,62%	0,99%	7,80%	0,54%	3,89%	4,08%	0,46%	1,89%
Val D'Aosta	0,50%	0,24%	0,97%	0,71%	3,00%	0,34%	0,96%	2,17%	3,92%	0,39%	0,14%	15,18%
Veneto	0,41%	0,11%	0,72%	0,78%	3,74%	3,06%	1,06%	0,43%	4,05%	0,60%	0,07%	1,00%

Own elaboration on ISTAT data

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Region of birth//Region of destination	Puglia	Sardinia	Sicilia	Tuscany	Trentino	Umbria	Val D'Aosta	Veneto
Abruzzo	1,98%	0,36%	0,71%	2,31%	0,53%	1,14%	0,12%	2,25%
Basilicata	11,93%	0,56%	1,44%	5,20%	0,51%	1,10%	0,11%	2,13%
Calabria	1,77%	0,49%	4,13%	5,94%	0,50%	1,42%	0,09%	2,71%
Campania	1,60%	0,52%	0,97%	2,70%	0,36%	0,64%	0,07%	1,75%
Emilia Romagna	1,86%	0,48%	1,11%	2,23%	0,92%	0,43%	0,08%	3,62%
Friuli	0,87%	0,30%	1,57%	1,40%	0,79%	0,24%	0,07%	11,05%
Lazio	2,42%	1,79%	2,76%	4,78%	0,72%	3,23%	0,13%	2,59%
Liguria	0,95%	1,19%	1,43%	6,13%	0,42%	0,36%	0,39%	1,82%
Lombardy	1,36%	0,45%	2,17%	1,97%	0,60%	0,31%	0,13%	2,46%
Marche	1,51%	0,37%	0,70%	2,47%	0,47%	2,21%	0,02%	2,48%
Molise	3,58%	0,55%	0,79%	3,74%	0,24%	1,57%	0,18%	2,65%
Piedmont	1,11%	0,67%	2,18%	1,77%	0,29%	0,34%	0,83%	1,54%
Puglia	52,68%	0,51%	1,05%	3,84%	0,66%	0,99%	0,09%	4,01%
Sardinia	0,58%	79,45%	1,16%	2,76%	0,20%	0,53%	0,07%	1,44%
Sicilia	0,83%	0,57%	73,72%	2,14%	0,39%	0,34%	0,12%	2,35%
Tuscany	1,04%	0,78%	1,11%	75,74%	0,36%	1,10%	0,08%	1,48%
Trentino	0,83%	0,28%	1,15%	1,77%	70,29%	0,40%	0,09%	8,25%
Umbria	1,51%	0,67%	1,07%	6,16%	0,50%	57,51%	0,10%	2,14%
Val D'Aosta	0,95%	0,65%	1,37%	1,04%	0,05%	0,30%	66,29%	0,84%
Veneto	0,86%	0,34%	1,19%	1,32%	1,56%	0,24%	0,03%	78,42%

Table B.5: **Variables description**

Variable	N.obs.	Source	Mean	Sd	Min.	Max.
Job level	3549	(e) Comunicazioni obbligatorie (Ministry of Labor)	5,026	3,313	1	12
Job level: 1		-	0,243	0,429	-	
Job level: 2		-	0,089	0,286	-	
Job level: 3		-	0,041	0,199	-	
Job level: 4		-	0,009	0,095	-	
Job level: 5		-	0,227	0,419	- -	
Job level: 6		-	0,073	0,26	-	
Job level: 7		-	0,078	0,268	-	
Job level: 8		-	0,02	0,14	-	
Job level: 9		-	0,099	0,298	-	
Job level: 10		-	0,048	0,214	-	
Job level: 11		-	0,051	0,22	-	
Job level: 12		-	0,018	0,134	-	
Job specialization	3549	(e) Comunicazioni obbligatorie (Ministry of Labor) and ISTAT (CP2011, 2 digits)	0,259	0,438	0	1
Last type of contract (1:temporary)	3549	Comunicazioni obbligatorie (Ministry of Labor)	0,781	0,413	0	1
Days worked/working days	3549	(e) Comunicazioni obbligatorie (Ministry of Labor)	0,423	0,307	0,001	0,997
Isee code	3549	Infostud data (Sapienza University)	1,654	0,847	1	5
Isee code: 1		-	0,524	0,499	-	
Isee code: 2		-	0,347	0,476	-	
Isee code: 3		-	0,09	0,286	-	
Isee code: 4		-	0,022	0,148	-	
Isee code: 5		-	0,014	0,12	-	
Specialization	3549	Almalaurea	0,056	0,23	0	1
Parent self employed	3549	Almalaurea	0,172	0,378	0	1
Public sector employee	3549	(e) Comunicazioni obbligatorie (Ministry of Labor) and ISTAT (CP2011, 5 digits)	0,043	0,205	0	1
Family social classes	3549	Almalaurea	1,784	0,661	1	3
Family social classes: 1		-	0,346	0,475	-	
Family social classes: 2		-	0,518	0,499	-	
Family social classes: 3		-	0,135	0,342	-	
Family study title	3549	Almalaurea	2,861	0,838	1	4

Family study title: both graduated		-	0,088	0,284	-	
Family study title: max graduated		-	0,163	0,37	-	
Family study title: max high school diploma		-	0,544	0,498	-	
Family study title: max elementary	-	0,202	0,401	-		
Age at graduation	3549	Infostud data (Sapienza University)	1,578	0,619	1	3
Age at graduation: up to 26		-	0,491	0,499	-	
Age at graduation: 27 to 30		-	0,438	0,496	-	
Age at graduation: over 30		-	0,069	0,254	-	
Field of study	3549	Infostud data (Sapienza University)	5,01	2,633	1	9
Scientific (matematical, physical and natural science)		-	0,058	0,235	-	
Pharma-chemical		-	0,174	0,379	-	
Engineering		-	0,158	0,365	-	
Architecture.		-	0,089	0,284	-	
Economic/Statistics		-	0,083	0,277	-	
Political and social science		-	0,117	0,322	-	
Law		-	0,004	0,069	-	
Humanistic		-	0,204	0,403	-	
Psychological		-	0,108	0,311	-	
Master degree	3549	Infostud data (Sapienza University)	0,346	0,475	0	1
Graduation mark	3549	Infostud data (Sapienza University)	2,871	1,166	1	4
Graduation mark: 78 to 100		-	0,191	0,393	-	
Graduation mark: 101 to 104		-	0,177	0,382	-	
Graduation mark: 105 to 109		-	0,197	0,398	-	
Graduation mark: 110 and 110 cum laude		-	0,432	0,495	-	
Male	3549	Comunicazioni obbligatorie (Ministry of Labor)	0,345	0,475	0	1
Number of contract	3549	(e) Comunicazioni obbligatorie (Ministry of Labor)	3,468	10,645	1	316
Erasmus	3549	Almalaurea	0,122	0,327	0	1
Last working area	3549	(e) Comunicazioni obbligatorie (Ministry of Labor)	2,865	0,783	1	5
North West		-	0,107	0,31	-	
North East		-	0,05	0,218	-	
Center		-	0,719	0,449	-	
South		-	0,113	0,316	-	

Island		-	0,009	0,094	-	
Origin Macro-area	3549	Infostud data (Sapienza University)	3,268	0,591	1	5
North West		-	0,016	0,126	-	
North East		-	0,017	0,129	-	
Center		-	0,658	0,474	-	
South		-	0,297	0,457	-	
Island		-	0,01	0,101	-	
Age first contract	3549	(e) Comunicazioni obbligatorie (Ministry of Labor)	1,809	0,645	1	3
Age at first contract: up to 26		-	0,321	0,467	-	
Age at first contract: 27 to 30		-	0,547	0,497	-	
Age at first contract: over 30		-	0,131	0,337	-	
Full time	3549	(e) Comunicazioni obbligatorie (Ministry of Labor)	0,678	0,467	0	1
Sector of activiy: Services	3549	(e) Comunicazioni obbligatorie (Ministry of Labor) and ISTAT (ATECO, 2007)	0,859	0,3476	0	1
Timing mobility	3549	(e) Comunicazioni obbligatorie (Ministry of Labor)	147,47	452,08	0	3894
Year	3549	Infostud data (Sapienza University)	0,567	0,495	0	1
Workplace mobility	3549	(e) Comunicazioni obbligatorie (Ministry of Labor)	0,145	0,353	0	1
Past relocation in 2002	3549	ISTAT	0,422	0,312	0,006	0,835

(e) Own elaboration

Table B.6: **Public sector employees: ATECO code, 5 digits**

ATECO code	**Classification**
1.1.1.1.0	Membri di organismi di governo e di assemblee nazionali con potestà legislativa e regolamentare
1.1.1.2.0	Membri di organismi di governo e di assemblee regionali e di Province autonome con potestà legislativa e regolamentare
1.1.1.3.0	Membri di organismi di governo e di assemblee provinciali con potestà regolamentare
1.1.1.4.0	Membri di organismi di governo e di assemblee sub-provinciali e comunali con potestà regolamentare
1.1.2.1.0	Ambasciatori, ministri plenipotenziari ed altri dirigenti della carriera diplomatica
1.1.2.2.1	Commissari di governo, prefetti e vice prefetti
1.1.2.2.2	Capi e vice capi della polizia di Stato, questori ed alti responsabili della sicurezza pubblica
1.1.2.2.3	Segretari generali e responsabili del controllo e della gestione nella amministrazione pubblica
1.1.2.3.1	Direttori degli uffici scolastici territoriali ed equiparati
1.1.2.3.2	Sovrintendenti al patrimonio culturale nazionale
1.1.2.4.1	Direttori generali, dipartimentali ed equiparati delle amministrazioni dello Stato, degli enti pubblici non economici e degli enti locali
1.1.2.4.2	Rettori di università, direttori di istituzioni dell'Alta Formazione e di enti di ricerca
1.1.2.4.3	Direttori generali ed equiparati nella sanità
1.1.2.5.0	Dirigenti scolastici ed equiparati
1.1.2.6.1	Dirigenti ed equiparati delle amministrazioni dello Stato, degli enti pubblici non economici e degli enti locali
1.1.2.6.2	Dirigenti ed equiparati delle università e degli enti di ricerca
1.1.2.6.3	Dirigenti ed equiparati nella sanità
1.1.3.1.0	Dirigenti della magistratura ordinaria
1.1.3.2.0	Dirigenti della magistratura amministrativa e delle giurisdizioni speciali
2.5.2.2.2	Esperi legali in enti pubblici
2.5.2.3.0	Notai
2.5.2.4.0	Magistrati
2.6.1.1.1	Docenti universitari in scienze matematiche e dell'informazione
2.6.1.1.2	Docenti universitari in scienze fisiche
2.6.1.1.3	Docenti universitari in scienze chimiche e farmaceutiche
2.6.1.1.4	Docenti universitari in scienze della terra
2.6.1.2.1	Docenti universitari in scienze biologiche
2.6.1.2.2	Docenti universitari in scienze agrarie, zootecniche e della produzione animale
2.6.1.2.3	Docenti universitari in scienze mediche
2.6.1.3.1	Docenti universitari in scienze ingegneristiche civili e dell'architettura
2.6.1.3.2	Docenti universitari in scienze ingegneristiche industriali e dell'informazione
2.6.1.4.0	Docenti universitari in scienze dell'antichità, filologico-letterarie e storico-artistiche
2.6.1.5.1	Docenti universitari in scienze storiche e filosofiche
2.6.1.5.2	Docenti universitari in scienze pedagogiche e psicologiche
2.6.1.6.0	Docenti universitari in scienze economiche e statistiche
2.6.1.7.1	Docenti universitari in scienze giuridiche
2.6.1.7.2	Docenti universitari in scienze politiche e sociali

2.6.3.1.1	Professori di discipline artistiche nelle accademie di belle arti e nelle istituzioni scolastiche assimilate
2.6.3.1.2	Professori di discipline musicali nei conservatori e nelle istituzioni scolastiche assimilate
2.6.3.1.3	Professori di arte drammatica e danza nelle accademie e nelle istituzioni scolastiche assimilate
2.6.3.2.1	Professori di scienze matematiche, fisiche e chimiche nella scuola secondaria superiore
2.6.3.2.2	Professori di scienze della vita e della salute nella scuola secondaria superiore
2.6.3.2.3	Professori di discipline tecnico-ingegneristiche nella scuola secondaria superiore
2.6.3.2.4	Professori di scienze dell'informazione nella scuola secondaria superiore
2.6.3.2.5	Professori di scienze letterarie, artistiche, storiche, filosofiche, pedagogiche e psicologiche nella scuola secondaria superiore
2.6.3.2.6	Professori di scienze giuridiche, economiche e sociali nella scuola secondaria superiore
2.6.3.3.1	Professori di discipline umanistiche nella scuola secondaria inferiore
2.6.3.3.2	Professori di discipline tecniche e scientifiche nella scuola secondaria inferiore
2.6.4.1.0	Professori di scuola primaria
2.6.4.2.0	Professori di scuola pre-primaria
2.6.5.2.0	Ispettori scolastici e professioni assimilate
5.4.8.1.0	Personale di guardiania territoriale
5.4.8.2.0	Vigili urbani
5.4.8.3.1	Agenti della Polizia di Stato
5.4.8.3.2	Agenti della Guardia di Finanza
5.4.8.3.3	Agenti del corpo forestale
5.4.8.4.1	Vigili del fuoco
5.4.8.4.2	Personale delle squadre antincendio
8.1.4.5.0	Operatori ecologici e altri raccoglitori e separatori di rifiuti
8.1.5.1.0	Bidelli e professioni assimilate
9.1.1.1.0	Ufficiali delle forze armate
9.2.1.1.0	Sergenti, sovraintendenti e marescialli delle forze armate
9.3.1.1.0	Truppa delle forze armate

All the codes are available at the following link: http://professioni.istat.it/sistemainformativoprofessioni/cp2011/

Table B.7: **Descriptive statiscts: full sample**

	Macroarea of birth	First mobility	Last place of work
Piemonte	0,20%	5,60 %	1,55 %
Lombardia	1,18%	32,43 %	8,62 %
Trentino-Alto Adige	0,11%	1,35 %	0,42 %
Veneto	0,68%	5,60 %	1,44 %
Friuli-Venezia Giulia	0,14%	0,58 %	0,37 %
Liguria	0,25%	1,93%	0,62 %
Emilia-Romagna	0,79%	11,20 %	2,79 %
Toscana	0,93%	8,30 %	2,06 %
Umbria	1,78%	1,74 %	1,04 %
Marche	1,55%	2,70 %	1,21 %
Lazio	57,73%		65,34 %
Abruzzo	3,86%	4,83 %	2,31 %
Molise	2,73%	1,74 %	1,72 %
Campania	10,51%	8,30%	4,54 %
Puglia	4,96%	3,28%	1,89 %
Basilicata	2,09%	1,35 %	0,54 %
Calabria	5,21%	2,12 %	1,30 %
Sicilia	4,25%	3,47 %	1,35 %
Sardegna	1,04%	3,47 %	0,90 %
Total (absolute value)	3549	518	3549

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Table B.8: **Probit model with alternative instrument: marginal effects**

Dependent variable: workplace mobility		
	Coeff.	**Stand.errors**
ISEE code: 8 to 14	-0.026**	(0.012)
ISEE code:15 to 21	-0.032	(0.028)
ISEE code:22 to 27	-0.004	(0.031)
ISEE code:28 to 34	-0.007	(0.030)
Post laurea specialization	0.007	(0.013)
Public sector employees	0.046	(0.033)
Parent self employed	0.009	(0.014)
Parent social class: medium	-0.001	(0.012)
Parent social class: low	0.013	(0.027)
Parent educational level: higher	0.006	(0.023)
Parent educational level: medium	-0.003	(0.027)
Parent educational level: low	-0.004	(0.032)
Age at graduation: >26	-0.002	(0.008)
Age at graduation: >30	-0.032	(0.024)
Chemistry/pharmacy	0.054***	(0.017)
Engineering	0.030*	(0.018)
Architecture	0.012	(0.025)
Economics	-0.002	(0.028)
Politics/social science	0.078***	(0.020)
Law	-0.022	(0.071)
Literature	0.068***	(0.018)
Psychological	0.062**	(0.024)
M.A.	0.041***	(0.011)
Grad. Mark 104	-0.017*	(0.009)
Grad. Mark 105-109	0.010	(0.015)
Grad. Mark 110 cum laude	0.007	(0.017)
Male	0.009	(0.012)
Erasmus	0.021**	(0.009)
Macro-area of birth: North East	0.043	(0.069)
Macro-area of birth: Center	-0.018	(0.060)
Macro-area of birth: South	-0.016	(0.062)
Macro-area of birth: Islands	0.098*	(0.059)
Past relocation: 1990-1999	-0.369	(0.227)
Year	0.011	(0.012)
N	3549	

(dy/dx) is for discrete change of dummy variable
Cluster Standard errors in brackets
*** p<0.10, ** p<0.05, *** p<0.010**

Table B.9: **Ordered probit with correction**

Dependent variable: job level

	Coef.	**Stand. errors**
ISEE code	-0.013	(0.015)
Post laurea specialization	-0.184***	(0.056)
Parent self employed	-0.062	(0.049)
Public sector employees	-0.195***	(0.065)
Parent social class	-0.059*	(0.030)
Parent educational level	0.066***	(0.014)
Age at graduation	0.349***	(0.030)
Field of study	-0.074***	(0.006)
M.A.	0.568***	(0.057)
Graduation mark	-0.029**	(0.012)
Male	0.177***	(0.052)
Number of contracts	0.004***	(0.0008)
Erasmus	-0.111***	(0.031)
Last working area	-0.015	(0.020)
Macro-area of birth	-0.084*	(0.044)
Age first contract (class)	-0.543***	(0.034)
Full time	0.258***	(0.033)
Activity sector: services	0.046	(0.030)
Timing mobility	-0.0001***	(0.00004)
λ	0.114*	(0.066)
Workplace mobility	0.214***	(0.040)
Year	0.133***	(0.023)
cut1	-1.078***	(0.274)
cut2	-0.795***	(0.279)
cut3	-0.672**	(0.271)
cut4	-0.645**	(0.270)
cut5	-0.001	(0.274)
cut6	0.218	(0.281)
cut7	0.482*	(0.279)
cut8	0.558**	(0.272)
cut9	1.019***	(0.281)
cut10	1.345***	(0.293)
cut11	2.012***	(0.284)
N 3549		

Cluster Standard errors in brackets

*** p<0.10, ** p<0.05, *** p<0.010**

Table B.10: **Descriptive statistics by workplace mobility**

	Stayers	— —	**Movers**	
Variable	**Mean**	**St.Dev.**	**Mean**	**St.Dev.**
Job level	4,996	3,332	5,201	3,201
Job specialization	0,259	0,438	0,259	0,438
Days worked/working days	0,420	0,312	0,443	0,285
Last type of contract (1:temporary)	0,782	0,412	0,774	0,419
ISEE code	1,659	0,845	1,624	0,861
Post graduate specialization	0,055	0,228	0,064	0,244
Parent self employed	0,172	0,378	0,176	0,381
Public sector employees	0,041	0,200	0,056	0,230
Parent social class	1,793	0,661	1,766	0,662
Parent educational level	2,870	0,837	2,807	0,844
Age at graduation	1,578	0,623	1,577	0,594
Field of study	4,964	2,637	5,282	2,618
Master degree	0,547	0,498	0,643	0,480
Graduation mark	2,847	1,173	3,010	1,120
Male	0,345	0,475	0,355	0,479
Number of contracts	3,255	10,338	4,745	12,224
Erasmus	0,117	0,322	0,153	0,360
Last working area	2,925	0,683	2,514	1,151
Origin Macro-area	3,252	0,576	3,361	0,669
Age first contract	1,816	0,648	1,766	0,626
Full time	0,667	0,471	0,741	0,438
Sector of activity: services	0,864	0,342	0,834	0,372
Timing mobility			1010,373	727,363
Year	0,567	0,496	0,569	0,496
Past relocation in 2002	0,468	0,301	0,155	0,239
N	3031		518	

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