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Contents

List of Tables

List of Figures

Summary

Tax and service induced mobility of economic agents is one of the most important factors in shaping regional and economic performances. Indeed, since the fundamental contribution of Tiebout (1956), it is acknowledged that individuals move among regions and countries to satisfy their preferences with respect to the bundle of tax and services that each jurisdiction is providing.

With this respect, the mobility of high-skilled individuals is a fundamental public policy issue. In fact, these agents play a fundamental role in fostering the local development given their high productivity and their ability to generate positive spillovers within jurisdictions' territories. Therefore, governments are incentivized to shape their policies to attract this kind of individuals and may compete with each other to reach this target. In this context, tax and services induced mobility of high-skilled individuals become a fundamental driving force that influences national and regional policies and economic performances. Therefore, understanding the determinants of economic mobility is paramount.

This doctoral thesis is devoted to investigating empirically the determinants of tax and service mobility by means of the discrete choice approach considering two specific cases. As for tax induced mobility, the effect of marginal income taxation on European football players' migration patterns is investigated in Chapter 2. As for service induced mobility, the effect of financial and in-kind aid policies on university students' location decision is considered in Chapter 3.

Chapter one provides an introductory overview of the tax and service induced phenomenon. The chapter starts by summarizing the theoretical literature regarding tax and service induced migration and the debate regarding this phenomenon. The second part of the chapter is devoted to a general discussion of the discrete choice approach in the context of individual economic mobility.

Chapter two analyzes the tax induced mobility of high-skilled workers from an empirical point of view. More specifically, the chapter investigates the effect of top marginal tax rates on turnover and migration patterns of football players in 16 European countries between 2007

and 2016. The analysis is carried by estimating a two-sided matching model using a maximum score matching approach. This strategy has permitted to estimate the structural parameters of the underlying decision process of footballers by accounting for the competition between agents in the market and get rid of factors affecting both the demand and supply side for which information is hardly accessible. These parameters are then exploited to quantify the sensitivity of the population of tax payers to taxation and the heterogeneity of these effects on the base of players' abilities and nationalities. Findings indicate a heterogeneous effect of marginal taxation.

Chapter three analyzes the service-induced mobility of university students by focusing on the effect of financial and in-kind aid policies on their choices of location. This phenomenon is analyzed by using a unique dataset with administrative data on Italian university students enrolled for the first time in the academic year 2014-2015, along with detailed information on the financial and in-kind policies of the *Diritto allo studio universitario* program. The analysis is by considering explicitly the heterogeneity in students' preferences. Firstly, a Conditional Logit model is estimated to identify the systematic variation in students' preferences by interacting individual characteristics with alternatives' attributes. Secondly, a the Latent Class Logit model in order to consider explicitly the heterogeneity in students' preferences. The latter approach allows to model systematic and random heterogeneity in preferences by exploiting the individual characteristics of students. The sensitivity of students' location decisions is quantified by computing willingness to pay and semi-elasticity measures. Findings indicate that policies that provide scholarships together with places in dormitories are effective in attracting more students.

Chapter 1

Discrete choice methods for the analysis of tax and services induced mobility

1.1 Introduction

Tax and services induced mobility is a fundamental driving force that influences national and regional economic performances.

Indeed, since the seminal contribution of Tiebout (1956), it is acknowledged that individuals move across regions and countries on the basis of their preferences regarding the bundle of tax and government services that the jurisdiction is providing. One of the most important consequences of this phenomenon is the introduction of inter-jurisdictional competition (IC). Indeed, in a context with mobile individuals, policymakers may have the incentive to shape their policies to attract specific groups of people and to expel others (Brueckner, 2000). This is especially true if we consider the mobility of high-skilled individuals, top incomes and businesses that can play a fundamental role in fostering the local development.

IC for high-skilled individuals can constrain the actions of independent governments in many aspects. Firstly, it can reduce the ability of governments to collect fiscal revenues and redistribute income with progressive taxation. A relatively high tax rate can incentivize top-incomes and high-skilled workers to leave the jurisdiction, this way reducing the tax base and fiscal revenues. This can ultimately cause a general setting of tax rates below the optimal level and reduce substantially the resources available in each jurisdiction. Secondly, it can cause a suboptimal provision of public goods and government services. Governments can be induced to over-provide services that attract high-skilled workers and to under-provide others those that can be fundamental for other social groups.

Because of this, a huge body of literature has been focused on the modeling tax and services induced mobility and its consequences on optimal tax rates and service provision. This has been done by taking into account several aspects of IC such as strategic interactions between jurisdictions, behavioral responses of individuals, externalities and spillover effects between different policies and levels of governments.

The first section of this chapter is devoted to summarizing the debate existing in this literature, focusing in particular on tax and service competition models that account for the mobility of workers and high-skilled individuals.

Tax and service induced mobility have been extensively analyzed even from the empirical point of view. In this respect, a great effort has been devoted to identifying adequate econometric approaches that can help to detect the elements that affect individual mobility and attractiveness of regions and countries. The discrete choice approaches seem to be among the most powerful tools available to researchers. These approaches are mainly based on random utility models (see Section 1.3 below) in which individuals choose their preferred alternatives by maximizing their utility. The second part of this chapter is dedicated to a general discussion of these methods in the context of individual mobility and migration.

1.2 Related theoretical literature

Tax and services induced mobility of individuals has been extensively analyzed by the theoretical literature. One of the fundamental contributions in this literature is the original model of Tiebout (1956). In this model, individuals decide the jurisdiction into which reside based on a set of fiscal packages that each jurisdiction provides. These fiscal packages are a combination of public goods, services, and tax rates. Under a set of strong assumptions, this mobility should be efficiency improving leading to the optimal provision of fiscal packages and a perfect match between individuals' preferences and jurisdictions supply.

More recently, some models have relaxed the assumptions of Tiebout's model leading to different conclusions. To quote just a few contributions, Wildasin (1988) and Wildasin (1991) have considered the presence of strategic interactions and fiscal externalities between jurisdictions in a Nash competition framework. They conclude that fiscal competition can lead to the underprovision of public goods and social inefficient allocation of labor. The same conclusion is reached by McGuire (1991), where jurisdictions compete for mobile workers in a context where individuals have preferences for redistribution. In this model, the competition may lead to a sort of prisoner dilemma scenario. Each jurisdiction has the same incentive to reduce taxes on rich individuals to induce them to migrate into their territory. This will result in a destructive competition with sub-optimal tax rates and the underprovision of public goods.

The overall literature on tax and service induced mobility can be generally related to the concept of inter-jurisdictional competition (IC). According to the review presented in Kenyon (1997), the IC can be defined as the competition between governments that try to win some scarce resource or avoid a particular cost. Free movement of goods, services, and people all contribute to this competition and can constrain the actions of independent governments.[1]

At the core of this literature, there is the necessity by jurisdictions to solve a trade-off between their attractiveness for high-skilled individuals and top incomes and pursue their objective in terms of public good provision, redistribution, etc. Therefore, the identification of instruments that allow governments to solve this trade-off is of fundamental importance. In this respect, a substantial amount of literature has been focused on the definition of optimal policies that allow solving this trade-off.

With regards to the tax-induced migration, since the seminal contribution of Mirrlees (1982), it is well known that the ability of countries to redistribute income through taxation and their optimal level of redistribution is negatively affected by the magnitude of the elasticity of mobility to taxation. Building on this concept, the literature has investigated different models of optimal taxation in the presence of migration which has shed some light on the tools available to countries for balancing the trade-off between redistribution and their attractiveness for top taxpayers. In particular, Simula and Trannoy (2010) have developed a model that considers a situation in which one highly redistributive country has to choose its marginal tax rate considering the presence of one foreign country characterized by a low and constant marginal tax rate. The model links directly the optimal tax rate schedule to workers' choices of location (extensive margin) and their labor supply (intensive margin). A similar situation is investigated in Piketty and Saez (2013) where a simple and estimable optimal tax rate formula is derived. The main result of these models is that the optimal tax rate is inversely related to the elasticity

[1] See Ferreira, Varsano, and Afonso (2005) for an extensive review on fiscal competition.

of mobility and the elasticity of taxable income.[2] These models have been generalized in Lehmann, Simula, and Trannoy (2014), who consider a framework with competition between non-symmetric Rawlsian countries, individual heterogeneity in the distribution of tax-payers skills and simultaneous interactions between government; and in Simula and Trannoy (2017) allowing the governments to differentiate the tax schedule between native and foreign workers. Considering revenue-maximizing countries, Kleven, Landais, Saez, and Schultz (2013) have derived a model of optimal taxation considering that the labor market demand can be either elastic or rigid. Moreover, considering the optimality degree of regional differentiation in tax rates, Milligan and Smart (2019) have developed a model considering a federation of states in which the optimal tax rate is a function of the elasticity of mobility on the state level and the elasticity of taxable income at the national level. In this framework, regions have the incentives to compete to attract more tax-payers reducing their tax rates. This competition can result in a general reduction of tax rates that can be suboptimal from the national perspective. However, given a set of elasticities of migration at the regional level, countries can internalize this competition effect and set the federal tax rates maximizing the tax revenues at the federal level. These studies have in common the importance of the elasticity of mobility as a measure of the sensitivity of tax-payers location choices to taxation. This fundamental parameter measures the percentage change in the number of taxpayers in one jurisdiction caused by a one percent change in the tax rate. It can be estimated through the discrete choice approaches that will be summarized in Section 1.3 below.

Much less effort has been devoted to the definition of optimal policies that account for service-induced migration. In this respect, to the best of our knowledge, the literature has analyzed the role of amenities (i.e. environment conditions, health facilities, teachers/ratio pupils, etc.) and specific public expenditures in attracting highly skilled workers. For example, Florida (2002) presented evidence that amenities can attract knowledge workers and affect the distribution of human capital. These results are then embodied in the theoretical model of Mathur and Stein (2004) that permits to understand under which conditions policies that aim to increase local amenities can attract more highly skilled workers and can succeed in fostering local development.

[2]See Saez, Slemrod, and Giertz (2012) for a review on the behavioral responses associated with marginal tax rates that considers various channels such as, for example, labor supply, career choices and tax compliance

More recently, some papers have started to consider these two instruments together by defining optimal policies that embody both taxation and public provision of amenities and services. For example, Krieger and Lange (2010) have developed a model in which revenue-maximizing governments compete for highly skilled workers suing two strategic variables: income tax rates and amenities provided to students. Their result suggests that an increase in student mobility can intensify tax and amenity competition and erode public revenues. Ruiz del Portal (2017) extends the optimal taxation models in the presence of migration to consider commodity taxation and the provision of public goods that can attract highly skilled individuals. His results indicate that the provision of such public goods can reduce the migration response of highly skilled workers and, therefore, permits governments to levy higher income tax rates.

These results depend crucially on the relative importance in individuals' utility functions of public goods, tax rates and amenities provided by jurisdictions. Therefore, to find an empirical approach that can quantify the impact of these elements on the attractiveness of regions and countries is paramount. The next section directly faces this issue discussing the recent advancements in the empirical approaches that can be used to understand the determinants of individuals' migration decisions.

1.3 The discrete choice approach

This section presents a schematic discussion of the approaches that can be used to understand the determinants of individuals' location decision process: the discrete choice approach.

These methods are based upon the Random Utility Models family (RUMs) (Train, 2003). RUMs assume that a decision maker maximizes her utility by choosing one alternative from a set of mutually exclusive alternatives that are characterized by their attributes. Formally, let assume there is a population of agents $n \in N$ and a set of alternatives $j \in J$ in time $t \in T$. In the context of individual mobility and migration, these alternatives may be countries, regions or jurisdictions in general.

If the agent n choose to locate in jurisdiction j at time t she obtains the following utility:

$$U_{njt} = \beta' x_{jt} + \epsilon_{njt} \tag{1.1}$$

where U_{njt} indicates the utility of agent n if she decides to locate in j at time t, x_{jt} is the vector of alternatives' observed attributes and ϵ_{njt} captures factors that enter in the utility U_{njt} but are not observed by the researcher. To save on notation, we drop the t subscripts in the rest of the chapter.[3]. Consisting with the assumption of utility maximization, agent n will choose alternative j only if:

$$U_{nj} \geq \max_{j'} U_{nj'} \text{ with } j \neq j' \tag{1.2}$$

therefore only if alternative j is with the highest utility in the choice set.

Given condition 1.2, the probability that agent n to choose alternative j is given by the following:

$$P_{nj} = Prob(U_{nj} > U_{nj'}) \ \forall \ j \neq j' \tag{1.3}$$

In order to estimate this probability, researchers can employ different methods and different assumption. Next sections will discuss some of the available alternatives.

[3]Without any loss of generality, we let the number of choice situations T to be equal to 1

1.3.1 The Conditional Logit Model

If we assume that the error term ϵ_{nj} is $i.i.d$ type I extreme value distributed (or Gumbel), the probability in Eq. (1.3) can be written as (Mcfadden, 1974):

$$P_{nj} = \frac{exp(\beta' x_j)}{\sum_{j=1}^{J} exp(\beta' x_j)} \tag{1.4}$$

this probability can be estimated through a Conditional Logit model (CL) by using a maximum likelihood approach. The CL is a very powerful tool that allows the researcher to understand the systematic effects of alternative's attributes on decision makers' utilities and her choice probabilities. This approach can be used to estimate utility functions such as the one presented in Eq. (1.1). Moreover, the probability formula in Eq. (1.4) exhibits several useful proprieties: the estimated probabilities are always comprised between 0 and 1, the probability to choose one alternative is increasing in the utility of the individual and the sum of all the probabilities attached to each alternative is always equal to 1.

The CL is the most standard discrete choice technique and is widely used in individual mobility literature. As for tax-induced migration, for example, the CL has been used to understand the effect of taxation on mobility decision of football players in Europe (Kleven et al., 2013) and on international location decision of top inventors (Stantcheva, Akcigit, and Baslandze, 2016).[4] This approach has been applied also in the empirical service-induced migration to analyze the determinants of location choices of university students in Italy (Pigini and Staffolani, 2015) and in the US (Long, 2004).[5]

To give an example of how previous literature has used the CL approach we will draw on the analysis of tax-induced migration of football players provided by Kleven et al. (2013). In this case, the utility of a player n in country j at time t is defined as:[6]

$$U_{njt} = \alpha \ln(1 - \tau_{njt}) + \alpha \ln(w_{njt}) + home_{nj} + Z_{nt} + \mu_j + \epsilon_{njt} \tag{1.5}$$

where τ_{njt} is the average tax rate valid in country j for player n at time t, w_{njt} is the gross wage

[4]See Chapter 2 for a summary of empirical tax-induced taxation literature

[5]See Chapter 3 for a summary of the empirical literature regarding the attractiveness of universities.

[6]We are referring to a different version of equation (3) of the paper. We have modified the original specification to better explain the characteristics of the CL approach.

of player n in country j at time t, $home_{nj}$ is a dummy that takes value 1 if player n is citizen of country j, Z_{nt} are player's individual characteristics such as age and age-squared, and μ_j is a set of country fixed effects.

Therefore, by identifying the parameter α in Eq. 1.5, the researcher can have an estimate of the sensitivity of football players to income taxation. These parameters can be further exploited to compute elasticities and estimate an optimal tax rate in the presence of migration.

One particular characteristic of this specification is the definition of Z_{nt}. Given that the parameters are identified by comparing the utilities attached to each alternative we have that all the determinants used in a CL framework need to vary over alternatives. Nevertheless, this element can be an issue if we consider decision maker's attributes included in Z_{nt}. In fact, these variables are likely to do not vary among alternatives. For example, the age of an individual who is deciding into which country migrates to does not vary among countries. However, it can be an important driver of individuals' preferences. In these cases, to account for individual characteristics, the researcher has to define them in a way that can be handled by the model. Kleven et al. (2013) have solved this caveat by defining Z_{nt} as:

$$Z_{nt} = \theta(z_{nt} \otimes \mu_j) \tag{1.6}$$

where θ is the vector of parameters related to each element in Z_{nt}. Therefore, each individual's attribute is interacted with the country fixed effects, this way permitting the effect of these variables to vary over alternatives. The same technique can be used to understand if there is any systematic variation in individuals' preferences related to their characteristics. In this case, assuming that x_{jt} represent alternatives' characteristics, the variable Z_{nt} can be defined as:

$$Z_{nt} = \theta(z_{nt} \otimes x_j) \tag{1.7}$$

therefore, each individual's characteristic is interacted with all the alternatives' attributes. By estimating a parameter for each interaction term in Z_{nt}, the researcher can have an estimate of the systematic heterogeneity in individual preferences.[7] For example, through this technique, we can understand how the effect of marginal taxation changes for individuals with different

[7]See Balia, Brau, and Moro (2020) for an example of the use of this technique in the context of mobility related to hospital choices.

age.[8]

Limits of the Conditional Logit

Along with its useful properties, the CL approach presents several limitations that are relevant in our context. Drawing on Train (2003), these limitations can be clarified considering three situations: repeated choices, heterogeneity in preferences and substitution patterns.

i. Repeated choices. The CL assumes that unobserved factors are independent across different choices. This assumption can be crucial if the same individual is observed to choose more than one time. If the unobserved factors are not correlated over time the CL is able to capture the dynamics of the choice process. However, if the unobserved factors are correlated over time, the assumption of independence of errors is violated. In this case, the CL is misspecified. This issue can be overcome by specifying the utility function to model explicitly the correlation between different choice situations or by using a Mixed Logit approach that is outlined in Section 1.3.3.[9]

ii. Heterogeneity in preferences. Although the CL is able to represent systematic variation in tastes by interacting individual variables with alternatives' attributes, it fails in capturing the unobserved heterogeneity that depends upon unobserved factors. These factors can be individuals' unobservables or idiosyncratic preferences. The existence of such heterogeneity, by implying a correlation between included regressors and the error term, can result in distorted estimates of utility parameters. In these cases, the CL is misspecified. For example, let us consider a simple version of the utility presented in Eq. (1.5) in which the utility of player n depend only upon the marginal tax rate τ_{nj}:

$$U_{nj} = (\alpha + \eta_{nj}) \ln(1 - \tau_{nj}) + \epsilon_{nj} = \alpha \ln(1 - \tau_{nj}) + \eta_{nj} \ln(1 - \tau_{nj}) + \epsilon_{nj} \tag{1.8}$$

where η_{nj} is a random variable that affect the preferences of worker n with respect to the

[8] As we will see in Chapter 3 this strategy can be unfeasible or sub-optimal if x_j and z_{nt} have many elements.

[9] With relationship to this limitation, another useful approach is given by the family of Dynamic Discrete Choice approaches. In these models, the individual's choice in time t affects her choices in time $t+1$ by affecting the utilities attached to the various alternatives or by changing agents' choice set. For example, if the agent chooses to enroll in high school at time t, she will have different career alternatives in time $t+1$. However, this work is focused on static discrete choice models, the reader interested in dynamic models should see the seminal contribution by Rust (1987) and the survey by Arcidiacono and Ellickson (2011) for an overview of these models. See Declercq and Verboven (2018) for an example of dynamic discrete choice on students' career choices.

marginal tax rate τ_{nj}. Given that η_{nj} is not observe, it will become part of the error term $\tilde{\epsilon}_{nj} = \epsilon_{nj} + \eta_{nj} \ln(1 - \tau_{nj})$. Consequently, given that $\tilde{\epsilon}_{nj}$ contains the variable of interest $\ln(1 - \tau_{nj})$, it is impossible to assume that the error terms are not correlated with included regressors. This issue can be overcome by applying more sophisticated techniques such as the Mixed Logit presented in Section 1.3.3.[10]

iii. Substitution patterns. Given that the sum of choice probabilities is equal to 1, if the probability of one alternative increases, the probabilities of other alternatives have necessarily to decrease. The way in which a specific model deals with how alternatives' choice probabilities are related to each other is called *substitution pattern*. CL assumes that substitution patterns are only one type of substitution pattern: the 'proportional substitution pattern'. This pattern is a consequence of a general property of the CL: the *Independence from Irrelevant Alternatives* (IIA). IIA states that the probability ratio between alternative j and alternative i is independent from other alternatives different from i and j. For example, suppose that agent n is choosing among three jurisdictions $A1$ and $A2$ that is located in country j and one jurisdiction B that is located in country j'. Country j and j' are very different in terms of language, culture, and other amenities. Suppose now that a reduction in the tax rate of jurisdiction $A1$ increases its choice probabilities by 1%. In this context, given that $A1$ and $A2$ are more similar, an increase in $A1$ choice probability should cause a stronger reduction in the probability to chose $A2$ rather than the one to chose B. However, given that the probability ratios between $A2$ and B are not affected by attributes of alternative $A1$ we will have that their choices probabilities need to decrease proportionally by the same amount to keep the same probability ratio. Therefore, we will overestimate the effect on the probability to choose B, and underestimate the effect on the one to choose $A2$. This problem can be overcome by using the Nested Logit approach presented in Section 1.3.2 or by using a specific definition of alternative attributes in the Mixed Logit outlined in Section 1.3.3.

[10]The issue of unobserved heterogeneity in preferences can be addressed also by using different techniques such as the Heteroskedastic Conditional Logit or the Generalized Multinomial Approach. These methods are supposed to identify two kinds of heterogeneity: scale and taste heterogeneity. The first refers to the situation in which there is some unobserved factor that affects some individuals in the sample so that their choice process appears more random from the researcher's point of view. The second refers to the simple variation of tastes due to unobserved factors. However, as pointed out by Hess and Train (2017), these two sources of heterogeneity cannot be separately identified and any estimates of their effect will result in a mix between scale and taste heterogeneity. The Mixed Logit overcome this problem by allowing to control for any kind of heterogeneity through a more general definition of estimated parameters.

1.3.2 The Nested Logit Model

The Nested Logit (NL) model allows the researcher to divide the choice set in subsets called nests. The nests are constructed by considering that two alternatives in the same nest are more correlated than two alternatives in different nests. In our previous example, the researcher may assume that jurisdictions in country j and j' belong to two different nests. The first contains $A1$ and $A2$, while the second contains B. Given this definition, the NL will be estimated considering that the IIA property is valid only inside one nest and that is not valid across nests. Therefore, the substitution patterns inside the same nest will be proportional, whereas the ones across nests will depend on the attributes of the alternatives in the other nest. For example, the increase in the choice probability of alternative $A1$ caused by the reduction of its tax rate will result in a stronger reduction in $A2$'s probability than the one estimated for the alternative B.

It is worth to remark that choices in different sets do not have to be sequentially ordered. Indeed, the formulation of nests regard only the correlation and the similarities between alternatives and does not depend in any way on the timing of the decision process.

Examples of NL can be found in the empirical literature regarding the service-induced migration of students. Pigini and Staffolani (2013) have applied the NL to understands the effects of university characteristics on students' education choices. In particular, they consider a two-level nested structure. In the first, the high-school leaver decides whether to enroll at university and the field of study. In the second, she chooses which university to attend. Kelchtermans and Verboven (2010) have studied the effect of tuition fees on choices regarding enrollment, the university to attend and the field of study into which enroll of students in Belgium.

Drawing on Kelchtermans and Verboven (2010), let assume that student n face a choice set made by $k \in K$ universities. Each university provides a set of courses $j \in J$.[11] In this case, we assume a nesting structure in which each university represent a nest that contains all the courses provided.

[11] For simplicity we do not consider the choice regarding the enrollment.

If student n chooses the study option j in university k she will obtain the following utility:

$$U_{nkj} = \theta' Y_k + \beta_k' X_{kj} + \epsilon_{kj} \tag{1.9}$$

where Y_k are universities attributes and X_{kj} are the characteristics of each course provided by university k. For example, the Y_k may contain the amount of tuition fees or some characteristics of the hosting region, whereas $X_k j$ may include the number of professors employed in the course j by university k.

If we assume that the error term ϵ_{kj} in Eq. (1.9) is distributed following a general extreme value distribution, we have that the probability that agent n chooses alternative j in nest $k \in K$ is (Mcfadden, 1978; Cameron and Trivedi, 2005):

$$P_{nkj} = p_k \times p_{j|k} = \frac{exp(\theta' Y_k + \rho_k IV_k)}{\sum_{l=1}^{K} exp(\theta' Y_l + \rho_l IV_l)} \times \frac{exp(\beta_k' X_{kj}/\rho_k)}{\sum_{r=1}^{J_k} exp(\beta_k' X_{kr}/\rho_k)} \tag{1.10}$$

where:

$$IV_k = \ln \sum_{r=1}^{J_k} \exp(\beta_k' X_{kr}/\rho_k) \tag{1.11}$$

where p_k and $p_{j|k}$ indicate, respectively, the probability to choose university k and the one to choose course j in university k, ρ_k is the scale parameter that is a measure of the correlation between the component of the nest K and IV is the inclusive value. This last term permit to consider the contribution of the choice regarding the course k in the probability regarding the choice of university k.

The NL can be generalized in many ways to consider three-level nests and overlapping nests. These extensions make this approach very flexible and permit researchers to have a better understanding of phenomenons that have more complex choice structures.

1.3.3 The Mixed Logit Model

The Mixed Logit (ML) model is the most general discrete choice approach, it nests all the models presented so far and can be used to overcome the CL limitations that we have presented in Section 1.3.1. McFadden and Train (2000) have shown that ML can be used to approximate any choice model with any distribution of preferences to any degree of accuracy. This result implies that the ML is not affected by any theoretical restriction in the definition of preference distributions and correlation structure between parameters. However, the choice of the distribution of preferences is crucial and will embody some theoretical restrictions.

In the ML framework, the utility that individual n obtains choosing alternative j can be denoted as (Hess and Train, 2017):

$$U_{nj} = x'_{nj}\beta_n + \epsilon_{nj} \tag{1.12}$$

where, differently from Eq. (1.1), the vector of parameters β_n vary randomly over people. This feature of the ML permits to control for the unobserved heterogeneity, this way solving the CL limitation regarding the heterogeneity in preferences.

Assuming that the error term ϵ_{nj} is *i.i.d.* extreme value we can write the probability that agent n chooses alternative j, conditional on the individual parameter β_n, as:

$$P_{nj}(\beta_n) = \frac{exp(x'_{nj}\beta_n)}{\sum_{j=1}^{J} exp(x'_{nj}\beta_n)} \tag{1.13}$$

this formula indicates that the conditional choice probability of individual n depends on her vector of utility coefficient β_n. In order to derive the unconditional probability of individual n the researcher need to specify the cumulative distribution function of utility coefficients in the population $F(\beta|\phi)$. This distribution depends on the parameter ϕ that is defined according to the preferred cumulative distribution. $F(\beta|\phi)$ can be continuous or discrete, differs among different elements of the vector β_n, and allow any type of correlation among parameters. This flexibility allow the ML to account for the existence of repeated choices, nesting structure and any kind of heterogeneity in preferences (Train, 2003).

Concerning heterogeneity in preferences, we have that the ML offers various solutions. For example, if the researcher believes that it exists only for one regressor, she can impose a random distribution for the respective coefficient and let the others to be fixed. Moreover, if the researcher believes that two regressors are correlated she can allow this correlation to be estimated by the ML. For example, suppose that people that are more sensitive to the jurisdiction tax rate are more sensitive also to jurisdiction's amenities. In this case, instead of interacting these two regressors with each other, the researcher can simply allow them to be correlated.

Furthermore, the individual distribution of parameters can be let to depend on individual characteristics, this way allowing the researcher to identify the systematic variations in individual tastes.

In respect to the nesting structure in agents' decision process, we have that the ML does not exhibit the IIA property and can be modeled to approximate any kind of substitution pattern. The nesting structure can be defined by using a dummy variable that indicates the nest and letting the coefficients associated with this regressor to be randomly distributed. The only drawback of this procedure is that the ML is computationally more intensive than the NL.

As we have seen, $F(\beta|\phi)$ can be defined to be continuous or discrete. This difference can lead to two different models that share all the advantages that we have outlined in this section. In particular, if $F(\beta|\phi)$ is defined to be continuous we will have an *infinite mixture Mixed Logit* or Mixed Logit. By contrast, if $F(\beta|\phi)$ is assumed to be discrete, we will have the *finite mixture Mixed Logit* or Latent Class Logit model (LCM). Given that the LCM is at the core of chapter 3, in this chapter we will focus only on the *infinite mixture Mixed Logit*.

The ML model has been used in health economics literature in order to understand the preferences of patients in choosing hospitals. For example, Sivey (2012) has applied a LCM model to understand the effect of travel time and waiting time on patients' decision regarding the choice of hospital for cataract operations; Gutacker, Siciliani, Moscelli, and Gravelle (2016) and Varkevisser, Geest, and Schut (2012) have applied an infinite mixture ML to understand the effect of hospitals' quality on patients hospital decisions considering UK and Netherlands.

For example, Balia et al. (2020), have applied an ML in estimating the demand for elective hospital care. In their model, patient n chooses a hospital j based on the following utility:[12]

$$U_{nj} = \beta' x_j + \theta(z_n \otimes x_j) + \epsilon_{nj} \tag{1.14}$$

where x_j include hospitals characteristics (e.g. distance, mortality rate, hospital's quality and size) and z_n contain observable individual characteristics (e.g. age, education and gender). As we have seen in Section 1.3.1, this specification can be estimated through a CL. It permits to understand if the effect of hospital's characteristics on patient's demand varies systematically on the basis of their individual characteristics.

In order to capture also unobserved heterogeneity, the authors have estimated a ML con-

[12]We refer to a simplified version of equation (1) in the paper.

sidering that parameters β may have a continuous distribution $F(\beta|\phi)$. In this case, we have that the β_n in Eq. (1.12) can be written as (Greene and Hensher, 2003):

$$\beta_n = \beta + \Gamma v_n \tag{1.15}$$

where β is the preference parameter estimated in the sample, and v_n is a random term that enters in the definition of the parameters. This last term is used to account for random variation in tastes and can be defined to allow for correlation between parameters. This specification has permitted to relax the IIA property and to derive a set of individual parameters.

Moreover, Eq. (1.15) can be modified in order to have a distribution of individual parameters that depend upon a vector z_n of patient individual characteristics:

$$\beta_n = \beta + \gamma z_n + \Gamma v_n \tag{1.16}$$

This definition of β_n embodies all the features of ML that we have outlined before. In fact, the individual distribution of parameters will depend on decision makers' characteristics and can be defined to allow any type of heterogeneity in preferences. Therefore, this individual parameter will give information on the effect of the respective regressor accounting for both random as well as systematic variation in individual tastes.

These parameters can be exploited to compute measures of agent's sensitivity to alternatives' attributes such as willingness to pay measures or semi-elasticities.

1.4 Recent advances in modeling mobility

1.4.1 The Maximum Score Matching Estimator

Until this point, we have assumed that individual choices depend only upon alternatives' and decision makers' characteristics. In our logic, for example, workers decide into which jurisdiction locate simply by comparing the utility that they can gain in each alternative. However, in reality, we have that workers' location decisions may depend upon firms hiring decisions. Indeed, if the worker wants to live in jurisdiction j she will need a firm in that jurisdiction that is willing to hire her. Moreover, in the same world, there could be other workers that want to be hired from the same firm. Therefore, workers will be competing with each other to match their preferred firm. On the other hand, we have that the same firm will have to choose the worker based on her characteristics. In this context, if more firms want to hire the same worker, they will compete with each other to match with their preferred partners.

Therefore, in this context, every workers' location decision that we observe is the outcome of a process of market interactions between workers and firms. In this case, using standard discrete choice approaches may lead the researcher to a wrong interpretation of the results. Indeed, if we model the choice of the workers without considering explicitly the role of firms, our estimates will be a mix between firms' and workers' behavioral responses (Stantcheva et al., 2016).

One possible solution to this issue is the Maximum Score Matching (MSM) estimator (Fox, 2018). This approach is presented in detail in Chapter 2.

The MSM is a semi-parametric estimator based on the single-agent multinomial choice maximum score developed by Manski (1975) that allows the researcher to estimate the parameters underlying the matching process between two types of agents in a specific market. In this kind of model, the agents have a role defined ex-ante (one can be either worker or firm), and the matches are the outcomes of a process of interaction between agents that take their decisions interdependently.

The MSM detains various advantages compared to other methods presented so far. First, it allows the estimation of parameters underlying the matching process without having data on the transfers that happens between individuals. This characteristic allows controlling for every transfer between agents that may affect the location decision process even though the researcher does not have data on them. Second, it allows a more general definition of the error term than the classical type I extreme value used in Logit models. Third, its computational simplicity enables the researcher to use a not artificially limited set of alternatives and individual covariates.

In order to provide a brief outline of this approach, we can take advantage of a simple example. Suppose that in there is a population of workers $n \in N$ and a set of firms $a \in A$. Each firm is located in one jurisdiction $j \in J$. Suppose to observe, in a market $m \in M$, a match ω_{an} between worker n and firm a in jurisdiction j. In this case, the local production function of the match observed is:

$$\pi(\omega_{an}) = V(n, a, j) + U(n, a, j) \tag{1.17}$$

where $V(n, a, j)$ indicates the utility that firm a obtain in matching with n in jurisdiction j and $U(n, a, j)$ is the utility that worker n obtains by matching with a in jurisdiction j. Therefore, the local production function is given by the sum of agents' utilities. Each agent utility depends on the characteristic of the partner and the jurisdiction considered. The aim of this approach is to estimate the local production function $\pi(\omega_{an})$.

Now, suppose that in the market m we observe another match between n' and a'. In this case we can write the local production function of the observed set of matches ω_m as:

$$\Pi(\omega_m) = \pi(\omega_{an}) + \pi(\omega_{a'n'}) \tag{1.18}$$

where $\pi(\omega_{a'n'})$ is the local production function of the match between worker n' and firm a'.

The last equation helps us to define the equilibrium concept used in the estimation process of the MSM: the pairwise stability condition (Kim, 2018; Fox, 2018; Kuehn, 2017). This condition states that the observed set of matches ω_m is a pairwise equilibrium if no coalition of agents prefers to deviate from the observed set of matches. Therefore, the set of matches ω_m is a pairwise equilibrium if:

$$\Pi(\omega_m) \geq \Pi(\tilde{\omega}_m) \tag{1.19}$$

where $\tilde{\omega}_m$ is a counterfactual match where the worker n is matched with firm j' and worker n' is matched with firm j. Therefore, the pairwise stability condition states that the set of matches ω_m is a pairwise equilibrium if the two workers cannot increase their utility by exchanging their job positions.

This equilibrium concept permits to compare the observed matches with the counterfactual ones to estimate the local production function of the single match. Moreover, it allows the estimation of the model without having data on equilibrium transfers between partners and agent-specific characteristics. In fact, everything that is exchanged between partners is erased from the equation.[13] Moreover, given that the same agent appears both in the real set of

[13]See Chapter 3 for a detailed explanation.

matches than in the counterfactual, every variable that is agent-specific and does not depend on the specific match is erased. Because of this element, the researcher can use only match-specific variables. However, this strategy allows controlling for unobserved factors that are agent-specific.

In order to proceed to the estimation we need to define the parametric local production function as:

$$\Pi(\omega_m) = \sum_{\omega_i \in \omega_m} \pi(\omega_i) = \sum_{\omega_i \in \omega_m} X(\omega_i)'\theta + \epsilon_{\omega_i} \tag{1.20}$$

where ω_i is one observed match in the set ω_m, $X(\omega_i)$ are the match-specific variables, θ is the vector of parameters that measure the effect of the variables on the $\pi(\omega_i)$, and ϵ_{ω_i} is the unobservable component of the local production function. Given the parametric local production function we can rewrite the pairwise stability condition as:

$$\sum_{\omega_i \in \omega_m} X(\omega_i)'\theta \geq \sum_{\tilde{\omega}_i \in \tilde{\omega}_m} X(\tilde{\omega}_i)'\theta \tag{1.21}$$

Finally, this condition can be used into the objective function of the MSM in order to estimate the vector of parameters θ:

$$\max_{\theta} Q_M(\theta) = \sum_{m=1}^{M} \sum_{g=1}^{G^m} 1\left[\sum_{\omega_g \in \omega_m} X(\omega_g)'\theta \geq \sum_{\tilde{\omega}_g \in \tilde{\omega}_m} X(\tilde{\omega}_g)'\theta \right] \tag{1.22}$$

where M is the number of observed markets, Q_M is the score function that we need to maximize and G^m is the set of pairwise inequalities in each market. This set is constructed comparing in each inequality one set with two observed matches ω_g with another set with two counterfactual matches $\tilde{\omega}_g$. The logic behind this maximization is very simple: every time that the pairwise stability condition in brackets is satisfied we add 1 to the score function. Therefore, when we reach the maximum of Q_M we will have identified the parametric local production function and the set of parameters θ.

The MSM permits the estimation of the matching process behind the location decision of workers by focusing on the matches utilities. This strategy allows the researcher to have a better understanding of the phenomenon by accounting for the fact that observed location choices can be a mix of workers and firm behavioral responses.

The MSM has been applied in different contexts. Just referring to ‘many-to-one’ applications, Yang, Shi, and Goldfarb (2009) estimate the brand alliances between basketball players and teams; Mindruta, Moeen, and Agarwal (2016) compare the MSM with standard discrete choice estimators in a context of strategic alliances in the biopharmaceutical industry; Baccara, İmrohoroğlu, Wilson, and Yariv (2012) quantify the effects of network externalities on choices of faculty regarding offices in a new building; Schwert (2018) investigates the matching process between firms and bank in the loan market. Moreover, the MSM is analyzed in the survey on the applications of empirical matching models made by Chiappori and Salanié (2016).

Chapter 3 is the first example of MSM applied to individual location choices. In particular, MSM is used to understand how marginal income taxation can affect football players’ location choices.

Chapter 2

Best Score in the Match: Marginal Taxation and Labor Mobility in the European Football Market

Abstract

The international mobility of high skilled workers represents a crucial public policy issue, especially when occurring in an environment characterized by low mobility costs and relevant international differences in top tax rates. In this work, we study the effect of top marginal tax rates on turnover and migration patterns of football players in 16 countries between 2007 and 2016. This phenomenon is analyzed both at the international and inter-regional levels by exploiting national and regional variations in the effective marginal tax rate. We estimate a two-sided matching model using a maximum score matching approach. This allows us to account for the competition on each side of the market, and get rid of factors affecting both the demand and supply side for which information is hardly accessible (namely, wages of top-level workers). The structural parameters of the underlying decision process are exploited to quantify the sensitivity of taxpayers' equilibrium locations to taxation, the existence of sorting effects and the heterogeneity of these effects based on the ability of the player. In a context of elastic labor demand, the elasticity of migration relative to the net-of-tax rate is between 0.07 and 0.12 for natives, 1.20 and 1.37 for foreigners while it is around 0.22 if when considering the whole population. The estimated elasticities are higher when considering top-players suggesting that lower tax rates can increase the average quality of workers in the country by attracting more high-ability players who, in a context of rigid labor demand, displace low-quality players.

JEL Classification: *H30, H21, C14, J61, L83*

Keywords: Income taxation, Geographic Labor Mobility, Maximum Score Estimation, Many-to-One Matching, Superstars

Introduction

International mobility of high skilled workers (and the related erosion of national tax revenues) represents a crucial public policy issue, especially when occurring in an environment, such as Europe, characterized by low mobility costs and relevant differences in top tax rates among countries.

In this context, governments are poorly able to collect fiscal revenue and redistribute income with progressive taxation, because 'best' taxpayers could leave the country, this way causing a reduction of the tax base, and ultimately of taxation revenue. On the contrary, countries and regions could have incentives to attract high skilled workers given their high productivity and their ability to generate positive spillovers within a country. Moreover, tax differentials can reduce the market power of firms in high-tax jurisdictions and distort the matching process between firms and workers. Indeed, Krenn (2017), in his theoretical model on firms competition for talented CEOs, shows that a large tax differential can induce the worker to match with the less preferred firm if it is located in a low tax jurisdiction. Therefore, understanding how the top earners' equilibrium locations are sensitive to income taxes and which are the determinants of their patterns of migration is paramount.

The importance of high-skilled migration in general, and its determinants have been highlighted in the literature[1] that has focused on its effect on both receiving and sending countries (Stantcheva et al., 2016). Starting from the seminal contribution of Mirrlees (1982), this phenomenon has been deeply analyzed by the theoretical literature in order to derive a model of optimal taxation in the presence of international migration and tax competition across countries. In more recent times, Lehmann et al. (2014) have derived a model of tax competition and international migration considering a framework with costly mobility, non-symmetric countries, individual heterogeneity in the distribution of workers' skills and simultaneous interactions between governments. This model has been further extended in Simula and Trannoy (2017) allowing governments to differentiate the tax schedule between native and foreign workers.

In spite of the presence of this body of theoretical literature, only recently this phenomenon has been empirically investigated, because of the lack of good microdata containing information

[1]See Kerr (2013) for an extensive review of the link between global migration and innovation in the US.

about the citizenship and work history of workers. Migration choices of highly skilled workers[2] have been studied in a few empirical works. Kleven et al. (2013) investigate the role of top tax rates on the international migration of football players in the European footballers market. Stantcheva et al. (2016) study the effect of taxation on the location choice of inventors across the United States and Europe. Preferential schemes for top earners in Denmark and the difference in the elasticity of mobility to taxation between foreigners and natives are instead the focus of the study by Kleven, Landais, Saez, and Schultz (2014).

Related to that, a few studies have been focusing more in general on inter-regional migration of high skilled workers. For example, Moretti and Wilson (2017) analyze the sensitivity of the migration choices of star scientist to changes in personal and business tax rates across US states. Agrawal and Foremny (2018) use administrative data to understand the role of taxation on the choices of migration of the entire universe of top incomes in Spain. All these works share the expected result that the probability of the worker to locate in one country or region is negatively affected by the marginal tax rate.[3]

Starting from this literature, we aim to understand how much migration patterns of top incomes are sensitive to income taxation using a new dataset on football players' careers and marginal taxation on both national and regional levels. In particular, we address two main empirical challenges pointed out by Kleven et al. (2019) and Stantcheva et al. (2016): i. the availability of precise data on earnings and tax rates; ii. the role of the firms in the location decision process. The first issue has been addressed in the literature using data on specific sectors where these data were available or using administrative data with detailed information on migration decisions and wages. The second issue is related to the fact that the observed choices are the outcome of market interactions between workers and firms and, therefore, the observed elasticities can be a mix between employers the employees' behavioral responses. Indeed, income taxation affects the surplus that workers and firms gain from their match on the base of their market powers and characteristics. For example, as highlighted in Stantcheva et al. (2016), the firms could have the incentive to internalize all the tax burden in order to attract star workers. Conversely, workers of poor quality can be more prone to bear all the cost of taxation. Moreover, workers' equilibrium locations can be affected also by firms'

[2] An important share of these top earners are the so-called superstars (Rosen, 1981)

[3] See Kleven, Landais, Muñoz, and Stantcheva (2019) for a review on the main empirical challenges and policy implications regarding the effect of personal taxation on the geographic mobility of people

characteristics that are independent of the taxation that the researcher cannot identify using data only on the migration decisions of workers in different countries. If it is not accounted for the firm's characteristics and agents' market power our results could be a mix between tax and non-tax responses and depend on taxation incidence.

We address these two challenges by using an innovative empirical strategy proposed by Fox (2018): the Maximum Score Matching Estimator. This technique allows us to consider that all location decisions that we observe are the outcome of market interactions between agents that compete in each side of the market to match with their preferred partners. With this modeling strategy, as we will see below, we account explicitly for the fact that income tax rates have an effect on the surplus arising from the employee-employer match that may impact on individual's equilibrium locations. Namely, given that individuals' migration patterns are the results of matches between firms and workers, the tax rate, by affecting the utilities related to these matches, contributes to the determination of individuals' equilibrium locations.

As a unit of observation, we use players-teams matches. This enables us to control for the agent-specific characteristics and isolate a pure taxation effect. Incidentally, by exploiting the matching nature of the phenomenon, this method allows us to get rid off of the lack of information on earnings, wages, and agent-specific unobservables.

Hence, our contribution is threefold. First, we model the workers' location process accounting even for the role played by firms by solving the problem of availability of precise data on earnings and agent-specific unobservables. Second, we use both regional and national variation in top tax rates and the information regarding the preferential schemes that allow specific kinds of workers to enjoy a reduced tax rate. This has permitted us to have a precise measure of the tax burden affecting a match in a specific region in Europe. Finally, a dataset on the careers of football players richer than that used by Kleven et al. (2013) is used. Namely, our dataset contains information on several individuals and team covariates (e.g. individual and team market value) that permits to identify the distribution of the skills among the top 16 European leagues over the period 2007-2016.

Our results suggest that the income taxation incentive is an important determinant of top-earning workers' migration patterns even when considering a matching model in which labor demand and supply interact. Indeed, we find evidence that, ceteris paribus, a match is more valuable if it happens in a lower tax jurisdiction. By means of a simulation procedure, the main results in terms of elasticities of mobility to the net-of-tax rates are as follows. The effect of income taxes is stronger when considering foreigners and top-players. This result has different consequences depending on the elasticities of labor demand. If we consider an elastic labor demand, we find an estimate of the elasticity of migration to taxation around 0.22 for the whole population, between 0.07 and 0.117 when considering natives and between 1.37 and 1.197 for foreigners. These results suggest that foreigners' equilibrium locations are more sensitive to the income tax rate than the native ones. Moreover, we find that elasticities are always positive but much stronger when considering top players. For example, if we consider natives, the elasticity of the population of bottom quality players ranges from 0.025 to 0.028 whereas the one estimated for top players ranges from 0.310 to 0.495. This result suggests that a reduction in the income tax rates can improve the average quality of top earners workers in the country. This conclusion is confirmed even if we consider a rigid labor demand. In this context, the elasticities are estimated to be negative at the bottom of the quality distribution and positive, even though lower in magnitude, for top players. Hence, we find evidence of a displacement mechanism in which top players migrate into low tax jurisdictions pushing away bottom quality players.

2.1 Background

2.1.1 Related literature

The importance of migration of talented workers and its consequences on the economy has been extensively analyzed in the literature (e.g. Kerr, 2013; Clemens, 2011; Freeman, 2006). This phenomenon has been studied considering its effects on human capital accumulation whether in sending as well as receiving countries (see, for example, the references in Stantcheva et al. (2016)) and countries' ability to attract high-skilled workers. Concerning this last element, this study tries to understand the determinants of high-skilled migration patterns and, in particular, the effect of taxation on their equilibrium locations. Indeed, as highlighted in Esteller, Piolatto, and Rablen (2016), labor mobility is a crucial phenomenon that has to be considered in the determination of optimal tax schemes. In fact, in a context of free mobility, workers may relocate into jurisdictions in which they are more productive on the base of their net-of-tax returns. However, the presence of tax differentials between jurisdictions can distort workers' location choices encouraging migration towards low-tax jurisdictions. Hence, to maximize efficiency, the optimal taxation models should take into account the tax induced mobility this way reducing the distortion in location incentives and recover a more efficient distribution of the labor factor. Therefore, understanding how much workers' locations choices are sensitive to taxation in general is paramount.

In this work, we focus on the migration of European football players among European countries. Regarding this point, the migration of football players and its effect on the quality of countries' leagues has been studied also in the sporting economics literature. For example, Vasilakis (2017) studies the effect of the reduction in mobility restriction followed by the so-called Bosman rule in 1995 in Europe on the football sector in general.[4] In particular, he finds that the liberalization of football players' mobility in Europe has increased the scale of the migration phenomenon and encouraged the production of talent in poor countries. However, his results suggest that the inequalities in prestige and performances among European countries have increased. Still regarding the Bosman, rule Balsmeier, Frick, and Hickfang (2018) have found a positive impact of high-skilled foreign players in Germany on the performances of their teammates. Finally, Berlinschi, Schokkaert, and Swinnen (2013) find that the migration of footballers in countries with high-quality teams has a positive effect on the performances of sending countries' national teams. Hence, besides the importance of migration of high-skilled in general, this literature suggests that understanding the effect of taxation on the migration decisions of football players can be relevant even to understand its role as an attractor for talents in this sport.

With regards to the tax-induced migration, since the seminal contribution of Mirrlees (1982), it is well known that the ability of countries to redistribute income through taxation and their optimal level of redistribution is negatively affected by the magnitude of the elasticity of mobility to taxation. Building on this concept, the literature has investigated different models of optimal taxation in the presence of migration which have shed some light on the tools available to countries for balancing the trade-off between redistribution and their attractiveness

[4]This rule allowed players to move to a new team at the end of their contracts without paying a fee to their old team. Indeed, before this rule, players, or their new teams, had to pay a transfer fee even if the contract between the old team and the player was ended.

for top tax payers. In particular, Simula and Trannoy (2010) have developed a model that considers a situation in which one highly redistributive country has to choose its marginal tax rate considering the presence of one foreign country characterized by a low and constant marginal tax rate. The model links directly the optimal tax rate schedule to workers' choices of location (extensive margin) and their labor supply (intensive margin). A similar situation is investigated in Piketty and Saez (2013) where a simple and estimable optimal tax rate formula is derived. The main result of these models is that the optimal tax rate is inversely related to the elasticity of mobility and the elasticity of taxable income.[5] These models have been generalized in Lehmann et al. (2014), who consider a framework with competition between non-symmetric Rawlsian countries, individual heterogeneity in the distribution of tax-payers skills and simultaneous interactions between government; and in Simula and Trannoy (2017) allowing the governments to differentiate the tax schedule between native and foreign workers. Considering revenue-maximizing countries, Kleven et al. (2013) have derived a model of optimal taxation considering that the labor market demand can be either elastic or rigid. Moreover, considering the optimality degree of regional differentiation in tax rates, Milligan and Smart (2019) have developed a model considering a federation of states in which the optimal tax rate is a function of the elasticity of mobility on the state level and the elasticity of taxable income at the national level. In this framework, regions have the incentives to compete to attract more tax-payers reducing their tax rates. This competition can result in a general reduction of tax rates that can be suboptimal from the national perspective. However, given a set of elasticities of migration at the regional level, countries can internalize this competition effect and set the federal tax rates maximizing the tax revenues at the federal level.

These studies have in common the importance of the elasticity of mobility as a measure of the sensitivity of tax-payers location choices to taxation.[6] Concerning this point, there is a growing body of empirical literature that has focused on the estimation of the elasticity of mobility.[7] These studies have been focused on both international and inter-regional migration. On the international side, the most closely related paper is Kleven et al. (2013) who investigate,

[5]See Saez et al. (2012) for a review on the behavioral responses associated with marginal tax rates that considers various channels such as, for example, labor supply, career choices and tax compliance

[6]Taxes are not the only policy tool that jurisdictions can use to attract high-skilled workers. For example, Buettner and Janeba (2016) explore the incentives of German jurisdictions to subsidize cultural activities in order to attract highly educated employee.

[7]See Esteller et al. (2016) and Kleven et al. (2019) for a review on both theoretical and empirical literature focused on the link between mobility and the choice of the optimal tax rate

through a model in which the players choose the country to migrate to, the effect of marginal income taxation on the migration choices of European football players. They estimate an elasticity of mobility close to one for foreign players and a smaller estimate (around 0.15) for natives. Moreover, the elasticities are higher for top-quality players than for the low-quality ones. This suggests that the tax rate could be a useful tool to attract high-quality foreign players. Stantcheva et al. (2016) study the effect of taxation on the international mobility of inventors and scientists finding similar results regarding domestic and foreign inventors. To our knowledge, this is the first paper that tries to consider the role of companies in the location decisions of workers in an international context. The authors highlight that tax rates can have a distortionary effect on the match between firms and workers and, therefore, the results can be a mix of firm and workers' behavioral responses. For example, firms could have the incentive to internalize all the tax burden in order to attract star workers or, conversely, workers of poor quality can be more prone to bear all the cost of taxation. Moreover, location choices can be affected by firms' characteristics that are independent of taxation and that could have effects that are not identifiable using data only on migration on the national level. With regard to the possibility for countries to use preferential tax schemes, Kleven et al. (2014) study the effect of a reduction of tax rates for high-income foreigners implemented in Denmark in 1992 on the immigration of top-tax payers in the country finding that these kinds of tools can be used by countries to attract more high-skilled workers. These results are confirmed also in the aforementioned paper by Kleven et al. (2013) that explore the effect of preferential schemes in several European countries. Top incomes' migration decisions can be influenced also by capital taxes. For example, using Forbes Magazine's data on billionaires and international capital tax rates, Sanandaji (2014), has found that very rich people are more likely to move to countries with lower capital taxes and higher per capita incomes.

With respect to the relationship between inter-regional migration and taxation, Moretti and Wilson (2017) have explored the determinants of migration choices of star scientists among US states. In particular, they exploit the regional differences in personal and corporate income taxation to understand the effect of taxation on both the supply and the demand of star scientists. In a similar context, Moretti and Wilson (2014) have studied the effect of subsidies and R&D tax credits on the biotech star scientist choices of location. They find that these policies have a direct positive effect on the supply of star scientists in the biotech industry. This positive effect extends indirectly to all the workforce in the sector, employment in local services and employment in closely related industries. The relationship between innovation and taxation in the US has been analyzed recently also in Akcigit, Grigsby, Nicholas, and Stantcheva (2018). Using data on patents dating back to 1920, the authors study the effect of both corporate and income taxation on the innovation process over the 20th century. In particular, they find that taxation has a significant effect on the number and the quality of patents and the supply of inventors at the state level. Interestingly, inventors are affected even by corporate taxation, especially if they work inside a corporation. This element suggests that the role of companies and their ability to transfer a part of the tax burden on workers has to be taken into account in estimating the sensitivity of migration choices to taxation. Although these papers point to a relevant role of taxation in attracting inventors from other states Bell, Chetty, Jaravel, Petkova, and Van Reenen (2019a) and Bell, Chetty, Jaravel, Petkova, and Van Reenen (2019b) have shown that the financial incentives, namely taxation, have a small effect on aggregate innovation at the country level. This result arises from the fact that these incentives affect only individuals who have already been exposed to the opportunity of an inventor career and inventors of marginal quality. The authors suggest that the most relevant tool to foster aggregate innovation is to increase the exposure to innovation career opportunities of children, especially if they come from underrepresented groups such as women or low income families.

Extending the focus on the entire universe of tax payers, Agrawal and Foremny (2018) use Spanish administrative data to understand the migration choices of the residents in Spain exploiting the variation of income tax rates among Spanish regions. They find that, conditional on moving, a one percent increase in the net-of-tax rate in a region increases the probability to move in that region by 1.5%. However, they estimate, on aggregate, an elasticity of top tax payers of 0.85. This means that an increase in tax rates generates a mechanical increase in tax revenues that is larger than the loss due to behavioral responses.

This result calls directly the theoretical argument of, among the others, Musgrave (1959) and Oates (1972) and tested in Feldstein and Wrobel (1998), according to which regions governments should refrain from redistributive policies because this will result in an out-migration response from the former, and, consequently, in an erosion of the tax base. This theoretical prediction has been tested also in Young and Varner (2011), Varner and Young (2012), and Young, Varner, Lurie, and Prisinzano (2016) using the natural experiment of the millionaire taxes in New Jersey, California and among US states.[8] The authors find that, in general, an increase in the top tax rate had little, marginally significant, effect on the migration choices of wealthy people. Their results show that rich people are less mobile than the general population and embedded in the regions in which they have success. These results have been confirmed also with respect to elderly wealthy people in Bakija and Slemrod (2004), who examine the effect of inheritance taxes in the US finding that there is strong evidence of a behavioral response to these taxes but that this effect is small in comparison to the mechanical effect given by the rise in tax revenues. By contrast, Schmidheiny and Slotwinski (2018), exploiting a preferential income tax regime for foreigners in Switzerland, find a strong response in location and migration choices for high-income earners and a non-significant effect for low-income earners. Interestingly, they find a significant effect on location choices and moving probability only for those foreigners that reside in high tax jurisdiction without finding a significant effect on those who live in low-tax jurisdictions suggesting that the effects of tax increases and tax decreases can be asymmetric.

2.1.2 Moving a step forward

Kleven et al. (2019) highlight that one of the most important challenges in studying tax induced migration is the lack of precise information on wages and earnings. This problem has been addressed previously by focusing on specific sectors where these data are available or using administrative data.

In this study we aim to overcome this empirical difficulty by using a different empirical strategy, namely, the Maximum Score Matching estimator (MSM) developed by Fox (2018). This method, among various advantages[9], allows the researcher to estimate a matching model between agents who compete in a market to match with their preferred partners. The MSM has been used in the literature in several different fields. Just referring to 'many-to-one' applications, Yang et al. (2009) estimate the brand alliances between basketball players and teams; Mindruta et al. (2016) compare the MSM with standard discrete choice estimators in a context

[8] The millionaire tax movement is a trend observed in the US consisting of states that start to raise the progressivity of their tax systems to compensate the general drop in federal top tax rates.

[9] See Section 2.4 for details on this estimator.

of strategic alliances in the biopharmaceutical industry; Baccara et al. (2012) quantify the effects of network externalities on choices of faculty regarding offices in a new building; Schwert (2018) investigates the matching process between firms and bank in the loan market. Moreover, the MSM is analyzed in the survey on the applications of empirical matching models made by Chiappori and Salanié (2016).

2.1.3 The market of European football players

The European football market is characterized by specific characteristics regarding teams, players and how their labor contracts are defined.

In each European country, there is one top-national league to which up to the 20 best football teams in the country take part. Teams can participate even to other competitions such as national or international cups.[10] The season of year t starts usually in August/September of year t and ends in May/June of year $t+1$.[11] Moreover, in each season there are two market windows, usually in summer and in January, in which teams can buy and sell players. This calendar poses some difficulties in the definition of the relevant tax rates. Following Kleven et al. (2013) we assume that the relevant tax rate for the year t season is the year t tax rate given that most of the teams' composition is decided before the beginning of the season.

Football teams are firms located in a specific city that use a specific stadium. This particularity hampers the possibility of relocating to other jurisdictions to take advantage of lower tax rates or other economic incentives. Hence, each observed migration pattern only depends on workers' mobility. Moreover, each team employs about 25-45 players in its squad.[12] The number of players in teams depends upon various factors such as the dimension of the market, number of fans, financial resources, number of competitions in which the team qualifies, and country-specific rules regarding the number of youths and national players. This number is naturally bounded by the fact that teams can employ, in each match, 11 players in the main line-up plus 3 players from the bench as substitutions. Given that the number of workers is neither fixed nor totally unbounded, there could be some complications in the definition of the

[10]In Europe there are two European competitions in which a restricted number of teams participates in, on the basis of their performances and country rankings: the European League and the Champions League

[11]This rule is excepted by the northern countries (such as Norway and Sweden) where the year t season starts in March of year t and ends in November of the same year.

[12]With 'squad' we refer to all the players who are employed by the team

market structure. Indeed, if the number of players is relatively fixed, we end up with a rigid labor demand. Conversely, if this number is totally flexible, we have an elastic labor demand. This has important consequences on both the empirical model to estimate and the choice of the optimal tax schedule to apply. As explained in Section 2.2, we overcome this problem by using an empirical approach enabling us to let the market structure to be endogenously determined in equilibrium. It turns out that our main econometric specification will not depend on any ex-ante assumption on the elasticity of the labor demand. However, in the computation of the elasticity of mobility to taxation we will consider two cases: one in which team's dimension is kept fixed at the one observed and one in which we let it to be freely determined in the simulation algorithm on the base of the results coming from the empirical model.

Teams and players sign contracts that define the affiliation duration, salary and other benefits related to players' performance, sponsorship and image rights on the merchandising sold by clubs. The combination of these payments makes very difficult to detect the overall compensation earned by the players. Indeed, where data are available, they only cover wages or provide information only on very important players. Moreover, during the affiliation, if a player wants to change his team before the end of his contract or, conversely, if a team want to hire a new player employed by some other teams, the clubs involved can negotiate a transfer and a transfer fee that is not part of players' taxable income. These rules have been established after the so-called 'Bosman rule', decided by the European Court of Justice in December 1995.[13]

Given these characteristics, each contract in the European football market can be seen as the equilibrium outcome of a many-to-one two sided matching model with transferable utility (Fox, 2018). In these kinds of models, the agents have a role defined ex-ante (worker or firm) and the matches are the outcomes of an interaction process between agents that consider the choices made by other agents (Yang et al., 2009). The maximum score matching estimator provides an empirical tool consistent with this theoretical framework by means of which to assess the effects of the marginal income taxation on the relocation and migration patterns of European football players.

[13]See note 4

2.2 Theoretical Framework

Building on Kleven et al. (2013) and Lehmann et al. (2014), let us assume that in Europe there is a population P of potential football players with an endowment of ability $s_i \geq 0$, in a set of countries C. The utility of the player to play in country $c \in C$ is given by:

$$U(s_i, c) = \mu(c) + (1 - \tau_{ic}) \times w_i(s_i, c) \tag{2.1}$$

where $\mu(c)$ measures the preference of the player for country c, τ_{ic} is the marginal tax rate in country c, and w_i is the wage earned by the player i. Following Lehmann et al. (2014), we refer to Eq. (2.1) as the 'gross utility'. This is the utility of player i if he decides to stay in country c and the level of his net utility if he decides to migrate in country $c' \neq c$ supporting a cost of migration m. The cost of migration depends on a variety of underlying factors such as the home country, the financial cost of migration, the differences in languages and culture, and the geographical distances. Therefore, the player will choose to migrate from c to c' only if:

$$U(s_i, c') - m \geq U(s_i, c) \quad \text{with} \quad c \neq c' \tag{2.2}$$

namely, a migration will take place only when the net utility that the player gains by migrating in country c' is bigger than the gross utility gained by staying in country c.

We want now to consider two important elements: the preferences of teams and regions' characteristics. On the one hand, players' migration patterns are the outcome of a matching mechanism in which players and teams are competing on both sides of the market to match with their preferred partners. On the other hand, each team is attached to a local stadium and a city and, therefore, the characteristics of the region that hosts the team plays a fundamental role in this decision process.

To account for these two elements, we assume that in country c there is a set of regions $n \in N_c$ and a set of teams in each region n called A_n. In this case, the utility of the player i with ability s_i to play in team $a \in A_n$, in region n and in country c is given by:

$$U(s_i, n, c, a) = \mu(n, c, a) + (1 - \tau_{in}) \times w_{ai}(s_i, a, n, c) + I \times m \tag{2.3}$$

where $\mu(s_i, n, c, a)$ measures the preference of player i to play in team a, in region n and in country c, τ_{in} is the marginal tax rate in region n for player i, w_{ai} is the salary paid by team a to a player with ability s_i in region n and in country c, and I is the indicator function that takes value 1 if the player i is supporting the cost of migration m. Given that the teams are located in a specific region and in a specific country, we can rewrite the Eq. (2.3) as:

$$U(s_i, a) = \mu(s_i, a) + (1 - \tau_{in}) \times w_{ai}(s_i, a) + I \times m \tag{2.4}$$

this include all the informations regarding countries and regions in the subscript that refers to the team a. A key feature of Eq. (2.4) is that the income tax rate is region-specific. Indeed, as we will see in Section 2.3.2, we are able to exploit the regional differences in tax rates in many countries of Europe and, therefore, modelling also the intra-national migration of footballers along with the international one.

Given Eq. (2.4), the player i is willing to play in team a only if the utility that he receives is greater than the utility that he can obtain when playing for other teams $a' \neq a$. Hence, he is willing to play for team a only if:

$$U(s_i, a) \geq \max_{a'} U(s_i, a') \quad \text{with} \quad a \neq a' \tag{2.5}$$

Therefore, player i decide his best partner comparing each team in the market and considering the region in which the team is located as well as the tax rate valid in that region. Consequently, we can indicate the mass of players that are willing to play in team a as:

$$\bar{P}_a(\tau_{in}, w_{ai}) = \sum_{i \in P} 1\big[U(s_i, a) \geq \max_{a'} U(s_i, a')\big] \tag{2.6}$$

where $1[.]$ is the indicator function that takes value 1 if the condition inside the brackets is satisfied. Hence, $\bar{P}_a(\tau_{in}, w_{ai})$ indicates the mass of players for whom the condition (2.5) is satisfied.

At this point, we can model the way teams choose their partners from the set of players $\bar{P}_a(\tau_{in}, w_{ai})$. Let assume that teams A_n have a defined number of vacancy spots. If the team a

hires the player i with ability s_i, it obtains the following net value:

$$V(s_i, a) = \phi(s_i, a) - w_{ai}(s_i, a) \tag{2.7}$$

where $\phi(s_i, a)$ is the value added by the player to the team evaluation function, and $w_{ai}(s_i, a)$ is the salary paid by the team. With respect to the determinants of $V(s_i, a)$, two important elements have to be pointed out. First, the term $\phi(s_i, a)$ depends on the ability of the player s_i and on the specific characteristics of team a such as the number of the players that are already playing for it and their characteristics. Second, the wage $w_{ai}(s_i, a)$ depends on the ability of the player s_i, the team a and the region n in which the team is located and can differ from players' marginal productivity because of agent's market power. This market power can be heterogeneous among players and teams and can derive from various sources: the dimension of the market in the region or in the country, the prestige of the team, scarcity of the player, the prestige of the player, etc. For example, with rigid labor demand and an excess in labor supply, teams can have an higher market power and, therefore, extract a positive surplus from players. On the other hand, the opposite can occur whether we consider the most talented players. In fact, in this case, due to the scarcity of talent, players can have an higher market power and extract a positive surplus from teams. It is worth pointing out that, because our estimation strategy and the fact that we are observing team-players matches, we do not need to define explicitly the elasticity of the labor demand or the teams' market powers. In fact, we can let the structure of the market to be endogenously determined in the equilibrium.

In this setting, the team a will choose to hire player i with ability s_i only if the value that it can gain from the hiring is greater that the one deriving from other players $i' \neq i$ and only if it has a vacancy spot. Therefore, it will hire the player i only if:

$$V(s_i, a) \geq \max_{i'} V(s_{i'}, a) \quad \text{with} \quad i \neq i' \tag{2.8}$$

However, considering the condition (2.5), we know that only a subset $\bar{P}_a(\tau_{in}, w_{ai})$ of the population P is willing to play in team a. Hence, we can rewrite the (2.8) considering the condition (2.5) as:

$$V(s_i, a) \geq \max_{i' \in \bar{P}_a(\tau_{in}, w_{ai})} V(s_{i'}, a) \quad \text{with} \quad i \neq i' \tag{2.9}$$

The inequality (2.9) shows that the team is actually choosing among the subset $\bar{P}_a(\tau_{in}, w_{ai})$ of players. In this way, we are accounting for both players and team preferences. Therefore, if the conditions (2.9) and (2.5) are satisfied, we will observe a match ω_{ai} between team a and player i with an associated utility equal to the the sum of agents' utilities:

$$\pi(\omega_{ai}) = V(s_i, a) + U(s_i, a) \tag{2.10}$$

where, as seen before, the utilities of players and teams depend on the characteristics of partners, the region where the match takes place and the tax rate valid in that region.

Using the condition (2.9), we can now define the number of players that are playing in team a as:

$$P_a(\tau_{in}) = \sum_{\bar{P}_a(\tau_{in}, w_{ai})} 1\big[V(s_i, a) \geq \max_{i' \in \bar{P}_a(\tau_{in}, w_{ai})} V(s_{i'}, a)\big] \tag{2.11}$$

consequently, the mass of tax payers that are playing in the region n is defined as:

$$P_n(\tau_{in}) = \sum_{a \in A_n} P_a(\tau_{in}) \tag{2.12}$$

The Eq. (2.12) indicates the sum of the team-players matches that we are observing in one region n. This number depends on the characteristics of the region n in the country c (such as market dimension and marginal tax rate τ_{in}), the preferences of teams located in n and those of the players in the market. In this setting we are considering a situation where the players choose in which team they want to play. However, the results are identical even if we consider a situation where the teams move first and the players choose in the set of teams that are willing to hire them.

Finally, from Eq. (2.12) we can derive our parameter of interest: the elasticity of mobility to taxation. This parameter indicates the sensitivity of tax payers' migration patterns to marginal tax rates and can be used to compute the optimal marginal tax rate in the presence of migration. In particular, the elasticity measures the change in the number of taxpayers caused by a one percent change in the tax rate and is defined as:

$$\varepsilon_n = \frac{dP_n}{d(1 - \tau_{in})} \times \frac{1 - \tau_{in}}{P_n} \tag{2.13}$$

where $(1 - \tau_{in})$ is the net-of-tax rate that measures how much the disposable income of the players i increases when the wage w_{ai} increases by one Euro.

2.3 Data

2.3.1 Football Data

We have collected data on the careers of football players that have played in the first leagues of 16 European countries: Austria, Belgium, Denmark, England, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Russia, Spain, Sweden, Switzerland, and Turkey. These countries have been chosen to consider all the top-25 European leagues according to the UEFA ranking.[14][15] These data are collected from various online sources such as *Transfermarkt.com, UEFA.com,* and *Footballsquads.co.uk*.

The most important source is *Transfermarkt.com*. This web site is one of the most important online community of football supporters in which are available data regarding various characteristics of teams and players that, in some cases, are available from 1996 to 2016. Although we use all the information available in the construction of our variables, we restrict our analysis to the matches observed between 2007 and 2016 because of the lack of complete taxation data before 2007. The information available at the player level consist of the name, the age, the foot, the height, the position in the field, the club affiliation with information on the data in which the contract has been signed, the nationality and the market value. The market value is particularly important because is used to assess the quality of the players. However, this variable has one important characteristic: it is not directly observed. Indeed, the market value is assessed by the registered users of *Transfermarkt.com* through a process of collective judgments (Peeters, 2018). This variable has been used previously in the sports economics literature. For example, Bryson, Frick, and Simmons (2013) uses this market value as a proxy for players' salaries while investigating the salary return to the ability to play soccer with both feet; Herm, Callsen-Bracker, and Kreis (2014) evaluate the accuracy of this market value in predicting real transfer fees finding that this community based market value is a good predictor

[14]The UEFA ranking is a measure of the leagues' quality based on the past results of the teams

[15]We do not include countries such as Serbia and Romania because of the scarce availability of marginal tax data. The data on top tax rates in Russia are available only since 2010.

of the fees actually paid by teams; and Peeters (2018) who finds that *transfermarkt*'s market value outperforms other standard predictors such as FIFA ranking in forecasting international soccer results. Because of these elements, we believe that the market value can be a good proxy for players' quality. Moreover, the fact that the market value is not observed allows us to have a quality indicator even when the player has not changed the team.[16] One possible limitation of this variable is that it does not represent only the intrinsic ability of the player but can be affected by the quality of the team in which the player is employed. Namely, players with the same intrinsic ability but in different teams can have different evaluations only because one of the teams is more prestigious. However, this limitation is common to all the indicators available and, most importantly, it permits to consider that players in high-quality teams can have other characteristics besides ability that can be an important element for a team such as, for example, the experience in European competitions.

At the team level, we observe: the country, the position in the league, the UEFA coefficient of the league and the city of the stadium were the team is situated. This latter variable is used to define the regions where the team is located and, therefore, the relevant marginal tax rate.

Following Kleven et al. (2013), we restrict our sample to those players aged between 17 and 43 years and that are citizens of one of the countries in the sample. We exclude the other players because we cannot observe their work history and, therefore, we cannot compute counterfactual alternatives for their location choices. Intuitively, this choice is made because, otherwise, the non-European players would be always foreigners in every country and, therefore, we cannot identify the effect of their foreigner status on their location choices. Indeed, in that situation, we cannot compare the country in which they play with their home country and estimate the cost of migration from their home country. In order to follow this strategy and to have a complete dataset, we drop also all the players for whom we do not observe the date of birth, the market value and the starting date of the contracts. This last information is very important because allow us to identify fake transfers in the dataset. Indeed, another characteristic of our dataset is that the matches that we observe could be the outcome of some trading strategy of teams. Namely, one team can buy a player only as a counterpart of some next transfer. In these cases, we could observe the same player in different teams in the same season. To avoid

[16] If the player has been playing in the same team for his entire career the *real* market value is unobservable since there is not a market transaction that regards the player.

these issues, we have used the information on the starting date of the contracts keeping only the last contract signed by the player in each season. We exploit this information even in the cases when the player changes the team in the middle of the season to impute the right tax rate. The last step of our strategy regards the nationality of players that have two or more citizenships. In these cases, we keep the information on the first nationality that is selected in *Transfermarkt.com*. This citizenship is the most associated with the player football history.[17]

Given this strategy, our analysis is based on a dataset with data on 12,380 players and 392 first-leagues teams observing 41,816 team-players matches.

2.3.2 Taxation Data

To choose the correct taxation data we need to solve two caveats: in which country (or region) the players are taxed and which kind of tax rate is relevant for their migration decisions. Indeed, the relevant tax rate for the migration decision is the average tax rate (ATR). However, to use the ATR is problematic because it depends non-linearly on earnings, with the related endogeneity issues, and because we do not use data on the salaries earned by footballers. To solve these issues, we exploit two characteristics of our sample. First, given that footballers have to train daily, it is plausible that they have to live next to the team's city. Hence, we can assume that they are taxed on the base of the tax system valid in the country (or the region) in which they work. Second, considering that footballers earn high salaries compared to countries' top tax brackets for income taxes and payrolls, we can assume that the relevant tax rate is the marginal tax rate (MTR).[18]

To compute the marginal tax rate we have combined three types of taxes: the top marginal income tax rates, the employer and employee social security contributions, and the value added tax. Following Kleven et al. (2013) and Mertens and Montiel Olea (2018) we define the marginal net-of-tax rate as[19]:

$$1 - \tau = \frac{(1 - \tau_i)(1 - \tau_w)}{(1 + \tau_{VAT})(1 + \tau_e)} \tag{2.14}$$

where τ_i is the top marginal income tax rate, τ_w is the uncapped social security contribution at

[17] For instance, the national team of the player.

[18] Kleven et al. (2013) and Moretti and Wilson (2017) show that their results are similar using ATR instead of MTR.

[19] The derivation of the marginal net-of-tax rate is in the Section 2.A of the appendix

the worker level, τ_{VAT} is the Value Added Tax, τ_e is the uncapped social security contribution at the employer level and τ is the combined marginal tax wedge. In this way, we can measure how much the disposable income of the worker increases when the marginal labor cost for the firm increases by one Euro.

To compute this marginal net-of-tax rate we have collected tax data from various sources: OECD tax database, European Commission tax databases, the International Bureau of Fiscal Documentation (IBFD) country surveys, the PriceWatersCoopers on-line sources, KPMG on-line sources, and various national sources. We cross-checked these sources with the tax rate time series available in Piketty, Saez, and Stantcheva (2014) in order to have a correct database.

To exploit both international and inter-regional variation, we have collected data on both national and regional levels. In particular, we observe a regional variation in marginal tax rates in 6 countries: Denmark, Italy, Norway, Sweden Switzerland, and Spain. Moreover, we account for preferential taxation schemes for footballers or top earners in many countries: Spain, Belgium, Netherlands, Denmark, France, and Turkey. In these countries, we observe that the marginal taxation is different for foreigner football players or football players in general. This latter characteristic of our dataset permits us to analyze how the preferential schemes affect the distribution of skills within a country comparing the native and the foreigner elasticities of migration.

Data on tax rates are combined according to the country-specific rules provided by national agencies. Moreover, we also cross-checked using the sub-central tax rate series available in the OECD Tax Database for representative regions and information on tax computations available in IBFD's country surveys.

2.3.3 Descriptive Statistics and Graphical Evidence

Table 2.1 reports the descriptive statistics of our sample showing the information on the characteristics of players and marginal tax rates by country. From the first column, we can see that Italy is the country with the highest number of observed matches (4,056), followed by Turkey (3,541) and Netherlands (3,336). Regarding the share of foreign players (column 2), we can notice that England has a share of foreign players which is more than twice the average share in the sample (43.05%) followed by Germany (28.53%) and Belgium (24.90%).[20] The third and the fourth column show, respectively, the share of *Top* and *Bottom* quality players. These two groups are identified on the base of players' locations in the quality distribution computed for each year and each position in the field. Indeed, we classify the players in four general positions (goalkeepers, defenders, midfielders and offenders) in order to have a quality indicator that accounts for the differences existing in the market value distributions among these categories. The players' quality is computed as the average of all the market values that we observe during the players' career until the year before the observed match. We use this strategy to account for the possibility that teams may consider players' entire growth path in term of quality in their evaluation decision.[21] We define as *Top players* those who are in the top 25% of the position-year specific quality distribution and as *Bottom players* those who are below this threshold. From these data, we can have a glimpse of the difference in quality distribution among countries. In particular, we can individuate a group of five countries (England, France, Germany, Italy, and Spain) that have a share of *Top players* way bigger than the average, confirming the common knowledge that these leagues are more able to attract the best talented players in Europe. Columns 5 and 6 report the average top marginal tax rates valid for native players and foreigners. In particular, we observe a difference between tax rates for foreigners and natives in Belgium, Denmark, France, Netherlands, and Spain. In these countries there are specific tax regimes for foreign top earners which aim to attract high skilled workers.[22] For example, the so-called *Beckham Law* in Spain established a flat tax system with a tax rate 24% for workers with an income higher than 600,000 Euro from 2004 to 2010.[23] [24]

Table 2.2 shows the variation in marginal top tax rates, the figures in the first three columns are computed as pooled average considering all the sample period whereas those in the last three columns are computed as absolute differences over time. We observe regional variation in 6 Countries: Denmark, Italy, Norway, Spain, Sweden, and Switzerland. These differences are small in all the countries except for Switzerland if we consider the average differences, and are substantial if we consider the absolute differences computed over time. Even though the differ-

[20]In Table 2A.1 in the Appendix we present the origin-destination flows by country-pairs.

[21]This strategy is similar to the one used in Kleven et al. (2013) where players' quality is computed considering the quality of teams in which the player has played during his entire career.

[22]In Figures 2A.1-2A.3 in the Appendix we show the evolution over the period 2007-2016 of top marginal tax rates for natives and foreigners in the 16 countries of the sample.

[23]See Kleven et al. (2014) for a comprehensive analysis of the Danish preferential system.

[24]Turkey has a special tax regime that reduces the income tax rate to 15% for football players in general.

Table 2.1: Descriptive Statistics

	N	Foreigners (%)	Top (%)	Bottom (%)	τ_n	τ_f
	(1)	(2)	(3)	(4)	(5)	(6)
All Countries	41816	18.52	22.76	77.24	57.38	50.76
Austria	1881	11.91	1.06	98.94	58.33	58.33
Belgium	2382	24.90	8.19	91.81	75.24	56.18
Denmark	2147	15.00	1.72	98.28	65.52	40.25
England	2943	43.05	65.92	34.08	59.75	59.75
France	2659	11.36	35.43	64.57	67.03	46.92
Germany	3277	28.53	39.27	60.73	55.86	55.86
Greece	2848	19.14	7.02	92.98	56.04	56.04
Italy	4056	16.07	36.76	63.24	56.37	56.37
Netherlands	3336	22.36	11.15	88.85	60.02	42.02
Norway	1795	15.77	1.39	98.61	60.87	60.87
Portugal	2036	11.94	14.05	85.95	70.97	70.97
Russia	1929	9.54	23.48	76.52	39.36	39.36
Spain	3246	17.50	46.95	53.05	55.64	36.09
Sweden	2202	8.81	1.73	98.27	73.64	73.64
Switzerland	1538	19.05	3.97	96.03	47.16	47.16
Turkey	3541	11.16	18.24	81.76	27.97	27.97

Notes: This table reports summary statistics for our sample covering the period 2007-2016. The sample includes the players that are citizens of one country in the sample and play in a European top league. Column (1) reports the number of player-team matches observed. Column (2) reports the percentage of foreign players. Columns (3) and (4) report the shares of players that are, respectively, in the top 25% and below the top 25% of the quality distribution computed according to players' market values. Column (5) and (6) report the average top marginal tax rate applying, respectively, to native and foreign players.

Table 2.2: Variation in top tax rates (2007-2016)

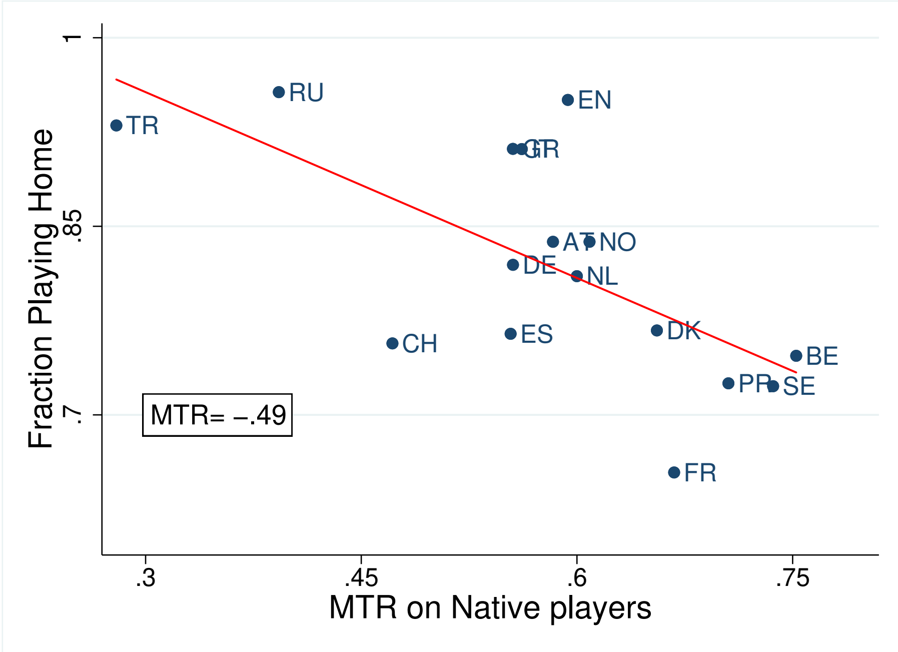
	Average			2007-2016		
	Min	Max	Δ	Min	Max	Δ
Sweden	72.96	74.81	1.85	72.83	75.07	2.23
Norway	59.33	61.21	1.88	58.29	61.21	2.92
Italy	54.08	57.65	3.56	53.25	59.20	5.95
Spain	52.27	57.15	4.87	34.48	63.64	29.15
Switzerland	42.03	54.93	12.89	27.67	56.52	28.85
Denmark	40.40	57.49	17.09	40.00	70.13	30.13
All Countries	27.97	74.73	46.76	27.67	75.36	47.68

Notes: This table reports the minimum and the maximum of top tax rates observed, and the average difference between regional and international top tax rates. The figures in columns from 1 to 3 are computed as pooled averages while the figures in columns from 4 to 6 show absolute differences considering all the sample period.

ences in average are small we need to consider that the migration within countries is likely less costly than the international one. Therefore, even a smaller difference in tax rates could cause a significant effect. For example, using administrative data on tax payers in Spain Agrawal and Foremny (2018) find that, conditional on moving, the probability of moving to one region increases by 1.5% when its tax rate decrease by 1%.

Figure 2.1 shows some graphical evidence of the relationship between MTR and the out-migration of native players (Panel A) and between MTR and the in-migration of foreign players (Panel B). Each plot presents the coefficient associated with MTR coming from a linear regression between players' shares, MTR and a constant. This coefficient can be roughly interpreted as an indicator of the correlation between the two variables. Panel A shows the relationship between the share of players who are playing in their home country with the MTR valid for native players. Panel B shows the relationship between the fraction of foreign players in each country and the MTR on foreign players. Focusing on panel A we can notice that the share of native players that migrate away from their home country is strongly negatively correlated with the top tax rates valid in the country. This result suggests that the MTR in the player's native country is important in the location decision process of footballers. However, panel B, shows that the fraction of foreign players in the country is weakly correlated with the top tax rate valid for foreigners. The difference between these two types of correlation seems to indicate that the players are more interested in the MTR valid in their home country than in the

Panel A: Out-migration of native players



Panel B: In-migration of foreigner players

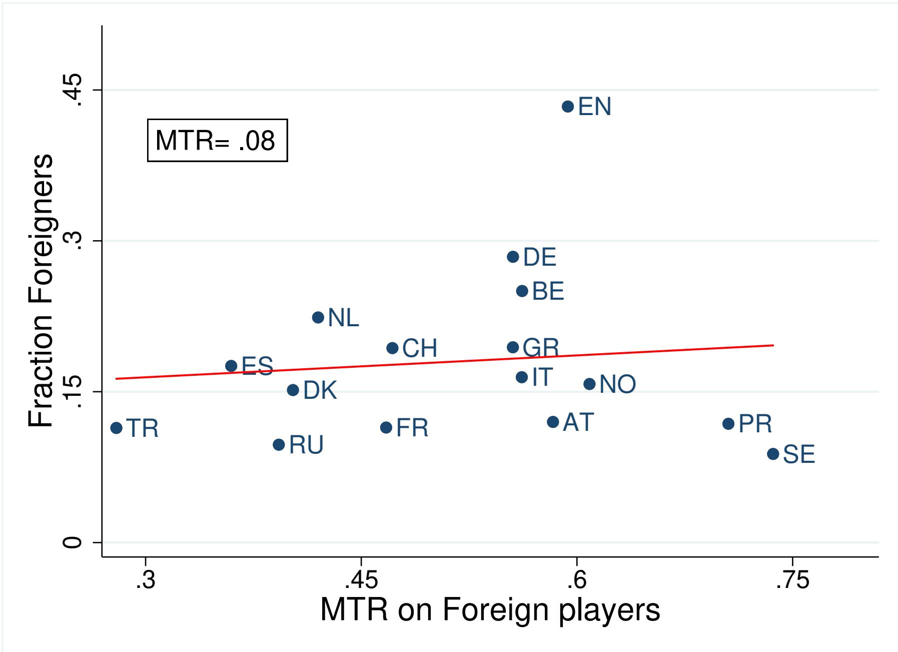


Figure 2.1: Cross-Country Correlation between Tax Rates and Migration, 2007-2016

Notes: Each dot stands for one country: AT=Austria, BE=Belgium, DK=Denmark, EN=England, FR=France, DE=Germany, GR=Greece, IT=Italy, NL=Netherlands, NO=Norway, PR=Portugal, RU=Russia, ES=Spain, SE=Sweden, CH=Switzerland, TR=Turkey. Panel A shows the relationship between the share of players who are playing in their home country with the MTR valid for native players in that country. Panel B depicts the relationship between the share of foreign players in each country and the MTR valid for foreign players in that country. In each plot we show the coefficient of the relevant MTR coming from a linear regression of the shares against MTR and a constant. All the plots refer to pooled averages computed on the entire period between 2007 and 2016.

Out-migration of native players by quality

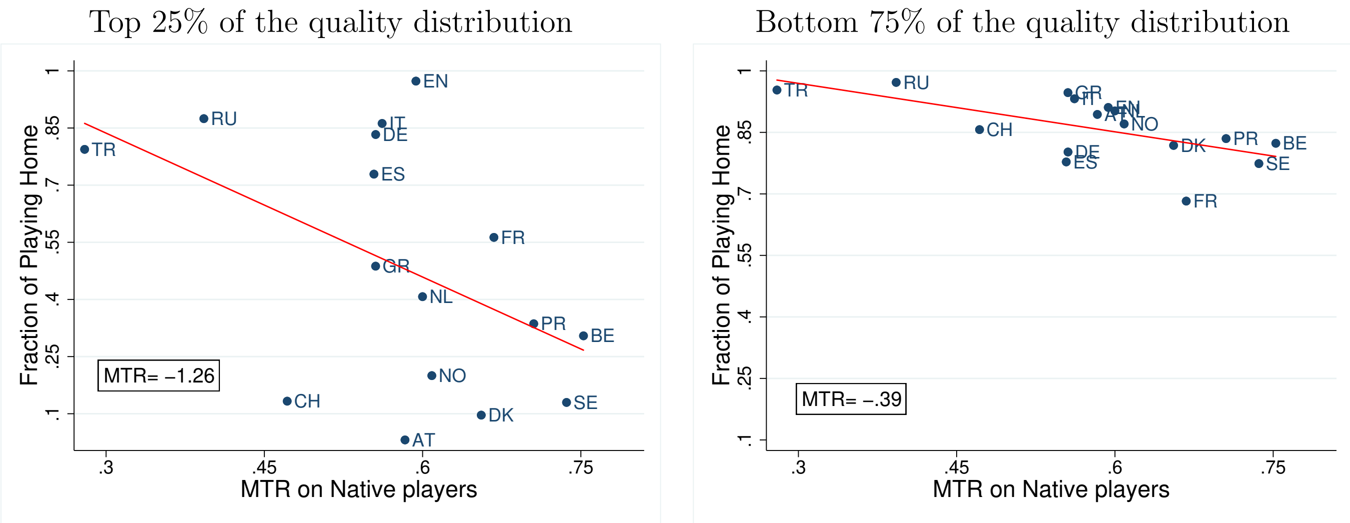


Figure 2.2: Cross-Country Correlation between Tax Rates and Shares of Natives by Quality, 2007-2016

Notes: Each dot stands for one country: AT=Austria, BE=Belgium, DK=Denmark, EN=England, FR=France, DE=Germany, GR=Greece, IT=Italy, NL=Netherlands, NO=Norway, PR=Portugal, RU=Russia, ES=Spain, SE=Sweden, CH=Switzerland, TR=Turkey. The two plots show the relationships between the fraction of players playing in their home country and the MTR valid in the origin country considering players in the top 25% of the quality distribution (on the left) and players in the bottom 75% of the quality distribution (on the right). The quality distribution is based on market values distribution in each year for each position in the field. In each plot we show the coefficient of the relevant MTR coming from a linear regression of the shares against MTR and a constant. All the plots refer to the entire period 2007-2016.

one valid in the destination country. This could be due to the fact that, when deciding where to locate, the players are always comparing the MTR of the country in which they live with the one valid in all the possible destination countries and, therefore, the first MTR appears in every comparison. We account for this in our estimation strategy in two ways. First, we control for a dummy that indicates whether the player is native of one country or not. Second, our estimation strategy is based on a comparison between an observed match and all the feasible counterfactual matches. Hence, the estimator compares the MTR of the country in which the player is playing with all the MTR that he will face matching with a different team in a counterfactual match.[25] The plots of Figure 2.1 shows the average correlation between the effective tax rates and the migration patterns assuming that the effect is homogeneous among all the sample. However, as shown in Kleven et al. (2013) and Stantcheva et al. (2016) the effect of the MTR could differ on the base of the worker's ability. Hence, in Figure 2.2, we present the correlation between the share of natives and the MTR in the origin country splitting our sample in *Top players* (on the left) and *Bottom players* (on the right). From Figure 2.2 we can

[25]These results are symmetric if we consider the fraction of players that play abroad and the share of natives.

see that the negative relationship between the share of players playing in their home country and the MTR in these countries depends on the quality of the player and is stronger for players with higher quality. Moreover, Figure 2.2 shows that *Bottom players* are less mobile and tend to stay in their home country more than *Top players*. This suggests that a higher tax rate could cause a reduction in league quality encouraging the out-migration of *Top players* and the in-migration of *Bottom players*. This effect could be due to two different causes: the relevance of the MTR and the market power of the player. Relating to the first, higher market value could be related to a higher wage for the player (Bryson et al., 2013). Therefore, in this case, the MTR could be more relevant given that the more is higher the income the more the MTR is similar to the ATR. Hence, the indicator of the position of the worker in the quality distribution could be seen as an index of the intensity of the treatment given by the tax rate (Stantcheva et al., 2016). Relating to the second cause, players with higher quality might have better job offers in the international market and have more opportunities to avoid a high-MTR country migrating towards a low-MTR one. Moreover, players with lower quality might be entrapped in their home country and fill the spots left by the high-quality players. Hence, in a context of rigid demand there could be a mechanism where the high-quality players that leave the countries are replaced by the low-quality ones and, on the other hand, the low-quality player in a country with lower tax rates are displaced by the high-quality foreign players. We account for this feature in two ways: exploiting the heterogeneity of the effect of marginal taxation through dummy variables indicating the position in the quality distribution, and estimating the elasticity of mobility considering that the vacancy spots in each country are fixed.

2.4 Maximum Score Matching Approach

This work takes advantage of the Maximum Score Matching estimator (MSM) developed in Fox (2018). The MSM is a semi-parametric estimator based on the single-agent multinomial choice maximum score developed by Manski (1975) that allows the researcher to estimate the parameters underlying the matching process between two types of agents in a specific market. This estimator detains various advantages compared to the standard discrete choice approaches used in the previous literature. First, it allows the estimation of parameters underlying the matching process without using data on wages. This characteristic is particularly important in our case given that the data regarding the players' wages are hardly accessible considering our sample of countries. Moreover, football contracts are characterized by various bonuses and benefits that, even when the information is available, complicate the computation of the exact total amount of money earned by the worker. Second, it allows a more general definition of the error term than the classical type I extreme value used in Logit models. Third, its computational simplicity enables us to use a not artificially limited set of alternatives and individual covariates. Moreover, it ensures the validity of the estimates in spite of considering a subset of all potentially available choice alternatives (Fox, 2007).

The MSM is well suited for the estimation of a many-to-one two-sided matching model (Fox, 2018). This model seems to be a good approximation of the European football market because it considers a market where the agents have a role defined ex-ante (one can be either player or team) and the matches are the outcomes of a process of interaction between agents that take their decisions interdependently.[26] This model is based on the concept of local production function that is defined as the sum of the utilities of agents who participate in the match. For example, if we observe a match between a team a and a player i we have that its local production function is given by the Eq. (2.10). Now, if we consider that the team a is matching with a set of players $P_a(\tau_{in})$ we can rewrite the local production function of the set of matches that refers to the team a as:

$$\pi(\omega_a) = \sum_{i \in P_a} \left[V(s_i, a) + U(s_i, a) \right] \tag{2.15}$$

where the local production function is given by the sum of the value added by the set of players P_a to team a and the utilities of the players P_a defined using equations (2.4) and (2.7). Moreover, each team competes in a specific session market for its preferred partners. Therefore, if we define with $m \in M$ a market in which we observe team a and team b we can write the local production function of the set of matches ω_m as:

$$\Pi(\omega_m) = \pi(\omega_a) + \pi(\omega_b) \tag{2.16}$$

where $\pi(\omega_a)$ and $\pi(\omega_b)$ are defined according to Eq. (2.15). $\pi(\omega_b)$ is defined considering the

[26]The many-to-one nature of the model derives simply from the fact that a team can enroll many players each season but a player can play only for a team at a time.

matches between team b and the set of players P_b. This last equation helps us to define the equilibrium concept used in the MSM estimator: the pairwise stability (Kim, 2018; Fox, 2018; Kuehn, 2017).

The pairwise stability condition states that no coalition of agents prefers to deviate from the observed matches. In our case, therefore, this condition states that the two teams cannot increase their utilities or profits exchanging each other two players. This concept of equilibrium is similar to the best response condition. Indeed, given the rest of the matches, two agents, when forming the coalition, compare the utility under the current relationship with the one that they would gain in the counterfactual matches (Kim, 2018). Despite each match is formed considering the entire assignment of observed matches, this condition is pairwise because it assumes that, when considering a possible deviation, teams assume that the other rivals stay at their current matchings (Kuehn, 2017). Formally, to define the condition of pairwise stability we need to define a counterfactual set of matches $\tilde{\omega}_m$ where at least one player from P_b is matching with team a and one player from the set P_a is matching with team b. Given this definition, the set ω_m is a pairwise equilibrium if:

$$\Pi(\omega_m) \geq \Pi(\tilde{\omega}_m) \tag{2.17}$$

where $\Pi(\tilde{\omega}_m)$ is the local production function of the counterfactual set of matches $\tilde{\omega}_m$. This stability condition has some important consequences. First, if the condition in Eq. (2.17) is satisfied we have that a *rank order property* holds (Fox, 2007):

$$Pr(\omega_m|a, b, P_a, P_b, m) \geq Pr(\tilde{\omega}_m|a, b, P_a, P_b, m) \tag{2.18}$$

The rank order property states that the probability to observe the actual set ω_m is greater than the one of observing the counterfactual set $\tilde{\omega}_m$. This useful property can be used to define the objective function of the MSM in a way that is similar to the usual maximum likelihood estimator (Fox, 2007). In fact, the identification of the parameters of the local production function, as we will see below, is based on the pairwise comparison between the local production function of the actual set of matches ω_m with a set of counterfactual matches $\tilde{\omega}_m$. Moreover, this equilibrium concept permits to use the inequalities defined in (2.17) to estimate the model without using data on the equilibrium wages.

In order to explain this advantage and to save notation let us assume that we observe only two matches: player i with team a and player j with team b. Recalling Equations (2.4) and (2.7) we know that, if we observe a match between team a and player i, the agents' utilities can be written as:[27]

$$U(s_i, a) = \mu(s_i, a) + (1 - \tau_{ia}) \times w_{ai} \tag{2.19}$$

$$V(s_i, a) = \phi(s_i, a) - w_{ai} \tag{2.20}$$

The pairwise stability condition states that if we are observing the match ω_{ai} instead of $\tilde{\omega}_{aj}$ must be the case that either team a prefers i to j at the equilibrium salaries or that player j prefers team b because it offers an higher wage than team a (Kuehn, 2017). However, if team a prefers j and the second condition is true the team may increase its utility simply increasing its salary offer to player j. In this case, team a could offer a wage $\tilde{w}_{aj}$ to make player j indifferent between the two teams so that:

$$\mu(s_j, b) + (1 - \tau_{jb}) \times w_{bj} = \mu(s_j, a) + (1 - \tau_{ja}) \times \tilde{w}_{aj} \tag{2.21}$$

taking logs and rearranging the equation we can isolate the counterfactual wage $\tilde{w}_{aj}$ as:

$$\ln \tilde{w}_{aj} = \ln \mu(s_j, b, \tau_{bj}) + \ln w_{bj} - \ln \mu(s_j, a, \tau_{aj}) \tag{2.22}$$

where $\mu(s_j, a, \tau_{aj}) = \mu(s_j, a) + (1 - \tau_{ja})$ and $\mu(s_j, b, \tau_{bj}) = \mu(s_j, b) + (1 - \tau_{jb})$. Given that the team a can offer $\tilde{w}_{aj}$ to player j, in order to not observe a deviation from the equilibrium matches ω_{ai} and ω_{bj} the following condition must hold:

$$\ln \phi(s_i, a) - \ln w_{ai} \geq \ln \phi(s_j, a) - \ln \tilde{w}_{aj} \tag{2.23}$$

this condition states that the observed matches are a pairwise stable equilibrium if team a prefers to match with i instead of j even if player j is indifferent between the two teams, i.e. if team a prefers i at the observed salaries. Now, substituting Eq. (2.22) into Eq. (2.23) we get

[27] To save notation we write w_{ai} instead of $w_{ai}(s_i, a)$.

the following:

$$\ln \phi(s_i, a) - \ln w_{ai} \geq \ln \phi(s_j, a) + \ln \mu(s_j, a, \tau_{ja}) - \ln \mu(s_j, b, \tau_{bj}) - \ln w_{bj} \tag{2.24}$$

the same equation can be derived considering player i and team b:

$$\ln \phi(s_j, b) - \ln w_{bj} \geq \ln \phi(s_i, b) + \ln \mu(s_i, b, \tau_{bi}) - \ln \mu(s_i, a, \tau_{ai}) - \ln w_{ai} \tag{2.25}$$

Finally, defining the local production function of a generic match ω_{ai} as $\pi(\omega_{ai}) = \phi(s_i, a) + \mu(s_i, a, \tau_{ai})$ and combining Eq. (2.24) and Eq. (2.25) we get:

$$\pi(\omega_{ai}) + w_{ai} - w_{ai} + \pi(\omega_{bj}) - w_{bj} + w_{bj} \geq \pi(\tilde{\omega}_{aj}) + \pi(\tilde{\omega}_{bi}) \tag{2.26}$$

$$\pi(\omega_{ai}) + \pi(\omega_{bj}) \geq \pi(\tilde{\omega}_{aj}) + \pi(\tilde{\omega}_{bi}) \tag{2.27}$$

from this equation, since the matches on the right hand side of the inequality are the counterfactual ones, we can cancel out wages and recover the pairwise stability condition showed in Eq. (2.17). Indeed, Eq. (2.27) states that the sum of the local production function of the observed matches is greater than the one coming from the counterfactual set. Moreover, this condition permits us to estimate the local production function constructing a set of inequalities based on Eq. (2.27) without using data on wages.

A third characteristic of the MSM estimator is that it prevents the use of agent-specific variables. This can be seen as a drawback of this estimator technique because force the researcher to use only match-specific variables or interactions between agent-specific variables. On the other hand, this characteristic permits to control for a full set of individual fixed effect and for all the unobservable that are agent-specific. This feature of the MSM comes directly from the condition Eq. (2.27). To understand this property of the estimator we need to define the parametric local production function of a generic match ω_{ai}:

$$\pi(\omega_{ai}) = \phi(a, i) + \mu(a, i, \tau_{ai}) = \alpha X_a + \beta X_i + \theta X_{ai} + \varepsilon_{ai} \tag{2.28}$$

where X_a are the team-specific variables, X_i are the player-specific variables, X_{ai} are the match-specific variables and ε_{ai} is the unobservable component of the local production function. Since the same agent appears in both sides of inequalities defined using Eq. (2.27), all the agent-specific variables cancel out and, therefore, we can identify only the parameters associated with the match-specific variables. Thus, for the match ω_{ai}, we can rewrite the Eq. (2.28) as:

$$\pi(\omega_{ai}) = \theta X_{ai} + \varepsilon_{ai} \tag{2.29}$$

Consequently, if we observe a set of matches ω_m in the market m we can write the set's local production function as:

$$\Pi(\omega_m) = \sum_{\omega_i \in \omega_m} (\pi(\omega_i)) = \sum_{\omega_i \in \omega_m} X(\omega_i)'\theta + \varepsilon_{\omega_i} \tag{2.30}$$

where ω_i is one match of the set ω_m, $X(\omega_i)$ is the matrix of match specific variables, θ is the vector of parameters that measure variables' effect on $\pi(\omega_m)$, and ε_{ω_i} is the unobservable component of the local production function of the match ω_i.

The MSM assumes that agents have preferences over the observables characteristics of the partners. This assumption lead to two main consequences. First, the estimate of the local production function is semi-parametric. This means that we can estimate parametrically the observable component of the local production function of the set of matches ω_m and non-parametrically its unobservable component. Second, we do not need to define a specific distribution for the unobservables. This estimator is consistent if observable and unobservable components are uncorrelated, if the unobservable component is $i.i.d.$ across matches[28] and if the parameter space θ is compact. Given these assumptions and the semi-parametric nature of this estimator we can rewrite Eq. (2.17) using only the observable components of the parametric local production function as:

$$\sum_{\omega_i \in \omega_m} X(\omega_i)'\theta \geq \sum_{\tilde{\omega}_i \in \tilde{\omega}_m} X(\tilde{\omega}_i)'\theta \tag{2.31}$$

[28]One consequence closely related to this assumption is that the conditional distribution of the unobservables conditioned on the observable component $F(\varepsilon_{\omega_i}|X(\omega_i))$ is continuous and exchangeable. $F(\varepsilon_{\omega_i}|X(\omega_i))$ is exchangeable if $F(\varepsilon_{\omega_i}|X(\omega_i)) = F(\rho(\varepsilon_{\omega_i})|X(\omega_i))$ where ρ is a permutation.

This last condition is used to define the objective function of the MSM as:

$$\max_{\theta} Q_M(\theta) = \sum_{m=1}^{M} \sum_{g=1}^{G^m} 1 \left[\sum_{\omega_g \in \omega_m} X(\omega_g)'\theta \geq \sum_{\tilde{\omega}_g \in \tilde{\omega}_m} X(\tilde{\omega}_g)'\theta \right] \tag{2.32}$$

where M is the number of observed markets, Q_M is the score function that we need to maximize and G^m is the set of inequalities in each market. Each inequality is constructed defined by comparing two observed matches ω_g with two counterfactual matches $\tilde{\omega}_g$. The set of parameters θ is identified by maximizing the objective function adding 1 to the score function every time that the condition in brackets is satisfied. The most important characteristic of MSM's objective function is its computational simplicity. In fact, to evaluate it we do not need to non-parametrically estimate the choice probabilities, the distribution of unobservables or to compute integrals used with the maximum likelihood approaches (Fox, 2018). Moreover, MSM's objective function is a step function. This feature complicates both its maximization and computation of the standard errors. These problems are solved by using a differential evolution algorithm (Storn and Price, 1997) that allows the maximization of a step function and a subsampling procedure to compute the interval of confidence (Politis, Romano, and Wolf, 1999; Romano and Shaikh, 2008).

We implement the MSM in R using a modified version of the toolkit provided in Santiago and Fox (2008). The new code is able to handle a huge amount of data more efficiently in order to allow us to estimate this model in a setting characterized by a huge number of agents on each side of the market.

2.4.1 Identification strategy

As we have explained in the previous section, the effect of the various determinants of matches utilities is identified by maximizing the objective function in Eq. (2.32). Namely, we identify our parameters of interest by comparing actual matches with the counterfactual ones. The latter matches are defined by constructing a new set of matches in which at least two players deviate from the observed equilibrium by exchanging their team. Therefore, identification is given by exploiting the differences between matches' attributes that agents observe in actual matches with those that they would observe in counterfactual matches. Nonetheless, there are various threats to our identification strategy that we should discuss.

The first threat to this identification strategy is that matches attributes should be not affected by matching assignments (Schwert, 2018). Indeed, this condition is violated we will have a very unlikely scenario in which choices in time $t-1$ (before the match) are the result of matches observed in time t (after the match). To avoid this problem we use all the information available to players one market window preceding the season, i.e. the data are observed in time $t-1$.

A second issue is related to the fact that our measure of MTR might be endogenous. This condition could be violated because tax policies may depend on the political or economic power of agents or be decided in response to migration patterns between different kinds of players. However, we can exploit some advantage of our estimation strategy to reduce this concern. First, agents' economic or political power can be seen as an agent-specific unobservable that may impact on tax rates. However, as explained in the previous sub-section, the MSM permits to control for all the unobserved agent-specific characteristics by exploiting the pairwise stability condition stated in Eq. (2.17). Second, as in Kleven et al. (2013), we use various policy changes in order to have quasi-experimental variations that permit us to identify the causal link between taxation and migration. We define the MTR that players would face in actual and counterfactual matches by exploiting: i. spatial and temporal variation across 16 countries; ii. spatial and time variation in regional tax rates within 6 countries; iii. preferential taxation schemes for foreigners in 5 countries.[29] Moreover, as explained in Section 2.3.2, the use of MTR instead of ATR has permitted to avoid the endogeneity issues related to the fact that ATR depend upon workers earnings and need the computation of counterfactual wages in destination countries.[30] [31]

Another possible limitation of our analysis is that we do not have data on agents that are outside of our observed market such as players without a contract or that are playing either in one country outside our sample or in a European lower league. This can be an issue given that, without this information, we cannot construct the complete set of counterfactual matches that

[29] Figures 2A.1-2A.3 and Table 2.2 show, respectively, the evolution over time of the MTR valid for native as well as foreign players across countries and the average variation at the regional level.

[30] See Kleven et al. (2013) and Agrawal and Foremny (2018) for more details on ATR simulation strategies.

[31] On top of these elements, more pieces of evidence on the causal link between marginal taxation and migration has been provided by Kleven et al. (2013) by exploiting exogenous policy changes using a synthetic control approach.

agents would face in reality. However, as explained before, the MSM ensures the validity of the estimates even though when considering a subset of all potentially available alternatives (Fox, 2007).

Therefore, we believe that given the nature of our data and our empirical strategy endogeneity is less an issue in our context.

2.4.2 Estimation Procedure

In this section, we describe the estimation procedure followed to estimate the effect of taxation on the match between players and teams and, consequently, on footballers' equilibrium locations. This procedure is defined to account for the specific characteristics of the MSM estimator.

Market definition

First, we need to define the set of independent markets. These are independent in the sense that one agent cannot compete in more than one market. Given that the players play in different positions we separate the players in offenders, defenders, midfielders, and goalkeepers to account for the fact that players are more likely to compete with players in the same position of the field.[32] Indeed, it is implausible that a goalkeeper or a defender is competing with an offender to match with its preferred team. However, players can change their role in their careers this way competing in more than one market.[33] To avoid this possible issue we define each season as a separate market obtaining 40 markets (10 years for 4 positions). In this way each market will be composed by players of one specific position in a specific season on the supply side and teams on the demand side.[34]

Match-specific variables definition

The second step of our estimation procedure concerns the definition of the match-specific variables that characterize the local production function of the matches. The first determinant used is the variable *Time in the Country* indicated as $\ln(Time_{country})$. This is defined as the

[32]A similar strategy is used in Yang et al. (2009) concerning basket players.
[33]We observe 13 players that change their category in our sample
[34]Given this definition, the teams are seen as the collection of different position-specific unities.

logarithm of the number of semesters that one player has spent in one specific country. We use semesters instead of years to consider that one player can change his team in the middle of the season. This variable is used to understand the presence of some persistence in players' choices regarding countries: a positive coefficient would indicate that the match utility increase when the player has already played in that specific country. Players, in this cases, can have some advantage in terms of knowledge of the language and the culture, and, especially, a more precise knowledge about the characteristics of rival teams and league's style of football.[35] The second and the most important determinant of the local production function is the logarithm of the *net-of-tax rate* indicated as $\ln(1-\tau)$ and computed according to Eq. (2.14). This variable allows us to understand the effect of the marginal tax rate on matches' utility. As we have seen in Section 2.1.3 we use, as year-t season tax rate the tax rate that was valid at the beginning of the season. A positive coefficient would indicate that matches are more likely to occur, or are more valuable, in relatively low-tax countries or regions. The third determinant is given by the logarithm of the *Quality of the match* indicated as $\ln(Match_{qual})$. This is computed as the interaction between the standardized qualities of players and teams. As explained in Section 2.3.3, *player's quality* is computed as the average of all the market values that we observe during the player's entire observable career until the year $t-1$, whereas *team's quality* is computed as the sum of the quality of the players that were playing in the team in year $t-1$. Moreover, *team's quality* is computed considering even players that are not born in one of the countries of our sample. This strategy is followed in order to account for the possible fundamental contribution that this kind of player can have on teams' performances and quality. In order to have an easier interpretation of our results, we normalize both quality indicators so that their values are comprised between 0 and 100 and we use as maximum for this standardization the highest quality observed in one specific market. In this way, we have a different quality distribution for each year-position cell that permits to account for the differences in average market values existing among different players' categories. This variable is used to understand if there is some positive sorting effect between teams and players based on their quality and how these characteristics influence matches' local production functions. The last determinant is the variable *Prior Relationship*. This is a dummy variable that takes value 1 if the two agents have already matched

[35] For example, Italian football is known to be more defense-oriented whereas English football is perceived as more physical.

in the past. This variable allows us to understand if there is some persistence in the preferences of both kinds of agents for their partners. Indeed, a positive coefficient would indicate that the match's utility increases when it comprises two agents that have already met in the past. The logic behind this variable is similar to the one explained for the *Time in the Country*: if the agents have already matched in the past it may be that the player has a better knowledge of the environment surrounding the team, the characteristics of other teammates and of the league in which the team compete. These elements can be very positive in the valuation of one partner because allow agents to reduce the uncertainty regarding the real quality and the real characteristics of their partners. To understand if there is heterogeneity in the effects of these determinants, we estimate a set of interactions that permits us to understand whether the effects of these determinants differ on the base of players' characteristics. In particular, we interact the logarithm of the *net-of-tax rate* with three dummies: Top_{year}, $Foreigner$ and $Foreigner \times Top_{year}$. The first dummy takes value 1 if the player located above the 25% of the year-specific quality distribution. These quality distributions are computed following the strategy explained before but without considering the player's position. This strategy is followed because the effect of the tax rate is more likely to be heterogeneous on the base of players' salaries that, as explained in Section 2.1.1, may be more related to the simple market value. The dummy $Foreigner$ takes value 1 if the player is playing in a foreign country and allow us to understand whether the effects of the various determinants on matches' utilities differ between foreigners and natives. The interactions with $Foreigner \times Top_{year}$ finally are estimated to understand if the effect of *net-of-tax rate* on matches' local production functions differs when considering a top foreign player. In this way, the baseline match used as a reference for the interpretation of the results is a match where one generic team is matching with a low-quality native player. The variables *Quality of the match* and *Prior relationship* are interacted with a slightly different set of dummies: Top_{mkt}, $Foreigner$ and $Foreigner \times Top_{mkt}$. In this case, we consider the dummy Top_{mkt} which is defined considering the market-specific quality distribution. This different strategy is used because it is more likely that teams consider the position occupied by players in the field when evaluating them rather than only their general market value. All the variables used in the estimation are computed considering the information available until the market window preceding the season so that agents' attributes are not affected by matching assignments (Schwert, 2018).

Pairwise stability inequalities

The third step regards the definition of the inequalities used in the objective function of the MSM. These inequalities are constructed on the basis of Eq. (2.31). In particular, for each observed couple of matches we construct the set of inequalities defining the counterfactual matches by exchanging two players at a time. For example, if we observe a set of matches in which Ronaldo is matched with Juventus FC and Neymar is matched with Paris Saint-Germain FC the counterfactual set will be composed by a match between Neymar and Juventus FC and another match between Ronaldo and Paris Saint-Germain FC. This logic is followed for each couple of matches observed and for any possible combination between the observed matches. The identification of the vector of parameters will be based on the pairwise comparison between observed and counterfactual matches using the objective function defined in Eq. (2.32). Given the combinatorial nature of this process, the final set of inequalities can be huge and cause an increase in the computational burden of the estimation process. However, Fox (2018) suggests that, when the number of inequalities becomes computationally intractable, is it possible to use a random subsample of the entire set of inequalities without losing the estimator's consistency. Therefore, in the estimation sample, we use only a 40% random subsample of the set of inequalities.[36]

Estimation of the matches' local production function

When the set of inequalities is constructed we can estimate the local production function by maximizing the objective function defined by Eq. (2.32). To maximize this objective function and identify the vector of parameters we need to fix one coefficient to +1 or -1 (Fox, 2007). This restriction is due to scale identification. Indeed, given the semi-parametric nature of the estimator, we can identify the set of coefficient up to an order-preserving transformation of the parameters (Manski, 1975).[37] This means that, as in standard discrete choice approaches, we can interpret only the relative magnitude of the coefficients and their sign. We choose the

[36] We have run the estimations several times with sample of different dimensions obtaining always similar results.

[37] Namely, the same matching patterns can be generated by an infinite variety of set of coefficients, which differs only by a constant that multiplies all the coefficients.

Table 2.3: Single Variable Explanatory Power (Percent)

Normalization	$\theta = +1$	$\theta = -1$
$ln(Time_{Country})$	90.94	0.81
$ln(1-\tau)$	1.65	22.39
$ln(Match_{Qual})$	43.02	42.29
$PriorRelationship$	31.47	0.36
N. of Inequalities used	10274607	10274607

Notes: The column headed $\theta = +1$ and $\theta = -1$ correspond to a positive or negative normalization for variables. The scores correspond to the percentage of observed inequalities statisfied using the objective function defined in Eq. (2.32).

variable to use as a reference by computing the objective function of Eq. (2.32) using one regressor at a time and estimating two models: one with the coefficient fixed to +1 and another with the coefficient fixed to -1. The choice of the reference variable is based on the model's goodness of fit that is given by the ratio between the value of the score function and the number of inequalities used (Fox, 2007). Table 2.3 shows the results of this procedure displaying the variables used in each estimation and the percentage of inequalities satisfied fixing the coefficient θ to +1 or -1. As we can notice the variable with the highest explanatory power is the logarithm of *Time in the Country* that satisfies, when considering a positive coefficient, the 90.94% of the inequalities used in the estimation. Thus, we estimate the local production function maximizing the objective function (2.32) using as reference regressor the variable *Time in the Country.*

Finally, we compute the interval of confidence using a sub sample procedure by estimating the same specification across 200 random samples of 4 markets each time. Given that the rate of convergence is $\sqrt[3]{N}$, the empirical sampling distribution of our vector of parameters is (Schwert, 2018):

$$\tilde{\theta}_s = \left(\frac{n_s}{N}\right)^{1/3} (\hat{\theta}_s - \hat{\theta}) + \hat{\theta} \tag{2.33}$$

where $\hat{\theta}_s$ is the estimate from the subsample s, $\hat{\theta}$ is the estimate from the full sample used in the estimation, n_s is the dimension of the sample s and N is the number of observation in the estimation sample. For a generic significance level α we construct the interval of confidence taking, as boundaries, the $\frac{\alpha}{2}^{th}$ and the $(1-\frac{\alpha}{2})^{th}$ percentiles of the empirical distribution of θ_s.[38] The coefficient will be considered as statistically significant if the constructed interval does not

[38] Given that the empirical distribution (2.33) is not uniform our interval of confidence can be asymmetric.

contain the value 0 and, therefore, the two boundaries have the same sign. We construct the intervals considering the three standard significance levels (1%, 5% and 10%) and we choose the interval that indicate a significant coefficient considering the lowest level of significance. If the three intervals contains the value 0 we will show the 10% interval of confidence in the results.

Given our estimate of the local production function, we are able to understand how the determinants of migration patterns highlighted previously affect football players' location decisions and their relative importance.

2.4.3 The Elasticity of Mobility to Taxation

In the previous literature (e.g. Kleven et al. (2013)) the elasticities of migration are computed using the probabilities estimated through a discrete choice model to estimate the expected changes in each country's population deriving from a 1% change in the *net-of-tax rate*. However, the semi-parametric nature of the MSM does not allow a direct estimate of the probability to observe the matches and, therefore, to compute marginal effects and elasticities. In this cases Manski (1975) suggest two different approaches. The first consists in recovering the probability to observe a match assuming an ex-post distribution for the error term. However, this approach will result in a loss of the advantage to use a more general definition of the error terms. Moreover, it does not ensure that the number of predicted matches will be equal to the one observed, this way arising complications in the computation of elasticities. Indeed, in this case, we cannot properly account for the rigidity of the demand and the eventual displacement effects between different categories of players. The second approach consists in estimating the probability of the match non-parametrically.[39] However, this procedure could be computationally expensive in our case given the dimension of our sample.

A third possible strategy is to estimate the elasticities through a simulation approach. This approach consists of using the estimates of the local production function to simulate the matching assignments. In this way, we can simulate the variation in the number of taxpayers caused by a change in the *net-of-tax rate* of 1% and compute the elasticity of mobility using Eq. (2.13). The matching assignments are simulated using the algorithm used in Schwert (2018).

[39] In a previous version of Fox (2018) the author suggests to use the sieve methods.

This procedure is made up of three steps:

1. Compute the local production function for each potential player-team match in each market according to our estimates;

2. Sort all the possible matches by the estimated local production function values;

3. Select the most valuable matches in descending order.

We repeat this procedure until we reach the number of observed matches and each player is matched with one team. Differently from Schwert (2018) we apply this procedure considering two scenarios: one in which teams have a maximum number of vacancy spots and one in which we let teams match with an indefinite number of players. In both scenarios, we consider that players can match with only one team at a time. This last assumption makes our strategy very similar to the one used in the standard conditional logit approach. Indeed, as noted by Schmidheiny and Brülhart (2011), the conditional logit represents a zero-sum world in which, despite the elasticity of the demand, the dimension of the supply is kept fixed. We use this strategy to have results that are comparable with those found in the previous literature and because we cannot estimate an exit option in which players can decide do migrate outside of Europe or to do not play at all.

The two scenarios differ in the assumptions regarding the elasticity of the demand and the dimension in the market. When fixing the number of vacancy spot, we assume that the labor demand is rigid and that the dimension of the market is fixed to the one observed. In this way, we can explore the existence of displacement effects between different kinds of players. On the other hand, in the second scenario, we are not assuming anything about the elasticity of the labor demand. Indeed, if we let the teams match with an indefinite number of players we are letting the dimension of the market to depend solely on the results of our estimation model. The results associated with this second strategy are more comparable with those found in the literature where the elasticities are usually estimated considering an elastic labor demand.[40]

[40] **??**One exception is, for example, Kleven et al. (2013) where the authors estimate two different specifications considering both elastic as well as rigid labor demand. In the first case the model used is a conditional logit with alternative fixed effects that allow to account for the dimension of the market and, therefore, gives estimates considering a context of perfectly elastic labor demand. In the second case they do not include country-fixed effects and, therefore, the coefficient are influenced, among the others determinants, by the dimension of the market in the countries.

In general, our strategy for the computation of the elasticities has three main advantages: we do not need to assume any error distribution, the procedure is computationally less costly than a non-parametric technique and, we can consider different scenarios to better understand the results of the structural model estimated with the MSM.

This strategy allows us to understand how footballers' equilibrium locations are affected by the marginal tax rate and how these elasticities change with respect to players' nationality and quality level. In particular, given that our estimates represent the firms' and workers' joint responses we can identify the effect on players' migration patterns by exploiting the fact that firms cannot migrate in order to avoid income taxation. Therefore, the effect of marginal taxation on equilibrium locations is identified by simulating its effect on matches utilities and comparing how these effects impact on players' migration patterns.

2.4.4 Results

This section shows the results regarding the estimation of matches' local production function obtained following the procedure explained in Section 2.4.2 and the results concerning the elasticity of mobility obtained using the simulation strategy explained in Section 2.4.3. This paragraph closes explaining the various advantage of the estimation strategy used in this study in the light of the estimation results.

Point estimates results

Table 2.4 reports the results for 7 different specifications of the match local production function. The table shows the estimated vector of coefficient, their interval of confidence, the number of inequalities used in estimation and the percentage of inequalities satisfied. This last element can be seen as a measure of the goodness of fit of the model (Fox, 2018). As we can notice all the specifications estimated satisfy a very high percentage of inequalities, always above the 90% of the set of pairwise stability inequalities used in estimation. This suggests that the fit of the model is very good with a percentage of satisfied inequalities which is higher or similar than those reported in other studies that use this estimation strategy (e.g. Fox (2018), Yang et al. (2009), and Schwert (2018)).

The columns (1)-(3) of Table 2.4 present the results of specifications in which matches' utility depend only upon the logarithm of the *net-of-tax rate* (indicated as $\ln(1-\tau)$) and the logarithm of *time in the country* (indicated as $\ln(Time_{Country})$) taking into account the effects of the agent-specific variables.[41] The positive coefficient associated with $\ln(Time_{Country})$ indicates that the matches' utilities are positively correlated with the semesters spent in the country by the player. This result is not surprising, by spending time in one country the players can learn more about the specific characteristics of the league and of the country in which they are playing and, therefore, become more useful for the teams. Moreover, this variable is useful for the interpretation of MSM's results. Indeed, as in every discrete choice approach, the coefficients can be interpreted only in terms of their relative magnitude and, therefore, we can use this coefficient to translate the effects of the other variables in terms of semesters of life in one country. For example, a coefficient of +2 indicates that a unitary increase in the variable gives the same utility to the match as 2 semesters of player's career in the country.

Turning to the effect of the *net-of-tax rate*, the first specification considers the effect of this variable in general ($\ln(1-\tau)$) and exploiting the heterogeneity of the effect based on the foreign status of the player ($\ln(1-\tau) \times Foreigner$). The positive coefficient associated with $\ln(1-\tau)$ indicates that the matches are more valuable if they happen in a country with a relatively higher net-of-tax rate or a lower tax rate. However, this effect is not the same for every group of players. Indeed, if the match includes a foreign player, the positive effect of the net-of-tax rate on the utility of the match decrease by -0.332. This effect is stable in terms of signs across all the specifications estimated and is related to the fact that, as shown in Table 2.1, the vast majority of observed matches are between teams and native players.

In specifications (2) and (3) we have added two different interactions terms to understand if the effect of taxation is different for matches in which the player is a *top player* ($\ln(1-\tau) \times Top_{mkt}$) or a *top foreign player* ($\ln(1-\tau) \times Foreigner \times Top_{year}$). The preliminary results of these two models indicate that the effect of taxation increase if the player in the match is a top-foreign player and that is not statistically different for matches that include a top player with respect to the baseline given by a low-quality native player. However, these results can be biased because the specifications examined do not account for the role played in the local production function by the *quality of the match* measured as the interaction between

[41] All the specifications used, as explained in Section 2.4, account for all the possible agent-specific variables and agent fixed-effects that are erased from the local production function thanks to the pairwise stability condition.

players' and teams' qualities and the *prior relationship* between teams and players. Therefore, in models (4)-(7) we extend the previous specifications considering the regressors $\ln(Match_{Qual})$ which measures the effect of the quality of the match and $PriorRelationship$ which account for the effect of the past matches between agents. Moreover, across the different models, we explore the effects of these variables considering different subgroups of players to understand if the effect is different when considering foreign and top-quality players. In particular, model (4) adds to the previous specifications three interactions terms: $\ln(Match_{Qual}) \times Foreigner$, $\ln(Match_{Qual}) \times Top_{mkt}$ and $\ln(Match_{Qual}) \times Foreigner \times Top_{mkt}$. These terms measure the effect on the local production function of match's quality when it includes, respectively, a foreign player, a top-quality player, and a foreign top-quality player. As we can notice, the model (4) does not include the term $\ln(Match_{Qual})$. This is due to the fact that, when including this variable, the estimation algorithm does not converge, failing in the identifications of the vector of coefficients. Therefore, in this model, we are assuming that the effect of match's quality on the local production function is null when the match includes a low-quality native player and we can interpret the other coefficients with relation to this baseline.

Table 2.4: Maximum Score Matching Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(Time_{Country})$	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Supercons.	Supercons.	Supercons.	Supercons.	Supercons.	Supercons.	Supercons.
$\ln(1-\tau)$	2.172***	2.170***	2.307***	2.263***	2.208***	2.436***	2.649***
	[1.17 3.21]	[1.16 3.58]	[1.44 3.55]	[1.51 3.15]	[1.22 3.07]	[1.38 3.43]	[1.68 3.82]
$\ln(1-\tau) \times Foreigner$	-0.332***	-0.332***	-0.469***	-0.431***	-0.491***	-0.716***	-0.753**
	[-0.36 -0.28]	[-0.37 -0.28]	[-0.54 -0.41]	[-0.48 -0.36]	[-0.55 -0.31]	[-0.89 -0.42]	[-0.92 -0.59]
$\ln(1-\tau) \times Top_{year}$		-0.002	-0.006	0.283	0.305	0.454*	0.786***
		[-0.46 0.46]	[-0.25 0.24]	[-0.05 0.61]	[-0.07 0.68]	[0.03 0.88]	[0.16 1.55]
$\ln(1-\tau) \times Foreigner \times Top_{year}$			0.344***	0.025	0.050	-0.223***	-0.038
			[0.26 0.42]	[-0.05 0.10]	[-0.05 0.15]	[-0.48 -0.13]	[-0.16 0.08]
$\ln(Match_{Qual}) \times Foreigner$				0.184***	0.168***	0.268***	0.179***
				[0.14 0.24]	[0.11 0.24]	[0.24 0.40]	[0.07 0.26]
$\ln(Match_{Qual}) \times Top_{mkt}$				0.660***	0.801***	0.865***	1.032**
				[0.49 0.78]	[0.59 0.92]	[0.35 1.09]	[0.81 1.25]
$\ln(Match_{Qual}) \times F. \times Top_{mkt}$				0.010	0.015	0.174***	0.136***
				[-0.05 0.07]	[-0.06 0.09]	[0.05 0.36]	[0.00 0.32]
$PriorRelationship$					1.089**	9.076***	7.056***
					[0.75 1.43]	[7.02 12.85]	[3.89 9.83]
$PriorRelationship \times Top_{mkt}$						-7.867***	-6.387***
						[-11.41 -5.51]	[-9.19 -3.40]
$PriorRelationship \times Foreigner$							0.785
							[-0.08 1.65]
% of Inequalities satisfied	92.42%	92.68%	92.74%	94.88%	96.09%	96.05%	96.05%
N. of Inequalities used	10274607	10274607	10274607	10274607	10274607	10274607	10274607

Notes: The parameter on $ln(Time_{Country})$ is fixed to +1 due to scale identification. The estimates of this paramater in a model with only one regressor finds the point estimate of +1, instead of -1. Given that the parameter can take only two values (+1, -1) its estimate is superconsistent. See Fox (2018) for details on superconsistency. All the variables are expressed in natural logarithms. Each estimation uses a 40% random sample of the entire set of inequalities. For each coefficient the table reports the interval of confidences computed through a sub-sampling procedure across 200 random sample of 4 markets at a time. One coefficient is statistically significant if its interval does not contain the value 0. The interval of confidence are reported considering the lowest level of significance for which the interval does not contain the value 0. ***, **, * indicate, respectively, that the coefficient is significant at the 1%, 5% or 10% level. If the coefficient is not significant at these levels the table reports the interval of confidence computed considering a 10% level of significance.

The models from (5) to (7) explore the effect of the past relationship between teams and players adding three regressors: $PriorRelationship$ that indicate the difference in term of utility between a match including two partners who have already matched and a match in which the two agents have never met, $PriorRelationship \times Top_{mkt}$ and $PriorRelationship \times Foreigner$ that measure how this difference can change when the match includes a top-quality player or a foreign player.

The first feature that is possible to notice is that the model's goodness of fit increases when we control for matches' quality and prior relationships. This indicates that these variables add explanatory power to our models. In particular, the model's goodness of fit increases from the model (1) to model (5) and remain relatively stable across specifications (5)-(7). These models satisfy more than the 96% of the pairwise stability inequalities used in estimation. However, if we compare model (5) with models (6) and (7) is it possible to notice that most of the coefficients change their magnitude and their signs compared with the previous specifications. This element suggests that, although the goodness of fit stays almost constant, these last two models are able to give us more complete information on the relationship between match's utility and the past experience of the partners. Therefore, our main result and our considerations will be based on these two specifications.

As in the previous models the baseline used to interpret these results is a match between a team and a native low-quality player. As we can see the results of these two models are qualitatively similar: although the coefficients' magnitude changes their signs remain the same. The net-of-tax rate has a positive effect on the matches' utility in general, the coefficient associated with $\ln(1-\tau)$ is positive and statistically significant. The effect of taxation, however, is weaker for matches with foreigners given that the coefficient of $\ln(1-\tau) \times Foreigner$ is negative and significant. As seen before, this effect is related to the fact that the majority of observed matches include a native player. Moreover, this result is in line with the graphical evidence presented in Figure 2.1 and it confirms the intuition that players are, in general, more interested in the tax rates valid in their origin country rather than the one valid in the destination country. Indeed, the negative coefficient indicates that the net-of-tax rate is less important for the utility of the match when it includes a foreign player. The coefficient attached to $\ln(1-\tau) \times Top_{year}$ is positive and statistically significant in both models indicating that the net-of-tax rate is more important when the match includes a top-quality player. This result is in line with the one presented in Figure 2.2 and can be due to two different reasons. First, top-players are likely to have a stronger market power than the other players in choosing their best partners and the country in which they play. Second, top-players have a higher wage and the marginal tax rate is a better proxy for the income taxation that these players face in reality. Therefore, this result can be driven by the fact that the taxation treatment is stronger for this kind of players. The effect of taxation on matches that include a top-quality foreign player differs across the two models. Indeed, although the sign is always negative the coefficients' magnitude changes strongly. In general, however, the effect of taxation seems to be weaker for these players for the same reasons that we have seen for foreigners in general.

Turning on the effect of the quality of the match we can notice that the coefficients associated with the three interaction terms are always positive and statistically significant. From these results, and recalling that our baseline is given by a match that includes a low-quality native player, three main results can be highlighted. First, the match's quality has a stronger effect if we consider a foreign player with respect to the baseline. One possible interpretation of this result is that players that are migrating prefer to match with partners that ensure a career opportunity and, therefore, are more interested in the resulting quality of the match. However, given the matching structure of our estimator, this result could indicate that teams are willing to hire a foreign player only when the resulting quality of the match is higher than the one that would result from a match with a native player. Therefore, matches that include a foreigner have a local production function that depends positively on the level of the resulting quality. The second element is that the role of the quality of the match changes strongly if we consider a top-player. Indeed, the coefficient associated with the interaction $\ln(1-\tau) \times Top_{mkt}$ has a positive coefficient which is way bigger in magnitude than the one attached to $\ln(1-\tau) \times Foreigner$. This result is not surprising: a top-player is obviously interested in matching with a very good quality team and, at the same time, very good quality teams are more interested in hiring top-quality players. Lastly, these two results are confirmed by the coefficient of the interaction term $\ln(1-\tau) \times Foreigner \times Top_{mkt}$. This coefficient is positive, indicating that the matches are more valuable when they include a top-quality foreign player and the resulting quality of the match increases.

The results regarding prior relationship indicate that a match is more valuable when the two partners have already matched in the past but is weaker if we consider top players. Moreover, we do not find evidence of a difference in this effect between natives and foreigners. These results depend on two elements: teams are more likely to prefer a player that already knows their characteristics and their rules and a player is more likely to prefer a known environment where he has already played. This effect is likely to be weaker for top players because, by changing teams, they can improve their career outcomes. Indeed, is it plausible that very good teams hire players only when they are already at the top of the quality distribution and, therefore, we will observe always very few top players matching with their old teams.

To improve the interpretation of our result in the next subsection we present the results of our simulation approach.

Simulation results

As explained in Section 2.4.3 our simulation strategy considers two different scenarios. The first assumes that the labor demand is *elastic*. This means that teams can match with an indefinite number of players on the base of the estimated local production function. The second scenario assumes that the labor demand is *rigid* and teams have a maximum number of vacancy spots equal to the number of players observed in the team during the 2016 season. In both scenarios each player can match with only one team at a time. However, differently from Kleven et al. (2013), both scenarios are estimated using the same econometric specification for the local production function. Indeed, one of the advantages of the MSM is that we do not need to assume a specific elasticity of the labor demand for the estimation and, therefore, all the coefficients depend on the observed market structure that is let to be endogenous determined in equilibrium. Therefore, in the first scenario we are not assuming that the labor demand is *perfectly elastic* but we are simply letting the number of players that match with each team to be freely determined on the base of the estimated local production function. On the other hand, the second scenario is extremely useful to understand the effects of marginal taxation in the context of rigid demand and competition between players. Indeed, when the number of vacancy spots is fixed at the team level, players with different quality levels can be affected differently by the marginal taxation. For example, on the base of the results shown in Table

2.4, the reduction of the marginal tax rate in one country is likely to attract both top-quality and low-quality players. However, if the labor demand is perfectly rigid, we will observe a sorting effect on the base of players' quality: top-players will enter the country pushing away low-quality players. Indeed, in this case, teams will have the opportunity to choose among top-players substituting the low-quality ones. In fact, the results of models (6) and (7) of Table 2.4 suggest that the effect on matches' utilities of the net-of-tax rate is stronger if they include a top-quality player.

Table 2.5 reports the results of our simulation approach in terms of models' goodness of prediction. This is measured comparing the observed set of matches with the one simulated considering a scenario in which tax rates are kept fixed. The first two columns of Table 2.5 report the number of observed and predicted matches. As we can notice, the simulation approach is able to predict the exact number of observed matches. This is a consequence of the fact that, as in the conditional logit approach, our simulation strategy represents a zero-sum world in which the labor supply is perfectly rigid at the European level and the number of players and matches is kept fixed to the one observed in the data. The columns 3-5 of Table 2.5 present the percentage of correctly predicted matches considering, respectively, team-player level, regional level, and country level. A simulated match is considered correctly predicted at the team-player level if it includes the couple of agents that we observe in the data. In the second and the third columns the simulated match is correctly predicted if, in the simulated scenario, the player is assigned to a team in the region or in the country in which he was playing in the observed data in 2016. In these cases, the regions are defined as the lowest tax decision unit available.[42]

As we can see the performances in terms of goodness of prediction of the two models are very similar in the two scenarios considered. In particular, if we consider an elastic labor demand we have that the algorithm predicts correctly the 38% of observed matches at the team level and around 60% and 82% of the observed matches on the regional and the country level. These results are similar in the rigid demand scenario in which the algorithm performs worse at team-player and country levels. This is somewhat surprising because the second scenario, by keeping fixed the number of teams' vacancy spots, should replicate better the observed set of matches forcing the algorithm to follow the distribution of tax-payers that we observe in

[42] In countries where tax rates do not vary on regional level the lowest tax decision unit is the country, conversely, if the country present regional variation in tax rates, we consider the region as the lowest tax decision unit.

Table 2.5: Goodness of Prediction

	Predicted Matches	Observed Matches	% Correct Matches	% Correct Regions	% Correct Countries
Elastic Demand					
Model (6)	5014	5014	38.23	60.91	81.89
Model (7)	5014	5014	38.25	60.99	81.93
Rigid Demand					
Model (6)	5014	5014	30.73	61.75	79.78
Model (7)	5014	5014	31.35	62.25	80.12

Notes: the table compares the goodness of prediction of the simulation approach based on model (6) and model (7) of tabel 2.4. Panel *Elastic Demand* considers a scenario in which a team can match with an indefinite number of players. Panel *Rigid Demand* considers a scenario in which the number of players that can match with the team is fixed to the one observed in the sample. The first and the second columns report, respectively, the number of observed and predicted matches. The columns 3-5 reports the percentage of correctly predicted matches considering, respectively, the team-player level, the regional level and the country level. Regions are the lowest tax decision unit available. The results are based on year 2016.

the data. However, given that our simulation approach is able to predict around the 80% of the observed country-player matches in all the scenarios considered we are confident that our specifications are able to describe correctly the phenomenon examined and, therefore, we can use our simulation approach to estimate the elasticity of mobility to taxation.

The results of this exercise are reported in Table 2.6. In particular, for each model and scenario considered, we have computed the average elasticity of international mobility to a 1% increase in the net-of-tax rate in general and considering only natives or foreigners. We have split our sample in top and low-quality players. Looking at the results of the elastic demand scenario we can see that, in general, a reduction of 1% in the tax rate can increase the number of tax payers by around 0.2%. This effect is stronger when considering top players (around 0.7) and weaker with respect to the population of low-quality players (around 0.07). These results confirm the conclusions drawn on the base of the estimated local production function and indicate that a reduction in the net-of-tax rate can, ceteris paribus, improve the quality distribution of players in one country. However, the most interesting results are those regarding the differences in the effect between natives and foreigners. In general, we have estimated an elasticity between 0.11 and 0.07 native population and between 1.20 and 1.37 for foreigners. These results are in line with the previous literature. For example, Kleven et al. (2013) find a point estimate for the elasticity of the number of native players around 0.15 and around 1 for foreigners. The differences in the results can be explained considering that our elasticity

Table 2.6: **Average Elasticity of International Mobility to Taxation**

	General			Natives			Foreigners		
	Avg	Top	Low	Avg	Top	Low	Avg	Top	Low
Elastic Demand									
Model (6)	0.220	0.758	0.066	0.117	0.495	0.028	1.197	1.655	0.681
Model (7)	0.210	0.710	0.067	0.077	0.310	0.025	1.370	1.817	0.768
Rigid Demand									
Model (6)	0.000	0.297	-0.084	-0.016	0.243	-0.082	0.119	0.523	-0.102
Model (7)	0.000	0.442	-0.126	0.036	0.494	-0.080	-0.260	0.240	-0.559

Notes: the table reports the elasticities of mobility to a 1% increase in the *net of tax rate* computed using the simulated assignments for the year 2016 based on the results of models (6) and (7) of table 2.4. Panel *Elastic Demand* considers a scenario in which a team can match with an indefinite number of players. Panel *Rigid Demand* considers a scenario in which the number of players that can match with the team is fixed to the one observed in the sample. Each elasticity is the weighted average of countries elasticities weighted by the ratio between the number of players in each group in the country and the number of players in each group in the sample. The results are shown for the general population of players, for natives and for foreigners. For each group we computed the average elasticity (Avg), the elasticities for top players (above the 25% of the quality distribution) and low quality players (below the 25% of the quality distribution).

estimation is computed considering the joint response of players and teams. Moreover, the difference of the magnitude of the effect between native and foreigner populations is related to the fact that the base of native players is much larger than the one of foreigners given that most players play at home (Kleven et al., 2013). These results suggest that a general reduction of the tax rate is less cost-effective than a reduction that targets only foreign players. Moreover, given that the effect is stronger when considering top players, we can confirm the previous result: a reduction in the tax rate can improve the quality distribution in one country, especially for foreigners.

The results of the rigid demand scenario present evidence of sorting effects given by the fact that the elasticities present positive values for top players population and negative values for low-quality players population. This suggests that when one country reduces its marginal tax rate, the share of top quality players that country increases this way pushing away low-quality players. This result is valid if we consider all the players as well as if we consider natives and foreigners. However, our results do not suggest that the foreign players will displace the native ones. Indeed, the values of the average elasticities for natives and foreigners present different signs in the two models. Model (6) predicts a negative elasticity of natives' population and a positive one for foreigners' population. This indicates that, according to model (6) foreign

Table 2.7: Average Elasticity of International Mobility to Taxation: Preferential Schemes for Foreigners

	General			Natives			Foreigners		
	Avg	Top	Low	Avg	Top	Low	Avg	Top	Low
Elastic Demand									
Model (6)	0.114	0.369	0.041	0.000	0.000	0.000	1.192	1.619	0.712
Model (7)	0.143	0.495	0.043	0.000	0.000	0.000	1.395	1.859	0.768
Rigid Demand									
Model (6)	0.000	0.139	-0.039	-0.054	0.000	-0.068	0.396	0.726	0.217
Model (7)	0.000	0.381	-0.109	-0.079	-0.051	-0.086	0.570	2.031	-0.315

Notes: the table reports the elasticities of mobility to a 1% increase in the *net of tax rate* valid for foreigners computed using the simulated assignments for the year 2016 based on the results of models (6) and (7) of table 2.4. Panel *Elastic Demand* considers a scenario in which a team can match with an indefinite number of players. Panel *Rigid Demand* considers a scenario in which the number of players that can match with the team is fixed to the one observed in the sample. Each elasticity is the weighted average of countries elasticities weighted by the ratio between the number of players in each group in the country and the number of players in each group in the sample. The results are shown for the general population of players, for natives and for foreigners. For each group we computed the average elasticity (Avg), the elasticities for top players (above the 25% of the quality distribution) and low quality players (below the 25% of the quality distribution).

players, on average, displace natives in the case of a reduction in the tax rates. However, model (7) predicts the opposite: natives' population has a positive average elasticity while foreigners' population have a negative point estimate. Therefore, we do not have conclusive evidence regarding the existence of a displacement effect between foreigners and natives. This result is in contrast with the one found by Kleven et al. (2013) that find evidence of displacement effect in the context of rigid labor demand.

The previous results indicate that the effect of taxation is stronger if we consider foreign players. Therefore, it can be interesting to simulate the effect of a preferential taxation scheme that targets only them. The results of this exercise are reported in Table 2.7 where the simulations are carried considering a 1% increase in the net-of-tax rate valid for foreign players.

Looking at the elastic demand scenario we can see that a preferential scheme has affected the native population of players. Moreover, the results of the effect of the tax rate on foreigners are very similar to those presented in Table 2.6. This is not surprising because, in this scenario, the number of vacancy spots in teams is let free and, therefore, we do not have any competition effect between different kinds of players. Therefore, a policy that targets only foreigners will not affect the distribution of natives across countries and will affect the foreigners in a way similar to the one caused by a general reduction in tax rates. Turning on the results of the rigid demand scenario we can highlight a very interesting element: the effect of the preferential scheme is, on average, positive when considering foreigners and negative if we consider natives. Therefore, we have evidence of a displacement effect between foreign and natives players. With respect to the sorting effect between foreigners, we can notice that the two models predict a very different effect of the preferential scheme on this population: model (6) predicts an elasticity lower than one for top players' population, while model (7) predicts an elasticity around 2 for the same population and a negative effect on low-quality foreigners' population. However, Table 2.7 suggests that a general reduction in the net-of-tax rate is more effective than a preferential scheme in increasing the number of top players. Indeed, the elasticities of top players following a general reduction of the marginal tax rate, presented in Table 2.6, are higher than the one found simulating a preferential scheme.

In conclusion, the results of our simulation approach are mostly in line with the previous literature even though we have found evidence of displacement effects between natives and foreigners populations only considering the preferential scheme scenario. Our results, however, confirm that taxes can be seen as an effective tool to attract highly productive workers that, depending on the rigidity of the labor demand, can displace low-quality players increasing the quality level of the country. The elasticities results presented here can also be used to compute the revenue-maximizing tax rates following the model of optimal taxation in the presence of migration of Mirrlees (1982) and used by Kleven et al. (2013) in the elastic demand scenario. In this framework revenue-maximizing tax rate is an inverse function of the elasticity of migration and can be computed using the formula:

$$\tau^* = \frac{1}{1 - \varepsilon_n} \tag{2.34}$$

where τ^* is the optimal tax rate and ε_n is the elasticity of mobility to taxation estimated in the elastic demand scenario. Using this formula our estimates yield an optimal tax rate of around 82%. This result is similar to the one found in Kleven et al. (2013) and is well above the average marginal tax rate observed in the data. Therefore, our results suggest that the observed tax rates are suboptimal and that an increase in their values can yield an increase in tax revenues without causing an excessive loss in terms of the population of highly skilled workers.

Was it worth?

The previous sections have presented the results of our estimation strategy. Although the point estimates are slightly different, these results are in line with those found in the previous literature concerning the effect of marginal tax rates on the mobility choices of footballers and top earners in general. At this point one question should interest the reader: was it worth to use this new methodology approach?

First, the results of our approach are similar to those found by Kleven et al. (2013). This element suggests that our estimation approach is consistent with those used in the previous literature although we do not use data on agent-specific variables and we do not assume ex-ante the market structure. Indeed, our simulation approach has allowed us to estimate the elasticities in the two contexts of rigid and elastic demand without requiring ad hoc specifications for each scenario but keeping the local production function of the matches unchanged.[43] This element is interesting because we can identify the utility of the match in general and then simulate the various scenarios to understand how these utilities can cause different matching assignments on the base of the assumed market structure or by changing the policies without assuming anything on the market structure and agents' market powers in the econometric specifications.

Second, the approach used in this study allows identifying directly the effect of the various determinants on the utility of the match rather than on the utility of the players. This element is extremely useful in the interpretation of the results. Indeed, in the conditional logit models all the coefficients are interpreted as the parameter of the worker's utility function although, as pointed out by Akcigit et al. (2018), the results could be a mix between firm and workers behavioral response. Therefore, allowing to explicitly consider the matching nature of the labor market, our approach permits a more reliable interpretation of the results in terms of matches' utilities considering the decision process of all the agents that are competing in the market.

Third, this approach allowed us to understand the effects of the various determinants of the matching process exploiting all the information available at the team level instead of focusing only on the country level. This permits us to use all the possible sources of variation present in the data estimating a model with a huge number of alternatives that would be infeasible using a conditional logit.

[43] See note **??** for an example of the strategy used in Kleven et al. (2013).

2.5 Conclusions

In this study, we have investigated the effect of marginal tax rates on equilibrium locations of highly skilled tax payers using a dataset on European football players between 2007 and 2016 and exploiting regional and national variation of tax rates.

We have analyzed this phenomenon by estimating a two-sided matching model using a maximum score approach. This strategy has permitted to account for the matching structure of this labor market and to get rid of factors that affect the matching process but are usually hard accessible (such as wages and transfers between agents).

With regards to the sorting patterns based on quality, our results indicate that matches' utilities are positively affected by the resulting quality of the match if it includes a top-quality player. This effect is stronger if we consider foreign players. The use of these variables has permitted us to identify the effect of taxation on the utility of the match accounting for the one deriving from the quality of the match.

Concerning the effect of taxation, our results suggest that the marginal income taxation incentive is an important determinant of top incomes' migration patterns even after considering the matching nature of the labor market. Indeed, the coefficient estimated indicates that matches' utilities are positively affected by the *net-of-tax rate* suggesting that matches are more valuable in jurisdictions with lower tax rates. This conclusion is confirmed by the estimated elasticities. Indeed, in a context of elastic demand, the point estimate of the elasticity of mobility to taxation is always positive and around 0.22 if we consider the whole population of football players. However, we find that the effect is heterogeneous on the base of the nationality of the player and his quality. Indeed, the estimated elasticities for the population of natives range from 0.077 to 0.117 in the two preferred specifications whereas the one of foreigners' population is always above 1 and comprises between 1.197 and 1.370. The effect of the *net-of-tax rate* is estimated to be stronger when considering top-players than bottom quality players. This result is in line with the one arising from the previous literature and suggests that the income tax rate can be an effective tool to increase the average workers' quality in one country. Moreover, these results are confirmed even considering a rigid labor demand. In this context, however, we find evidence of a cross-effect between different populations of players. Indeed, the elasticity results suggest that an increase in the *net-of-tax rate* can attract more top players that displace bottom quality ones through a displacement effect.

Although these results are in line with the one arising from the previous literature the estimation technique used here has proved to be effective in analyzing these kinds of phenomenons without assuming ex-ante, in the estimation process, the structure of the labor market. Indeed, our results are obtained using the structural parameters coming from the same model and assuming the structure of the market only in the simulation approach. This is a clear advantage that allows simulating different scenarios without assuming that neither a supply-driven nor a demand-driven location model. Moreover, the method has allowed the estimation of these fundamental parameters without using data on wages, transfers and agent-specific unobservable. In the future, this method can be applied in different contexts and markets such as CEOs, academic professors, and inventors.

Appendix

2.A The Net-Of-Tax Rate

In order to have a comprehensive net-of-tax rate we have collected data on different tax rates:

- τ_i top marginal income tax rate
- τ_e social security contributions on employer
- τ_w social security contributions on employee
- τ_{VAT} value added tax

Following Kleven et al. (2013) we define the net-of-tax rate as the increase in the worker's consumption when the firm's labor cost increases by 1 Euro. This rate is given by:

$$1 - \tau = \frac{(1-\tau_i)(1-\tau_w)}{(1+\tau_{VAT})(1+\tau_e)} \tag{2.35}$$

We derive this formula following Kleven et al. (2013) and Mertens and Montiel Olea (2018) and considering the specific rules that apply in each country. The first step to derive this formula is to compute the marginal increase in the firm's labor cost coming from the payroll taxes (Mertens and Montiel Olea, 2018):

$$T_p = \frac{\tau_e + \tau_w}{1+\tau_e} \tag{2.36}$$

where $(1+\tau_e)$ is the labor cost for the employer. Then, the marginal income tax T_i is computed on net earnings after that the payroll taxes are deducted:

$$T_i = \left(1 - \frac{\tau_e + \tau_w}{1+\tau_e}\right) \times \tau_i \tag{2.37}$$

Now we can compute the VAT using the same logic used for the payroll taxes. Indeed, we use the marginal increase in the VAT measured by:

$$\frac{\tau_{VAT}}{1+\tau_{VAT}} \tag{2.38}$$

Therefore, the marginal VAT tax T_{VAT} is computed as:

$$T_{VAT} = \left[1 - \frac{\tau_e + \tau_w}{1+\tau_e} - \left(1 - \frac{\tau_e + \tau_w}{1+\tau_e}\right) \times \tau_i\right] \times \frac{\tau_{VAT}}{1+\tau_{VAT}} \tag{2.39}$$

Now we can derive the marginal tax wedge step by step:

1. Marginal payroll taxes:

$$\frac{\tau_e + \tau_w}{1+\tau_e}$$

2. Marginal payroll taxes plus marginal income tax:

$$\frac{\tau_e + \tau_w}{1+\tau_e} + \left(1 - \frac{\tau_e + \tau_w}{1+\tau_e}\right) \times \tau_i = \frac{\tau_e + \tau_w + (1-\tau_w)\tau_i}{1+\tau_e}$$

3. Marginal payroll taxes plus marginal income tax plus marginal VAT tax:

$$\frac{\tau_e + \tau_w + (1+\tau_w)\tau_i}{1+\tau_e} + \left[1 - \frac{\tau_e + \tau_w + (1-\tau_w)\tau_i}{1+\tau_e}\right]\frac{\tau_{VAT}}{1+\tau_{VAT}}$$

Rearranging the previous equation we can derive the tax wedge τ^*:

$$\tau^* = \frac{\tau_e + \tau_w + (1-\tau_w)\tau_i + \tau_e + \tau_{VAT}}{(1+\tau_e)(1+\tau_v)}$$

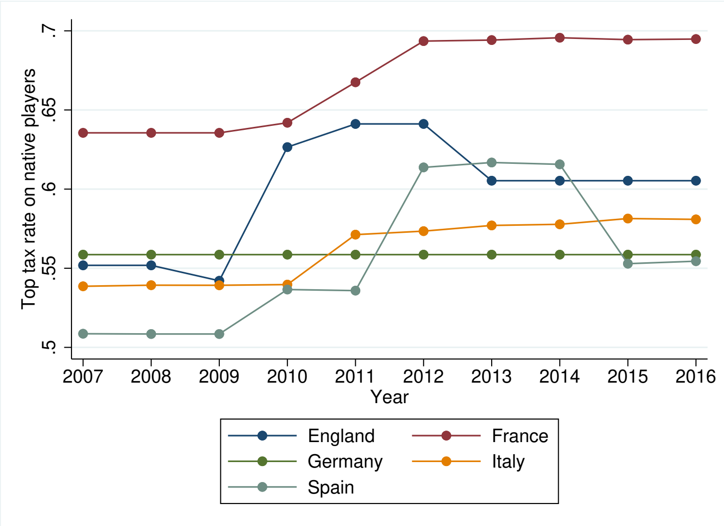
Now we can compute the *net-of-tax rate*:

$$1 - \tau^* = 1 - \frac{\tau_e + \tau_w + (1-\tau_w)\tau_i + \tau_e + \tau_{VAT}}{(1+\tau_e)(1+\tau_v)}$$

$$1 - \tau = \frac{(1-\tau_i)(1-\tau_w)}{(1+\tau_{VAT})(1+\tau_e)}$$

In Figures (2A.1) - (2A.3) we show the evolution over the period 2007-2016 of top marginal tax rates for natives and foreigners in the 16 countries of the sample.

Native players



Foreign players

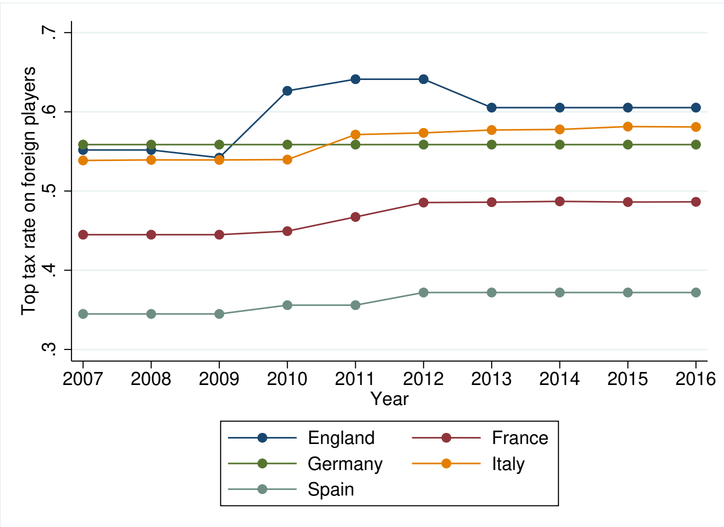


Figure 2A.1: Top Marginal Tax Rates in the 5 Top Countries

Notes: Top marginal tax rates include income taxes, payroll taxes and VAT. In case of regional variation the average tax rate is shown. The five top countries are defined on the base of the average market values of players employed in the country's first league. In panel A is plotted the average national top marginal tax rate valid for native players. Panel B shows the evolution of the top marginal tax rate valid for foreigners that meet the eligibility conditions

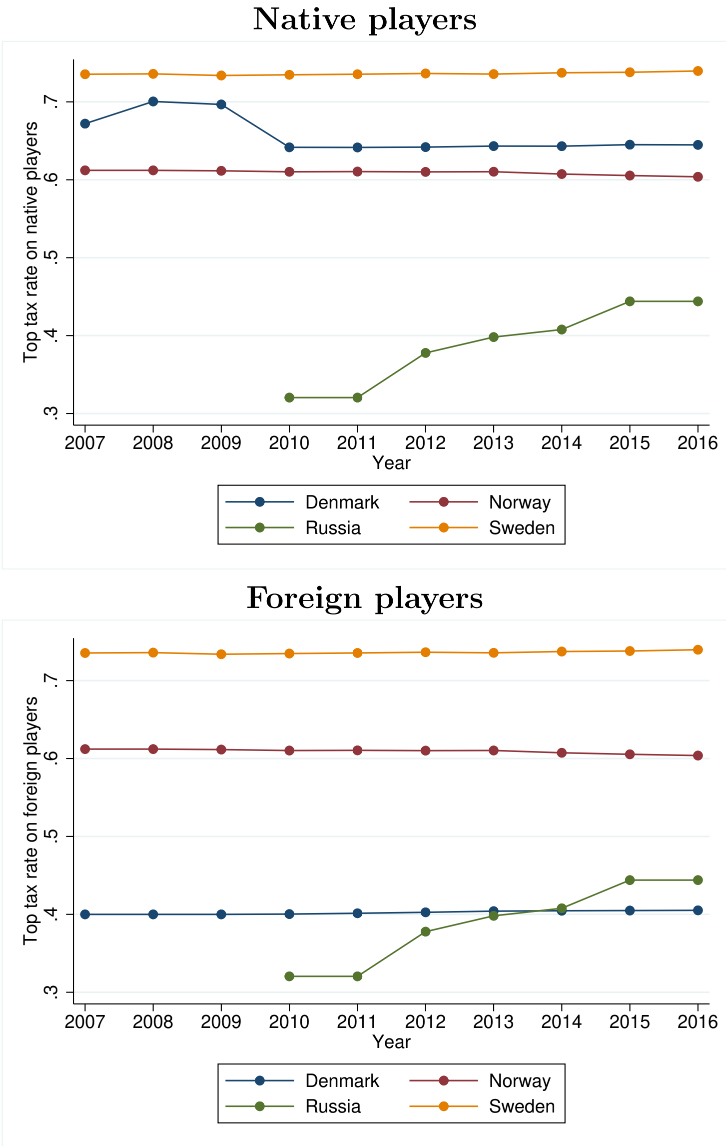


Figure 2A.2: Top Marginal Tax Rates in Northern countries

Notes: Top marginal tax rates include income taxes, payroll taxes and VAT. In case of regional variation the average tax rate is shown. In panel A is plotted the average national top marginal tax rate valid for native players. Panel B shows the evolution of the top marginal tax rate valid for foreigners that meet the eligibility conditions. Russian data are available only since 2010.

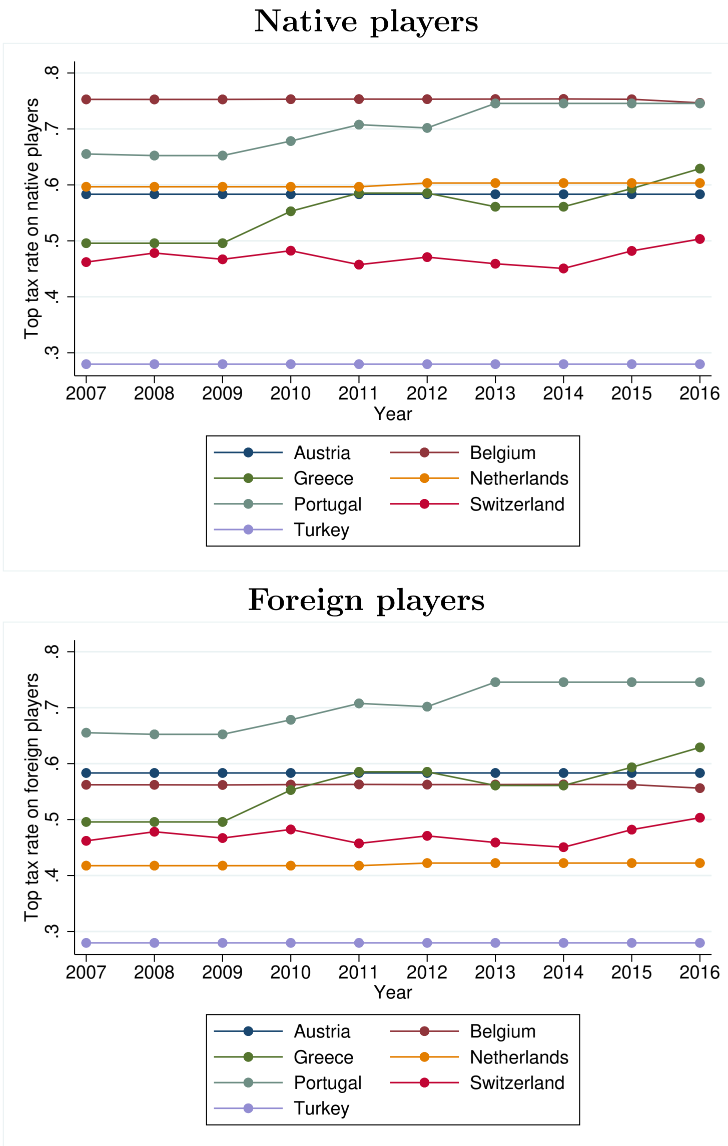
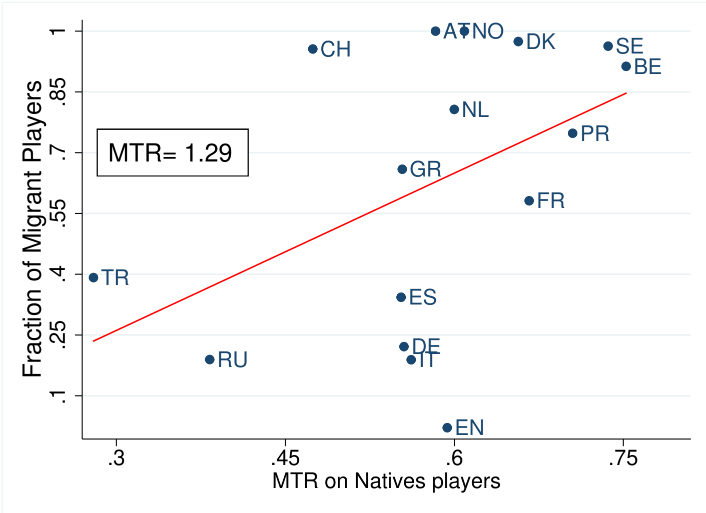


Figure 2A.3: Top Marginal Tax Rates in the other small leagues

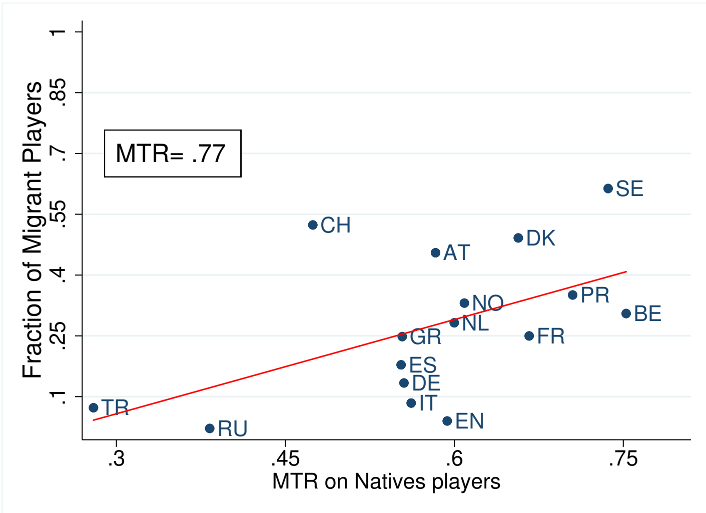
Notes: Top marginal tax rates include income taxes, payroll taxes and VAT. In case of regional variation the average tax rate is shown. In panel A is plotted the average national top marginal tax rate valid for native players. Panel B shows the evolution of the top marginal tax rate valid for foreigners that meet the eligibility conditions

In-migration of foreign players by quality

Top 10% of the quality distribution



Top 10% to Top 50% of the quality



Below the 50% of the quality distribution

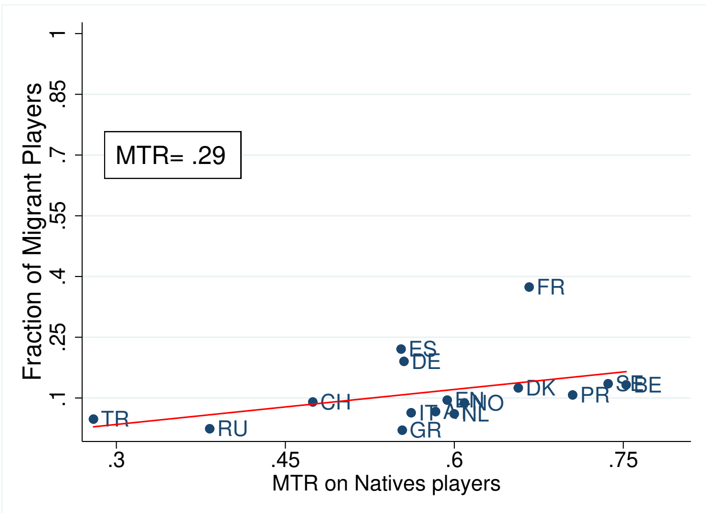


Figure 2A.4: Cross-Country Correlation between Tax Rates and Shares of Foreigners by Quality, 2007-2016

Notes: Each dot stands for one country: AT=Austria, BE=Belgium, DK=Denmark, EN=England, FR=France, DE=Germany, GR=Greece, IT=Italy, NL=Netherlands, NO=Norway, PR=Portugal, RU=Russia, ES=Spain, SE=Sweden, CH=Switzerland, TR=Turkey. The three plots show the relationships between the fraction of native players in each quality subgroup and the MTR valid in the origin country. In each plot we show the coefficient of the relevant MTR coming from a linear regression of the shares against MTR and a constant. All the plots refers to the entire period 2007-2016.

Table 2A.1: Origin-Destination flows

	Destination															
Origin	**AT**	**BE**	**DK**	**EN**	**FR**	**DE**	**GR**	**IT**	**NL**	**NO**	**PR**	**RU**	**ES**	**SE**	**CH**	**TR**
Austria	1657	1	18	23	1	128	22	19	17	7	12	4	3	1	28	37
Belgium	1	1789	5	104	41	46	18	40	265	5	8	19	21	0	6	19
Denmark	9	44	1825	55	33	73	4	30	116	83	1	2	18	64	5	10
England	1	6	7	1676	5	3	12	8	7	1	4	1	1	22	0	7
France	7	282	8	292	2357	74	76	144	33	14	69	20	134	4	73	23
Germany	92	20	22	72	8	2342	27	22	64	10	12	12	36	11	24	83
Greece	6	30	3	22	4	53	2303	52	16	0	11	1	15	1	2	6
Italy	2	7	0	63	31	44	28	3404	9	0	12	17	59	0	45	6
Netherlands	11	77	36	147	18	93	15	50	2590	3	23	20	42	17	11	38
Norway	7	11	60	41	16	33	6	7	30	1512	3	4	2	66	1	7
Portugal	0	18	5	76	58	33	88	54	8	1	1793	26	191	3	45	69
Russia	4	1	2	12	0	19	4	3	6	2	14	1745	6	1	3	1
Spain	49	45	2	237	8	48	199	92	25	1	58	27	2678	2	11	22
Sweden	12	22	152	57	28	41	26	44	121	156	7	19	11	2008	32	56
Switzerland	20	14	0	53	32	150	8	84	4	0	4	2	10	1	1245	11
Turkey	3	15	2	13	19	97	12	3	25	0	5	10	19	1	7	3146

The table shows the number of times when players citizen of one origin country have played in the destination countries considering all the sample period between 2007 and 2016

2

Chapter 3

The Educated Moves: The Determinants of Interregional Mobility of Students In Italy

Abstract

The attractiveness of universities for students represents a crucial public policy issue given the role that these institutions have in fostering local development. In this work, we aim to understand the effect of financial and in-kind aid programs on the location decision process of students. This phenomenon is analyzed by using a unique dataset with administrative data on Italian university students enrolled for the first time in the academic year 2014-2015 along with detailed information on the need-based policies comprised by the *Diritto allo studio universitario* program. We consider explicitly the heterogeneity in students' preferences concerning these policies. First, we estimate the systematic variation in students' preferences by interacting individual characteristics with alternatives' attributes in a Conditional Logit framework. Second, we take advantage of the Latent Class Logit model. The latter approach allows to model systematic and random heterogeneity in preferences by exploiting the individual characteristics of students. The estimated parameters are exploited to quantify the sensitivity of student's location choices by computing willingness to pay and semi-elasticity measures. Our results suggest that policies that provide scholarships and places in dormitories together affect positively students' choice probabilities, this way indicating that these policies are effective in attracting more students in specific universities. Semi-elasticities results indicate that students with better high school diploma grades are more sensitive to these policies, this way suggesting that these services can be used as a tool to attract better students.

JEL Classification: *C25, I23, I28*

Keywords: Financial and in-kind aid policies, Student mobility, University choice, Geographical distance, Latent Class Logit, Heterogeneity in preferences.

3.1 Introduction

In the last decade, the Italian system of higher education has faced a reduction in both the amount of public fundings as well as the number of students enrollments (EUA, 2019; Viesti, 2016). The entry rate to tertiary education has decreased from 65.8% in 2008 to 49.1% in 2015 and it has started to increase only recently reaching the 50.3% in 2017 (ISTAT, 2019). At the same time, the migration flows of students from southern to central and northern regions have increased (Cammelli and Gasperoni, 2015) this way contributing to the widening of the existing gap between northern and southern regions in terms of economic growth (Fratesi and Percoco, 2014). These phenomenons, along with government policies that incentivize universities to attract more students, have created an environment in which universities compete for students (Cattaneo, Malighetti, Meoli, and Paleari, 2017).

The role of universities in fostering the local development has been recurrently studied by the empirical literature concerning higher education. For example, Salter and Martin (2001) have reviewed the existing literature regarding the public funding of basic program research noting that universities play a positive role in the process of knowledge creation at the local level allowing regions and nations to benefit from the global scientific process. Moreover, universities contribute to increase the productivity of local workers (Moretti, 2004) and are a fundamental player in the human capital accumulation process which is a key factor for the economic competitiveness of regions (Bratti and Verzillo, 2019). From a regional perspective, the migration of students has been recognized as a potential source of regional disparities (Krugman, 1991).

These elements have stressed the importance of understanding the determinants of universities' and regions' attractiveness. Indeed, an increasing body of literature has focused on both international and intra-national migration of students highlighting the role played by universities and hosting areas characteristics in attracting students and foster the formation of human capital. For example, Long (2004) has studied the determinants of students' enrollment and migration decisions finding that tuition fees have a negative effect on students' probability to enroll in a specific university; Bratti and Verzillo (2019) and Biancardi and Bratti (2019) have investigated the role of quality in determining the attractiveness of universities; Hübner (2012) and Dwenger, Storck, and Wrohlich (2012) have analyzed the effect of tuition fees on enrollment probability in Germany.

In this study, we focus on the role of financial and in-kind aid policies in fostering universities' attractiveness. Although the Italian education system has been extensively analyzed, to our knowledge, the role of these policies is still unexplored. The only exception is the work by Pigini and Staffolani (2015) in which the effect of financial and in-kind aid policies on enrollment as well as location decisions of students has been investigated. By using survey data on Italian high school leavers in a Conditional Logit (CL) framework the authors have found that these policies have a positive effect on the probability to enroll in a specific university.

We aim to enrich this debate by analyzing the effects on Italian students' location choices of the financial and in kind policies provided by the *Diritto allo Studio Universitario* (DSU) program. This program aims to guarantee the access to the Italian Higher Education System to less advantaged students by providing different services such as scholarships, places in dormitories and canteens. In the analysis, we take advantage of a unique dataset that includes administrative data regarding the entire population of students enrolled in the academic year 2014-2015 for the first time along with detailed information regarding universities' characteristics and DSU's policies. In particular, these data have allowed us to exploit the variability existing in the provision of DSU's services at the university level to separately identify the effects of the different policies provided by the program.

The analysis is carried out explicitly accounting for the existence of heterogeneity in students' preferences. This is done by splitting the sample of students considering the field of study chosen, this way exploring the existence of differences in tastes between different kinds of students. Moreover, we take advantage of a more sophisticated discrete choice approach that has not been used for modeling students' choices: the Latent Class Logit Model (McFadden and Train, 2000). This technique has permitted to overcome various limitations of the approaches used previously in the literature. In particular, it allows to model the heterogeneity in students' preferences by permitting the estimation of an individual set of taste parameters that depends on students' characteristics. This feature of the model allowed us to understand whether different kinds of students have different tastes with respect to universities as well as hosting areas characteristics and to identify which kind of students are more affected by the aid policies considered. Another distinctive feature of our estimation approach is that it has permitted to consider a more realistic nested structure in which universities situated in the student's province of residence are in a separate nest with respect to those located outside. As a consequence, we are able to consider more realistic substitution patterns compared with the ones assumed in the CL approach.

Our results provide clear evidence of the presence of heterogeneity in students' preferences among different fields of study and based on students' characteristics. Moreover, we found evidence that even students with similar characteristics may react differently to aid policies and universities' characteristics depending on the field of study in which they are enrolled.

As for the results of financial and in-kind aid policies in attracting students, we have found that scholarships that are provided without a place in the dormitory are not effective in attracting students. Our interpretation of these results is that these policies cover only partially migration and location costs of students. This interpretation is confirmed by the results related to places in dormitories with and without scholarships. In particular, these policies have a positive effect on students' choice probabilities and can be effective in attracting a higher number of students. Moreover, semi-elasticity results indicate that these effects are stronger for students with a higher high school diploma grade. This last element suggests that these policies can be a useful tool in increasing the average quality of students.

However, willingness to travel results indicate that, in order to attract students from distant areas, DSU's offices should increase significantly their supply of in-kind benefits.

3.2 Related literature

The attractiveness of universities and hosting areas has been at the core of an increasing body of literature that has analyzed this phenomenon across different contexts and using different empirical strategies. In this section we review the existing literature highlighting the various determinants of universities' attractiveness that have been studied.

As outlined in Section 3.1, the role of universities in fostering local development has been extensively analyzed in the previous literature (see for example Salter and Martin, 2001; Moretti, 2004). However, since Krugman (1991), the literature has recognized that the migration of students and graduates might increase regional disparities, especially in contexts in which these gaps are already relevant such as the Italian one (D'Agostino, Ghellini, and Longobardi, 2019). In fact, as highlighted in Fratesi and Percoco (2014), the migration of highly educated people in Italy has caused a brain drain effect that has reduced the stocks of human capital in southern regions increasing it in central and northern regions. Moreover, students' migration decisions are ultimately related to their future choices after graduation. For example, Oggenfuss and Wolter (2019), analyzing the migration of students and graduated among Switzerland cantons, have found a strong relationship between location choices at the moment of the enrollment and the choice of migration after graduation. Their results suggest that, once a student decides to migrate to enroll at the university is less likely that she will decide to come back to her place of origin after graduation. Interestingly, this result is even stronger for students with better high school grades, this way increasing the negative effects of students' out-migration. In addition, Valero and Van Reenen (2019), analyzing information on universities in 78 countries between 1950 and 2010, have found evidence that the increase in the number of universities in one region is positively related to its future growth capacity and that the presence of universities has positive spillover effects on neighboring regions.

In light of these results, the empirical literature has been focused on understanding which are the principal determinants of migration and enrollment decisions of students to shed some light on the elements that affect students' preferences and universities' attractiveness.

Since Long (2004), the distance to institutions, tuition fees, and college quality have been considered the most important determinants of enrollment and mobility decisions. In this work, the author has studied the determinants of students' enrollment and location decisions by using data on US high school graduates between 1972 and 1992. The results suggest that distance and tuition fees negatively affect the decision on where to study but have a lower effect on the probability to enroll, while the quality of the college is an important determinant of location decisions. The second contribution of this paper is the introduction of the CL in analyzing students' choices. In particular, the estimation strategy used is based on a multinomial choice model used to shed light on students' location decisions and a binary Logit to analyze the enrollment choices. Starting from this paper, the literature has been focused on understanding how these determinants of universities' attractiveness and the various hosting areas' characteristics affect students' location preferences using different empirical strategies.

The role of the distance as a deterrent in the location choices of students has been extensively analyzed. For example, Kelchtermans and Verboven (2010) studied the effect of distance and tuition fees on students' enrollment, location, and field of study decisions using data on the Belgian region of Flanders in a Nested Logit framework. Their results suggest that travel costs are an important determinant of the decisions regarding where and what to study but that they hardly affect the enrollment decision. These results are confirmed also in Gibbons and Vignoles (2012) who, taking advantage of administrative data regarding UK students, have found that the distance to the institution has a deterrent effect only on the decision regarding the university to attend but does not affect the enrollment decisions. By contrast, Spiess and Wrohlich (2010), focusing on German students, have found that the distance from the closest university has a negative effect on the enrollment decision by increasing transaction costs such as transport and housing expenditures. As for the field of study decision, Suhonen (2014) have found evidence that the choice of a specific field of study is negatively related to the distance between student's residence and the first institution which provide a degree in that specific field using data on a random sample of the Finland population in 2001.

Other works have used different empirical strategies to assess the role of the distance on the aggregate flows of students between competing regions. For example, Agasisti and Dal Bianco (2007) have studied the mobility patterns of students in Italy using a gravity model approach on the aggregate flows of students between Italian provinces. Their results suggest that once controlling for the distance as a deterrence, the characteristics of universities such as the amount of resources invested in financial aid programs or the number of professors per student have a positive role in increasing the aggregate in-flow of students in one specific province. Cattaneo, Malighetti, Paleari, and Redondi (2016), using a competing destination model and data on 39 airports in Italy, have analyzed the effect of the presence of airports on the long-distance mobility decisions of Italian students between 2003 and 2012. They find that the presence of airports increases the long-distance migration flows of students by reducing the costs of migration and the deterrence effect of distance in general.

Besides the role of the distance, these papers have highlighted also the one played by characteristics of universities and hosting areas. These elements have been at the core of various papers in the recent literature. For example, Giambona, Porcu, and Sulis (2017), focusing on the Italian context, have analyzed the role of various characteristics of universities and hosting provinces to assess how much of the differences in attractiveness between different institutions are related to hosting areas' characteristics rather than universities' one. Their results highlight that the economic features of the hosting areas (e.g. the labor market conditions), along with the university quality of research, are key determinants of the attractiveness of hosted universities. These results are confirmed in D'Agostino et al. (2019) who, using a Multilevel Logit model and micro-data on Italian students, have found that the characteristics of the hosting provinces are important determinants of the out-migration flows from southern to northern regions of Italy even after controlling for students' characteristics.

Another important characteristic of universities that have been explored is the quality of the research. For example, Ciriaci (2014) have explored the effect of the Italian Evaluation Research Exercise (VTR) on migration flows from south to north Italy finding that the migration choices are positively influenced by the quality of research and teaching. Still focusing on the VTR, Biancardi and Bratti (2019) have found that the results of this exercise have affected significantly only top-performing universities and that this effect is larger for students with better high school diploma grades. This result suggests that the effect of the quality of research may be heterogeneous on the basis of the individual characteristics. Bratti and Verzillo (2019) have confirmed the positive role of the quality of research by analyzing various research quality indicators. The authors have found that, although the quality of research has a positive effect on universities' attractiveness, the cost of migration for students in Italy is still the most important determinant of migration decisions. This result suggests that there is still room for universities and regions to improve their attractiveness by reducing students' migration, transportation and accommodation costs that can be potential barriers for students' mobility. In fact, Lupi and Ordine (2009) have found that students' mobility decisions are constrained by family income and that less advantaged students tend to enroll in their region of residence. Moreover, Türk (2019) has extended the standard gravity approach including, along with the distance, a set of socio-economic indicators to assess the overall accessibility to Italian universities. His results highlight that the quality of institutions has a heterogeneous effect on the base of the socio-economic background of students and that the accessibility to Italian higher education depends strongly on parents' income and education. Therefore, the author suggests that a policy targeting less advantaged students with scholarships and grants could be very effective in increasing the accessibility to tertiary education for less advantaged students. These results are in line with the one arising from Pigini and Staffolani (2013) who have analyzed the effect of university quality, migration costs and distance to the institution on the choices of a sample of Italian high school leavers in 2004. The authors have highlighted the presence of a strong heterogeneity in the effect of these variables based on the socio-economic background of students and their performances in high school. In particular, weaker students are more affected by university costs in general. The framework used is a Nested Logit model in which students choose in two nests: the first considers together the enrollment and the field of study decisions; the second considers the university choices. This empirical specification has allowed the authors to explore the heterogeneity in the effects of these determinants by means of interaction terms between alternative and individual characteristics. Therefore, this literature has clearly outlined the presence of a difference in preferences and opportunities between students with different backgrounds.

In this respect, the literature has focused on two determinants of enrollment and migration costs: tuition fees and financial aid policies. The effect of tuition fees on the probability to enroll in a specific university is mixed and depends on the specific characteristics of the education system considered. For example, Murphy, Scott-Clayton, and Wyness (2019) have analyzed the effect of the introduction of tuition fees in England finding, surprisingly, that it has caused an increase in enrollment rates without widening the disparities of access between students with different economic backgrounds. However, tuition fees can have a fundamental role in shaping the migration patterns of students. For example, Dwenger et al. (2012), by exploiting the introduction of tuition fees part of Germany with a difference-in-difference approach, have found that the introduction of tuition fees in students' home state can incentivize them to migrate outside the region. This result is confirmed by Hübner (2012) who, analyzing the choices of German high school graduates between 2002 and 2008, have found a reduction in the probability of enrollment in a state which charges tuition fees by 2.74%.[1] Despite the presence of this mixed evidence on tuition fees, the literature has found evidence of the positive effects related to financial aid policies. For example, considering the US, Deming and Dynarski (2009)

[1] See Dwenger et al. (2012) for a more detailed analysis of the recent literature on the effect of tuition fees on enrollment rates.

have found evidence that these policies can increase college attendance rates. These results are confirmed in Castleman and Long (2016) who have found, through a regression discontinuity design approach, a positive effect of the Florida Student Access Grant[2] in terms of enrollments, university outcomes, and degree completion.

Considering the Italian case, we have that very few papers have explicitly analyzed the role of financial aid policies on students' behavior. For example, Modena, Rettore, and Tanzi (2018) have measured the effect of the need-based grants provided by the DSU programs on the academic achievements of Italian students. They find that first-year students dropout rates are negatively affected by these policies that can even prevent students from low-income families to drop out of higher education. Moreover, the impact of these policies is heterogeneous on the base of student's residence, type of high school diploma and final grade. Vergolini and Zanini (2015) have investigated the effect of a provincial program provided by the province of Trento that had the aim to increase access to higher education of less advantaged students. Using a regression discontinuity design they have found that the program has incentivized the out-migration of students from their place of residence without increasing the enrollment rate. The most closely related work to our research is the one by Pigini and Staffolani (2015). This work has investigated the effect of the enrollment costs and financial incentives on both enrollment as well as migration decisions of Italian high school leavers using survey data containing also information on the social-economic background of students and the data regarding the DSU program. In particular, the authors have applied a CL estimator assuming that the outside option (non-enrollment) and the alternative universities belong to the same nest. Their results indicate that the average number of fees has a negative effect on the probability to enroll and that the financial incentives have a significant positive effect on the probability of enrollment in a specific university.

The next section presents the institutional background of our study.

[2]The Florida Student Access Grant is a need-based grant program with the aim to increase college access and improve student's success in higher education.

3.3 Institutional background

The Italian Higher Education (HE) system, differently from other European countries (e.g. the UK or Ireland), relies upon an ex-post screening admission procedure.[3] In this system, every high-school graduated can enroll into an Italian university in any subject.[4]

Therefore, given the minimal selection process of this system, the choices regarding the enrollment decision, the field of study and the university to attend depend almost solely on students' and families' preferences. In this context, the role played by universities' attractiveness is paramount (Pigini and Staffolani, 2013). Moreover, the Italian HE system is mainly public and funded by the central government. The shares of public funds to be transferred to universities are decided on the base of various indicators such as the number of enrollments and the institutions' ability to attract more students (Giambona et al., 2017). This feature, as outlined in Giambona et al. (2017) and Cattaneo et al. (2017), has fostered the competition between institutions incentivizing them to increase their attractiveness taking into consideration the characteristics embodied in their hosting areas. These elements stress even more the importance of understanding the determinants of student migration and the various tools that universities can use to attract more students and, therefore, more resources for their activities.

As outlined in section 3.2, one of the most important determinants of students' choices is given by universities' costs and by the distance between students' home and the institutions. Therefore, one of the tools that universities (and regions) can use to improve their attractiveness is given by policies that aim to reduce these costs such as scholarships and places in dormitories. In Italy, these policies have been organized inside a financial and in-kind aid program called *Diritto allo studio Universitario* (DSU) program. This program has been outlined to encourage enrollment and attendance by students from disadvantaged families. The DSU program is under the exclusive competence of regions and has the objective to encourage motivated students to enroll and obtain higher education regardless of their income (Prime Ministerial Decree, April 9, 2001).

[3]See Declercq and Verboven (2018) for a comparison between ex-ante and ex-post screening system in the Belgian context

[4]This minimal selection process has some exceptions regarding faculties of medicine, health-related professions, primary education and the five-years bachelor course of architecture. In these courses, the number of students is defined ex-ante and is evaluated with an entry test. These rules can be extended by universities also to other subjects that require laboratory activities.

The DSU program offers students three principal kinds of benefits: scholarships or grants, places in dormitories without scholarships and places in dormitories with scholarships. The application for these services is submitted voluntary each year by students to the local DSU office responsible for the territory in which the chosen university is located.[5] At the moment of the enrollment, all the students that apply are ranked on the basis of the family economic situation measured with an equivalized economic indicator called the *Indicatore della Situazione Economica Equivalente* (ISEE).[6] This indicator measures the economic situation of families on the basis of various family's socio-economic characteristics such as their income, wealth and number of family members.

Each student that has applied to the DSU program can be classified into three categories on the base of their residence: on-site students, commuting students and out-of-site students. The first category is made up of students who reside in the hosting city. They can be eligible only for scholarships and canteen services and the amount of the grant is lower than the one available to other students. Commuting students are those who reside in a city that is close to the hosting city and can be reached daily with public transportation. They can be eligible only for scholarships that are higher than the one available for the first category but lower than the one available to out-of-site students. Out-of-site students are the residual category, they are eligible for the maximum amount of scholarships and places in dormitories. These services are provided on the basis of two rankings: one for scholarships, in which all the students are competing, and one for places in dormitories, in which only out-of-site students compete. Therefore, we can have three kinds of benefits: scholarships, places in the dormitory and a package that provide the two services together (Student Package).

If one student applies and wins a student package, the scholarship is reduced by an amount that varies among DSU offices and that should cover the annual rent of the dormitory. The minimum amount for the scholarships are decided by the Italian Ministry of Education, University and Research (MIUR) but varies among territories. For example, in 2014 the minimum amounts proved by the DSU office of the city of Palermo (Sicily) ranged from 1,284 Euro for

[5] In general each Italian region has one DSU office that is responsible for the regional territory. However, in some region, these programs are managed at the provincial (e.g. Veneto) or the university level (e.g. Lombardia)

[6] If two students have the same ISEE the rank is given accordingly to a rule that is decided by each DSU office. These rules can depend on a patrimonial indicator, students' age, high school diploma grade or other information.

on-site students to 3,909 Euro for off-site students.[7] On the other hand, if one student wins only the place in the dormitory she has to pay a rent accordingly to her ISEE. Even though students in dormitories have to pay a rent (or a reduction of the scholarship) we have to consider different advantages connected with this service. Indeed, the rent is usually lower than the market one and is a function of students' economic situation and it covers all the expenses (e.g. Internet connection, electricity consumption, etc.). Moreover, students do not have to find an apartment on their own in a new city and have the opportunity to live in an environment full of other students.

Another distinctive characteristic of the DSU program is that, for the first year of enrollment, the rankings are based only on the economic situation of students. Therefore, they do not depend on a merit or performance measure and is not directly related to the high-school grade of pupils. To account for this feature, we focus our analysis only on students that are enrolling for the first year for the first time in an Italian university. Unfortunately, we are not able to control for the economic situation of students and we treat the benefits connected to DSU programs as a general characteristic of the university systems considered. However, given the detail of our dataset, we are able to separately identify the effects of scholarships, places in dormitories and student packages.

3.4 Data

3.4.1 Students' Data

The data regarding students' choices and characteristics are collected from the administrative archive of the MIUR called *Anagrafe Nazionale Studenti* (ANS). The ANS contains information on the entire population of students that have enrolled in an Italian university in 2014.[8] This work focuses on students that have taken their high-school diploma in 2014 and have enrolled for the first time in an Italian university in the academic year 2014-2015.

The information available at the student level are the city of residence; gender; age; high-

[7] http://www.vivereateneo.it/bando-ersu-richiesta-borse-studio

[8] These data have been provided by the University of Cagliari (Italy) and are collected inside the research project *From high school to job placement: micro-data life course analysis of university student mobility and its impact on the Italian North-South divide.* financed inside the projects of relevant national interest (PRIN) 2017.

school diploma grade and type; chosen university. In particular, for each university chosen we have information on the city in which the university is situated and the degree course chosen by the student.

The sample used in this work is selected considering the characteristics of the Italian HE system on the bases Italian HE' characteristics and the information available in the ANS archive as follows. First, we do not consider the students enrolled in distance learning universities. These institutions are not considered because they do not require students to live in the hosting area and allow them to participate in university activities from their home. Therefore, students that choose to enroll in these universities are not moving or choosing to move and their choice is not influenced by hosting area characteristics or financial aid offered by universities. Second, we do not consider students that enroll in courses of medicine, health-related professions, primary education, sport, and in the field of study architecture. This choice depends on the characteristics of the admission systems valid in these specific areas. In particular, as shown in Section 3.3 these courses have an ex-ante screening system in which the number of students is chosen ex-ante on the basis of an entry test. Hence, students that 'choose' a specific university in these fields are less likely to choose freely. For example, medical entry tests are national and the university in which the student is enrolled is assigned on the basis of her ranking position. Only very high-ranked students are able to choose their university and all the others are distributed on the base of available places in all the national territory. Moreover, we do not consider all the students that are enrolled in architecture even if they have chosen a course without the ex-ante screening system. This choice is made to avoid sample selection bias in the results. Indeed, the five-year course of architecture is the most important degree in this field of study absorbing the 30% of students in our sample.

Moreover, we do not consider students enrolled in agricultural and defense degrees because these courses are offered by very few institutions in Italy and the choice of enrollment in a specific region could depend more on the simple availability of the course than on university's and hosting area's characteristics. We further restrict our sample excluding those students for whom we do not observe the diploma grade. Following this strategy, we have retained a total of 176,136 students.

Following the recent literature (e.g. D'Agostino et al., 2019; Kelchtermans and Verboven, 2010), we have grouped the students in different subsamples on the basis of the information regarding the degree chosen. In particular, we consider 11 fields of study: business & statistics, chemistry & pharmacy, education, engineering, humanities, languages, law, life & natural sciences, mathematical and physical sciences, psychology, social & political sciences.[9] All the analyses presented in this work are carried considering these groups as separate samples to consider that students that prefer different fields might have different preferences regarding the various university's and hosting region's characteristics. Moreover, as noted in Biancardi and Bratti (2019), even the same university can have different characteristics on the base of the field of study considered. For example, one institution that has a very high-quality research department in economics may have a poor quality research department in psychology. The use of different subsamples has two additional advantages. First, it reduces the computational burden of the estimation by considering that students can choose only among universities that provide a course in the same field of study.[10] The second advantage is related to our sample selection strategy. Indeed, the arbitrary exclusion of students on the base of the field of study chosen might introduce selection bias in our results. However, given that we analyze each field of study separately we have that each subsample represents the entire population of students that have chosen that specific field. The only exception is given by the subsample of students enrolled in education in which we have excluded those courses that apply an ex-ante admission system. In this case, the sample selection bias might be still present but it will affect only the results related to this specific group.

Moreover, we are not modeling the choices of students' regarding enrollment and the field of study decisions. In this respect, we are assuming that there is a fixed overall demand for education in Italy and that our analysis regards only the choice between different universities which provide a degree course in the field of study chosen. Therefore, we focus on the third stage of a three stages decision process in which students decide whether to enroll in the first stage, the field of study in the second and the university to attend in the third.

[9]The definition of each field of study is based on the official terminology provided by ISTAT.

[10]Indeed, if we consider that each student can choose among all the degrees provided the resulting dataset will be composed by 108,852,048 rows (618 alternatives for 176,136 students).

3.4.2 DSU data

The information regarding the DSU program are collected from the open data portal USTAT[11] managed by the MIUR. USTAT is made by various sections that contain detailed information on various areas that characterizing services supplied by universities and DSU offices.

This data contain various information such as the number of scholarships, places in dormitories and canteens, the presence of a college that provides services to universities[12], the number of applications for the different services and the number of accepted applications. Moreover, these data are provided considering two different levels: DSU offices and universities. In particular, the information regarding places in dormitories and canteens are available at the DSU office level, whereas the ones regarding scholarships are available at the university one. Therefore, it is possible to know exactly how many scholarships are provided by the DSU office in its territory and the distribution of these scholarships among the different universities.

To account for these features, we have assigned all the information regarding places in dormitories and canteens at each university on the basis of their geographical position. This is an important feature of the dataset because some universities have dislocated branches in more than one province (for example the university of Cattolica). In these cases, we have used the information regarding the DSU office responsible for the area that is hosting the specific branch of the university to assign the right amount of places in dormitories and student packages. As for scholarships, we have exploited the information available at the university level. Moreover, given that in some cases the scholarships are given together with a place in a dormitory, we have computed three indicators: the number of scholarships, the number of places in dormitories without scholarships and the number of places in dormitories that are provided together with scholarships (student packages). To consider all the possible services offered by local agencies, we consider even the services that some regions (namely, Trentino Alto Adige and Valle d'Aosta) provide to students that have their residence in the region but study outside its territory. Using this strategy we have a very complete and unique dataset that allows us to measure precisely the effect of these services on the students' location decisions.

[11] http://ustat.miur.it/opendata/

[12] Colleges are a different kind of institutions that are present only in some Italian provinces and provide different services such as scholarships and places in dormitories on the basis of specific criteria. Given that these criteria change among the different colleges we use only the information regarding the presence of the college in the city that hosts the university.

We have collected DSU data considering the academic year preceding the one for which we have collected information on students' choices (2013-2014). This strategy is followed for two reasons. The first is related to possible endogeneity issues that could arise using the data regarding the academic year 2014-2015. In that case, the number of applications and services provided would depend on the number of students enrolled in that specific year, this way introducing a simultaneity bias. The second is related to the information available to students before enrollment. In fact, all the information regarding the number of applications received and services provided in previous years are easily available to students that make expectations on the probability to win a scholarship or a place in a dormitory. To further control for this element, the analysis is carried considering the expected number of services available at the universities computed as the number of places or scholarships available weighted for the probability to win the service. This probability is computed as the ratio between accepted and received applications.

3.4.3 Universities' characteristics and geographical controls

The data regarding universities' and hosting areas' characteristics are collected from different sources.

The information related to the education supply of Italian universities are collected from USTAT. To follow the sampling strategy outlined in section 3.4.1, we have collected the information regarding the courses provided by universities and the city that hosts the principal branch of the university.[13] The information regarding the city is used to compute the distance between students' city of residence and institutions and to assign the right DSU office to the university. In order to control for the characteristics of universities' supply, we have collected data regarding the number of professors and researchers employed by the university for each field of study considered, the share of foreign professors and the number of members of the administrative staff.

The USTAT archive provides also the information related to the average tuition fee paid by students, and the number of scholarships and places in dormitories provided by the universities

[13]Some universities have branches in different cities inside the same province that are served by the same DSU office. In these cases, we have assigned at each university the city that hosts the principal branch defined as the branch with the highest number of students enrolled in 2013.

outside the DSU program. The first variable is computed as the total contribution of students over the number of students enrolled in 2013-2014. It permits to control for differences in enrollment costs that exist among universities. The information regarding the number of non-DSU scholarships and places in dormitories are used to control for other kinds of policies that can be used by universities to foster their attractiveness not comprised in the DSU program. All the data gathered from the USTAT archive refers to the academic year 2013-2014.

As for the quality of researchers employed at the universities, we have collected the number of departments that were awarded in the *dipartimenti di eccellenza* (departments of excellence) project. This project, managed by the National Agency for the Evaluation of Universities and Research Institutes (ANVUR), consists in a standardized assessment of the research's quality of Italian departments and is based on the results of the third Italian Research Evaluation Exercise (VQR) which concerned the period 2011-2014.[14]

The last variable used at the university level is the amount of public funding that the universities have received in the academic year 2014-2015. This variable is used to further control for the dimension of universities in terms of resources that they are able to spend during the academic year. These information are gathered from the tables available from the MIUR.

Another important determinant of the decision process of students is given by the characteristics of hosting areas such as labor market conditions and cost of life (Dotti, Fratesi, Lenzi, and Percoco, 2013; Giambona et al., 2017). To control for these variables, we have collected the data regarding the provincial unemployment rate, the regional value added and the average provincial housing price. The information regarding value added and unemployment rates are collected from ISTAT. In particular, unemployment rates are computed as the average rate between 2011 and 2013. For housing prices, we have collected the average purchase price per square meter in 2013 from the Real Market Observatory (OMI) database.

From ISTAT we have also gathered the euclidian distance between students' city of residence and the city that is hosting the university. This variable is used to control for a possible deterrence effect connected with the costs of transportations, accommodation and for the psychological costs related to the distance from home.[15]

[14]See Biancardi and Bratti (2019) for the evaluation of the effects of the Italian Research Evaluation Exercises on the students' enrollment choices.

[15]See, for example, Cattaneo et al. (2016) on the effect of air transportation services on the mobility of

Table 3.1: Descriptive statistics on DSU policies

	N	Scholar. (Prob)	Scholar. (Exp. N)	Dormitory (Prob)	Dormitory (Exp. N)	Student Package (Exp. N)
South	44294					
Islands	17914					
Centre-North	113928					
Social & Political sciences	19739	76.63%	2544	51.82%	87	282
Psychology	5561	84.30%	2607	46.98%	95	244
Math. & Physical sciences	8991	78.36%	2725	55.40%	85	321
Life & Natural sciences	12704	82.88%	2187	50.12%	70	259
Law	18822	80.69%	2533	51.72%	85	266
Languages	16252	80.50%	2113	56.96%	112	245
Humanities	14440	76.88%	3104	54.82%	85	325
Engineering	32628	87.34%	2901	48.44%	110	271
Education	6656	86.75%	2266	52.31%	83	253
Chemistry & Pharmacy	8964	77.15%	2730	52.19%	94	317
Business & Statistics	31379	84.23%	2145	53.34%	130	256

Notes: The table reports descriptive statistics regarding the sample students who have enrolled in an Italian HEU for the first time in 2014 and the services provided by DSU offices. All the data regarding DSU services refer to the academic year 2013-2014. Column (1) reports the number of students enrolled; Column (2) reports the average probability to win a scholarship computed as the ratio between applications and scholarships provided by the DSU office; Column (3) reports the average expected number of scholarships in destination computed as the number of scholarships available weighted for the probability to have a scholarship; Column (4) reports the average probability to obtain a place in one dormitory computed as the ratio between the number of applications and the number of places in dormitory provided by the DSU office; Column (5) reports the average expected number of places in dormitories without scholarship in destination computed as the number of places available weighted for the probability to win a place in a dormitory; Column (6) reports the average expected number of student packages (places in dormitories with scholarship) in destination computed as the number of student packages available weighted for the probability to win a place in a dormitory.

All these data are combined into a unique dataset using the information regarding the geographic position of universities. Moreover, given our sample selection strategy and that some universities have separate branches in different areas, we define each alternative as a Higher Education Unit (HEU) to indicate one specific branch of one Italian university in one specific field of study.

In the next section, we provide some descriptive statistics regarding the variables used in the estimation and students' characteristics.

3.4.4 Descriptive evidence on students' choices and main statistics

Table 3.1 reports the number of students and the descriptive statistics regarding the services provided by the DSU by region of residence and field of study. The majority of students in our sample reside in one region in the central or northern Italy, the most chosen field of study is Engineering whereas the least one is Psychology. Concerning the services provided by the DSU, we can see that the figures are similar among the various fields. In particular, the probability to win a scholarship ranges between 76.63% for students enrolled in Social & Political sciences and 87.34% for students enrolled in Engineering. The figures related to the probability to win places in dormitories are lower in magnitude and range from 46.98% for students enrolled in Psychology to 56.96% for those in Languages. Therefore, DSU offices are able to satisfy more efficacy the applications related to scholarships than the ones regarding places in dormitories. Moreover, it is remarkable that the expected number of scholarships provided is way bigger than the sum of the places in dormitories with and without scholarships. These differences can be related to the fact that the provision of places in dormitories is more expensive than the provision of scholarships and requires the existence of buildings that can be used for this purpose.

Table 3.2 reports the descriptive statistics regarding the main individual variables used in the estimation. The first column reports the average distance traveled by students to reach their chosen HEU measured as the distance between students' city of residence and HEU's hosting city. Students from islands and southern regions of Italy travel, respectively, 4 and 3 times more than students from central or northern regions. These differences are in line with the findings highlighted in the previous literature regarding the out-migration of students from southern regions and islands into central and northern regions (e.g. Cammelli and Gasperoni, 2015). We take into account this difference in our empirical strategy by exploiting the role of the macroregion of residence in shaping the preferences of students.

With respect to the gender composition of students, we can see that the majority of students observed are females. Although the share of female students is very similar among macroregions it differs when considering the field of study. It ranges from a minimum of 23.7% in Engineering to a maximum of 93.5% in Education. These differences indicate that females and males have

students in Italy

Table 3.2: Students' characteristics by field of study and macroregions

	Distance (KM)	Female (%)	Dip. Grade (Avg)	Distance (KM)		Diploma Grade (Avg)	
				Female	Male	Female	Male
South	144.3	57.0%	81.8	136.4	154.6	82.9	80.2
Islands	212.0	56.3%	80.8	195.6	233.1	81.9	79.3
Centre-North	47.5	54.6%	78.5	48.1	46.7	79.5	77.4
Social & Political sciences	78.0	68.4%	75.7	78.3	77.3	76.8	73.3
Psychology	91.5	80.2%	80.0	91.4	91.7	81.0	75.9
Math. & Physical sciences	74.4	27.5%	80.5	78.3	72.9	84.0	79.1
Life & Natural sciences	78.7	64.9%	80.2	82.1	72.5	81.9	77.0
Law	93.8	63.4%	79.0	90.2	100.0	80.3	76.9
Languages	92.1	83.1%	80.2	91.8	93.5	80.9	76.9
Humanities	80.1	67.4%	79.5	78.9	82.7	80.4	77.7
Engineering	112.8	23.7%	82.5	126.4	108.6	85.9	81.4
Education	53.3	93.5%	74.7	53.0	59.1	74.9	71.9
Chemistry & Pharmacy	80.7	64.5%	81.2	84.1	74.5	82.6	78.8
Business & Statistics	86.1	44.4%	78.9	86.1	86.2	81.7	76.6

Notes: The table reports the descriptive statistics of the sample of Italian university students who have enrolled for the first time in academic year 2014-2015 divided by fields of study and macroregions. Column (1) reports average distance traveled by students to reach the HEU chosen from their city of residence in kilometers; Column (2) reports the average percentage of female students; Column (3) reports the average diploma grade; Column (4) and column (5) report the average distance traveled considering, respectively, female and male students; Column (6) and column (7) report the average high school diploma grade considering, respectively, female and male students.

different tastes regarding the field of study chosen.

The third column of Table 3.2 shows students' average diploma grades by macroregions and field of study. Students from southern regions and islands have better grades than the others. However, this fact can be related to the differences in high school evaluation policies existing at the regional level. We control for this element controlling for the students' macroregion of residence in our empirical specification. The second part of Table 3.2 presents the information regarding the differences existing between males and females in the average distance traveled and average diploma grades. It is remarkable to note that, although males in general travel more than females, we have that this difference is not constant among fields of study. Interestingly, in all the fields considered female students have a higher diploma grade compared to male students. Because of these elements, we explore the existence of heterogeneity in preferences due to differences in taste parameters based on students' gender in the empirical specification.

Table 3.3 reports the shares of students that have enrolled in their province of residence

Table 3.3: Shares of stayers and movers students by field of study and macroregions

	Stayers (%)	Movers (%)	Movers	
			In Region (%)	Out of Region (%)
South	53.37%	46.63%	44.97%	55.03%
Islands	50.94%	49.06%	51.79%	48.21%
Centre-North	50.58%	49.42%	66.72%	33.28%
Social & Political sciences	51.87%	48.13%	60.93%	39.07%
Psychology	39.26%	60.74%	55.03%	44.97%
Math. & Physical sciences	53.72%	46.28%	63.35%	36.65%
Life & Natural sciences	50.31%	49.69%	64.57%	35.43%
Law	56.35%	43.65%	55.31%	44.69%
Languages	43.43%	56.57%	60.26%	39.74%
Humanities	49.29%	50.71%	61.31%	38.69%
Engineering	50.35%	49.65%	58.31%	41.69%
Education	51.92%	48.08%	69.16%	30.84%
Chemistry & Pharmacy	47.87%	52.13%	64.09%	35.91%
Business & Statistics	56.71%	43.29%	57.54%	42.46%

Notes: The table reports the descriptive statistics concerning the shares of stayers and movers students by field of study and macroregions. Column (1) reports the percentage of students that have enrolled in an HEU located in their province of residence; Column (2) reports the share of students that have enrolled outside their province of residence; Column (5) reports the share of students that have enrolled in one HEU situated in their region of residence but outside their province of residence; Column (6) reports the percentage of students that have enrolled in an HEU located outside their region of residence.

(Stayers) or outside of it (Movers). With respect to the second group, we have presented also the shares of students that have enrolled in their region of residence (In Region) or outside it (Out of Region). From the table, we can see that the majority of students from southern regions tend to remain in their province of residence while the other students are almost split equally between movers and stayers. However, considering only the sample of movers, almost two-thirds of students from Centre-North tend to enroll in their region of residence.

Table 3.4 reports the information regarding the differences in terms of gender composition and diploma grade between stayers and movers. With respect to the gender composition, it is possible to remark that, with the exceptions of Engineering, Math & Physical sciences and Business & Statistics, the share of female students is always higher than the 50%. However, the shares are highly heterogeneous across groups and tend to be higher when considering students that move outside their province but inside their region of residence. Concerning the high school diploma grade, we can see that it tends to be higher in the group of movers, especially if when considering students that have chosen an HEU outside their region of residence.

Table 3.4: Characterstics of stayers and movers by field of study and macroregions

	Stayers		Movers		Movers: In Region		Movers: Out of Region	
	Female	Dip. Grade	Female	Dip. Grade	Female	Dip. Grade	Female	Dip. Grade
South	55.43%	80.97	58.71%	82.65	60.18%	82.15	57.50%	83.05
Islands	56.57%	79.52	56.09%	82.04	60.40%	80.79	51.45%	83.38
Centre-North	52.70%	77.80	56.55%	79.27	56.69%	78.73	56.27%	80.36
Social & Political sciences	67.41%	75.00	69.57%	76.51	69.66%	75.84	69.42%	77.56
Psychology	79.80%	79.64	80.49%	80.24	80.10%	79.77	80.97%	80.81
Math. & Physical sciences	26.52%	79.92	28.70%	81.09	28.49%	80.68	29.05%	81.81
Life & Natural sciences	64.28%	80.15	65.55%	80.17	64.99%	79.74	66.56%	80.93
Law	62.98%	78.30	64.05%	79.98	66.15%	78.83	61.45%	81.41
Languages	82.11%	79.41	83.79%	80.89	84.55%	80.31	82.65%	81.76
Humanities	66.90%	79.01	67.84%	79.96	68.86%	79.61	66.22%	80.52
Engineering	22.91%	81.52	24.41%	83.51	23.27%	82.15	26.01%	85.41
Education	92.94%	74.39	94.19%	75.09	95.03%	75.27	92.30%	74.69
Chemistry & Pharmacy	62.57%	80.99	66.36%	81.47	66.04%	81.56	66.92%	81.31
Business & Statistics	43.31%	77.90	45.86%	80.20	46.75%	78.79	44.65%	82.10

Notes: The table reports the descriptive statistics concerning the share of female students and the average diploma grade for stayers (columns 1 and 2) and movers (columns 3 and 4) by field of study and macroregions. The rightmost part of the table provides information on the share of female students and the average diploma grade for students that have enrolled outside their province of residence but inside their region (columns 5 and 6) and students that have enrolled in an HEU outside their region of residence (columns 7 and 8).

Table 3.5 shows the descriptive statistics regarding HEUs' characteristics by field of study and hosting macroregions. The first column reports information regarding the average contribution paid by students computed as the ratio between total contributions and the number of students in 2013. HEUs in Centre-North collect, on average, more resources from students. Since the tuition fees in Italy are progressive, this element can be related to differences in income among students. Because of this, we control for housing prices, unemployment and regional GDP at HEU's location as well as student's residence levels in the estimation. The second column reports the total amount of public funding received on average by HEUs. Universities in Islands receive a higher share of public funding compared to universities located in Centre-North and Southern Italy. Moreover, the amount of public funding differs among fields of study. Indeed, the total amount ranges from 111.2 millions of Euro for Social & Political sciences to 161 millions of Euro for Chemistry & Pharmacy. However, this difference is related more to differences in the amount of money received by universities rather than to actual differences existing between fields of studies. Indeed, the amount of public funding is observed at the university level and we cannot identify the exact amount of resources that are dedicated to each field. However, given that our estimates are field-specific, we can exploit this information to control for the relative differences in terms of resources received from the central state between universities.

The second part of Table 3.5 presents information on scholarships and places in dormitories provided by HEUs outside the DSU program. As we can note by comparing Table 3.5 and Table 3.1, the provision of these services outside the DSU program is residual. Indeed, if we consider for example Psychology, the number of scholarships provided in the DSU program is around 132 times the one provided outside the DSU program. The last part of Table 3.5 shows the information concerning the academic staff composed by professors and researchers. In particular, the table shows the average number of members of the academic staff employed and its composition in terms of nationality and field of study. It is remarkable to note the very low percentage of foreign academics in every field of study considered. With respect to the regional distribution, we can note that universities in the Centre-North employ a higher share compared to the others.

Table 3.5: **Characterstics of HEU by field of study and macroregions**

			non-DSU policies			Academic staff		
	Avg Contr. (€)	Pub. Fund. (Mill. €)	Scholar. (N)	Dorm. (Prob)	Dorm. (Exp. N)	Tot (N)	Foreign (%)	Field (%)
South	934	101.2	33	19.8%	21.2	790	0.8%	
Islands	1038	136.1	224	32.6%	26.9	1115	0.7%	
Centre-North	1673	134.3	222	20.5%	18.5	1059	1.5%	
Social & Political sciences	1453	111.2	162	23.6%	21.3	893	1.3%	3.3%
Psychology	1750	137.7	198	17.0%	15.1	1133	1.1%	9.3%
Math. & Physical sciences	1197	145.0	211	20.3%	17.1	1128	1.5%	10.3%
Life & Natural sciences	1381	125.0	176	23.0%	18.2	979	1.1%	11.6%
Law	1643	117.8	176	20.4%	19.5	940	1.1%	8.8%
Languages	1513	122.3	166	21.2%	16.1	981	1.4%	10.4%
Humanities	1438	126.1	184	25.1%	20.2	1002	1.3%	9.9%
Engineering	1331	137.4	223	26.0%	35.9	1025	1.1%	14.9%
Education	1447	138.3	209	19.9%	15.8	1130	1.2%	9.9%
Chemistry & Pharmacy	1081	161.0	217	19.0%	14.7	1211	1.1%	6.4%
Business & Statistics	1689	116.6	158	19.6%	18.7	955	1.4%	9.0%

Notes: The table reports the descriptive statistics concerning the characteristics of Italian HEUs by field of study and hosting macroregions. All the data refers to the academic year 2013-2014. Column (1) reports the average contribution paid by students computed as total contributions over the number of students; Column (2) reports the total amount of public funding received on average by HEUs for the academic year 2014-2015; Columns (3)-(5) report information on, respectively, the average number of scholarships, the probability to obtain a place in a dormitory and the average expected number of available places in dormitories considering policies provided by HEU outside the DSU program; Columns (7)-(9) show, respectively, the average number of professors and researchers (academic staff) employed by HEU, the share of non-Italian academics and the share of academics that are employed in the specific field of study.

3.5 Empirical framework

3.5.1 The Conditional Logit Model

In order to estimate the various determinants of students' location decision process, we base our estimation strategy on the random utility models family (RUMs) (Train, 2003). RUMs assume that a decision maker chooses one alternative from a definite choice set, by maximizing her utility. The choice set is composed of mutually exclusive alternatives that are characterized by their attributes. In our case, decision markers are students who choose the HEU into which enroll. As explained in section 3.4.1, in this work we are modeling the choices related to the third choice of a three-stage process in which students choose whether to enroll in the first stage, the field of study in the second and the university into which enroll in the third stage. Therefore, students' choice set is made of all the HEUs that provide a degree in the field of study chosen.

Formally, let us assume that in Italy there is a population of students $n \in N$ and a set of HEUs $j \in J$. If the student n chooses to enroll into HEU j, she obtains the following utility:

$$U_{nj} = x_j'\beta + \epsilon_{nj} \tag{3.1}$$

where U_{nj} indicates the utility of student n if she decides to enroll into HEU j, x_j is the vector of observed attributes of alternative j and ϵ_{nj} captures factors that enter in the utility U_{nj} but are not observed by the researcher. Consisting with the assumption of utility maximization, student n will choose to enroll in university j only if:

$$U_{nj} \geq \max_{j' \in J} U_{nj'} \text{ with } j \neq j' \tag{3.2}$$

therefore, only if the chosen HEU is the one that maximizes her utility. Given this condition, the probability that student n chooses HEU j is given by the following:

$$P_{nj} = Prob(U_{nj} > U_{nj'}) \;\forall\; j \neq j' \tag{3.3}$$

if we assume that the error term ϵ_{nj} is $i.i.d$ type I extreme value distributed, the probability that student n choose the HEU j is given by the standard Logit formula (Mcfadden, 1974):

$$P_{nj} = \frac{exp(x_j'\beta)}{\sum_{j=1}^{J} exp(x_j'\beta)} \tag{3.4}$$

In the Conditional Logit framework, this probability is estimated using a maximum likelihood approach. CL has been widely applied in exploring the determinants of students' choices (e.g. Pigini and Staffolani, 2015; Long, 2004).

The probability formula in Eq. (3.4) exhibits several useful proprieties: i. the estimated probabilities are always comprised between 0 and 1; ii. the probability to choose one alternative is positively related to choice maker's utility; iii. the sum of all the probabilities attached to each alternative is always equal to 1. This last propriety derives from the assumption that all the relevant alternatives are observed and included in the choice set faced by student n.

Another characteristic of CL is that all the elements contained in the vector x_j need to vary over alternatives. This element can be an issue if we consider the student's attributes. Given that these characteristics are constant among alternatives, the CL is not able to identify any parameter associated with them. However, individual characteristics can be an important driver of students' preferences. For example, the effect of financial and in-kind policies may change on the basis of students' region of residence or high school diploma grade. In these cases, to consider individual variables in the estimation, the researcher has to define them in a way that can be handled by the model. One solution is to interact agent's characteristics with the alternatives' attributes, this way obtaining a regressor that depends upon individual characteristics but varies among alternatives.

However, along with its useful proprieties, CL presents several limitations that are relevant in our context. Drawing on Train (2003), these limitations can be classified into two categories: heterogeneity in preferences and substitution patterns.

With respect to the first category, the CL approach permits, by interacting choice-makers' and alternatives' attributes, to represent only the systematic variation in decision markers' preferences that depend upon their observable characteristics. However, CL is not able to represent the variation in tastes that depends on unobservables or that are purely random from the researcher's point of view. This is an important limitation of the CL approach since this unobserved heterogeneity introduces a correlation between regressors and the error term, this way causing an omitted variable bias. In these cases, the CL is misspecified.

The second limitation of the CL approach is related to substitutions patterns. These represent how the choice probabilities of the alternatives considered in the choice set are related. Indeed, given that the sum of choice probabilities is equal to 1, if the choice probability of one alternative increases, those of the other alternatives have necessarily to decrease. The substitution patterns assumed by the CL are called 'proportional' and are a consequence of the well known *Independence from Irrelevant Alternatives* (IIA) property. This property states that the probability ratio between two alternatives j and i depends only on the attributes of these two alternatives. The consequences of this property can be clarified using the concept of cross-elasticities. Cross-elasticities measure the percent change in the choice probability of alternative i when the attribute x_j of alternative j changes by 1%. In the case of the CL, these cross elasticities are given by:

$$\varepsilon_{ij} = -x_j P_{nj} \beta_j \tag{3.5}$$

as we can see, although the cross elasticity is between alternative i and alternative j, the formula depends only on attributes of j. This indicates that if the probability of alternative j increases, the probabilities of all the other alternatives reduce proportionally by the same amount. However, in reality, one would expect that the cross elasticities between these two alternatives should depend on their relative similarities and differences. For example, let us assume that one agent is choosing between three drinks: coke A, coke B, and water. Suppose that the price of coke A decreases by 1%. In this case, the probability to choose coke B should decrease more than the one to choose water. However, in the CL framework, the two probabilities will increase by the same amount, this way overestimating the effect on the probability to choose water, and underestimating the one on the probability to choose coke B.

To overcome this problem, the researcher needs to define a nesting structure in the choice decision process by splitting the alternatives into different sub-samples called nests. Each nest will contain groups of alternatives that are more correlated with each other. In our example, the researcher can define a nest for the cokes and another nest for the water. However, nesting structures are not allowed by the CL framework.

To solve these two limits of the CL approach, this work takes advantage of a more sophisticated discrete choice approach: the Latent Class Model.

3.5.2 The Latent Class Model

The Latent Class Logit model (LCM) belongs to the general class of Mixed Logit (ML) models and can be used to overcome the limitations of CL that we have summarized in Section 3.5.1. Indeed, McFadden and Train (2000) have shown that ML can be used to approximate any choice model with any distribution of preferences to any degree of accuracy. This result implies that the ML can be specified to control for any source of heterogeneity in preferences and the presence of nesting structures in the observed choice set.

In the ML model, the utility that individual n obtains choosing alternative j can be denoted as (Hess and Train, 2017):

$$U_{nj} = x'_{nj}\beta_n + \epsilon_{nj} \tag{3.6}$$

where, differently from Eq. (3.1), we have that the vector of taste parameters β_n now varies over students. This feature allows us to consider explicitly the presence of heterogeneity in individual preferences by estimating a different vector of preference parameters for each individual.

Assuming that the error term ϵ_{nj} is *i.i.d.* extreme value we can write the probability that agent n chooses alternative j, conditional on the student parameter β_n as:

$$P_{nj}(\beta_n) = \frac{exp(x'_{nj}\beta_n)}{\sum_{j=1}^{J} exp(x'_{nj}\beta_n)} \tag{3.7}$$

this formula indicates that the conditional choice probability of individual n depends on her vector of utility coefficient β_n. To derive the unconditional choice probability of individual n, the researcher need to specify the cumulative distribution function of utility parameters in the population $F(\beta|\theta)$. This distribution can be assumed to be continuous or discrete, to differs among different elements of the vector β_n, and to allow any type of correlation among parameters.

With respect to heterogeneity in preferences, we have that the ML is a flexible method that, by allowing all the parameters to be randomly distributed and correlated, allows us to consider any source of preference heterogeneity that may depend on students' observable characteristics or be caused by individual's idiosyncratic preferences.[16] Moreover, given that

[16]ML permits to control also for scale heterogeneity. Scale heterogeneity is a shift in the vector of taste parameters that is related to some unobserved factor that affects different individuals in different ways. One consequence of this heterogeneity is that the choices of individuals that are strongly affected by the unobserved

preference heterogeneity can be let to depend on individual characteristics, the ML permits to identify the systematic variations in individual tastes.

With respect to the nesting structure in agents' decision process, we have that the ML does not exhibit the IIA property and can be modeled to approximate any kind of substitution pattern and nesting structures. This is done by defining a dummy variable that refers to the nest and letting the coefficients associated with this regressor to be randomly distributed. In our case, we can suppose that HEUs located in the student's region or province of residence are more correlated with each other compared to all the other alternatives. Hence, in our empirical strategy, we will control for this nesting structure by inserting a dummy that takes value 1 if the HEU is in the student's region or province of residence. This strategy permits to consider more realistic substitution patterns with respect to the standard CL approach.

The LCM is a special case of the ML. In particular, LCM arises when the cumulative distribution of individual parameters $F(\beta|\theta)$ is assumed to be discrete. Because of this, LCM and ML with continuous $F(\beta|\theta)$ may lead to different results. Indeed, the ML permits to choose various parameter distributions and its results may differ depending on the distribution chosen. On the other hand, LCM approximates the true distribution of the parameters without imposing any specific distributional assumptions on coefficients (Sivey, 2012). However, as outlined in Greene and Hensher (2003), there is no reason to prefer one specification to the other. In this work, we have chosen the LCM in order to have a more tractable and less computationally intensive estimation approach.

The LCM assumes that students are sorted in a set of $q \in Q$ latent classes. For each latent class identified, the model estimates a vector of class-specific parameters β_q that can be used to have an estimate of the individual set of taste parameters β_n. It is worth noting that latent classes do not contain any particular individual but that the class membership is probabilistic and can be defined to depend on the individual's characteristics.

In the LCM, the probability that student n chooses HEU j, conditional on the fact that she

factor appear more random from the researcher's perspective (Hess and Train, 2017). In these cases, the ML allows to put a lower weight on the choices of individuals that are more affected by the unobserved factor, by letting the scale of their vector of coefficients to be lower in magnitude.

belong to the latent class q, can be written as:

$$P_{njq} = \frac{exp(x_j'\beta_q)}{\sum_{j=1}^{J} exp(x_j'\beta_q)} \tag{3.8}$$

where β_q is the class-specific vector of parameters.

In order to estimate the individual distribution of parameters, we need to define the probability that one individual belongs to class q. Following Greene and Hensher (2003), this probability assumes the standard Logit form:

$$H_{nq} = \frac{exp(z_n'\gamma_q)}{\sum_{q=1}^{Q} exp(z_n'\gamma_q)} \tag{3.9}$$

where z_n is the vector of individual characteristics of student n that enters in the class membership probability model and γ_q are the parameters that links z_n to the class membership probability H_{nq}. Therefore, for each class, we will have two vectors of parameters: β_q and γ_q. The first vector contains the taste parameters associated with alternative's attributes. The second permits to estimate the class membership probability on the basis of individual characteristics. Given this definition, the unconditional probability that student n chooses alternative j is given by:

$$P_{nj} = \sum_{q=1}^{Q} H_{nq} P_{njq} \tag{3.10}$$

These elements, along with the information on students' observed choices, can be used to estimate the posterior class membership probability:

$$\hat{H}_{q|n} = \frac{\hat{P}_{nq}\hat{H}_{nq}}{\sum_{q=1}^{Q} \hat{P}_{nq}\hat{H}_{nq}} \tag{3.11}$$

where $\hat{P}_{nq}$ denotes the class-specific probability for the specific choice made by student n. Therefore, student's posterior class membership probability is estimated conditional on his own individual characteristics and class-specific choice probabilities. In other words, $\hat{H}_{q|n}$ is computed by attaching an higher weight to the latent class that permits to predict the higher probability to choose the alternative actually chosen by student n.

Given the probability in Eq. (3.11), the set of taste parameters of individual n are defined as:

$$\hat{\beta}_n = \sum_{q=1}^{Q} \hat{H}_{q|n} \hat{\beta}_q \tag{3.12}$$

Therefore, the individual set of parameters will depend on decision makers' characteristics on the basis of their posterior class membership probabilities.

3.5.3 Endogeneity

In order to interpret our estimates of students' utilities non-distorted estimates of the effect that DSU policies have on students' choice probabilities, we need that all the observed variables are exogenous. In our case, we have various possible sources of endogeneity sources that need to be addressed.

The first threat to our identification arises from the fact that DSU offices and HEUs, through a process of adaptation, could increase their supply in response to a higher demand for services. For example, the supply of DSU services in time t (2014-2015) can be affected by the demand for services in time $t-1$ (2013-2014). Therefore, changes in the demand can affect the supply, this way raising endogeneity concerns through inverse causality. However, as explained in Section 3.4, all the information regarding DSU's supply and HEUs' characteristics are collected with respect to academic year $t-1$ (2013-2014) and should be directly affected by changes in demand in time $t-2$ (2012-2013). Thus, to have a simultaneity bias, changes in demand in time $t-2$ should affect supply in time t. This problem is even less problematic if we consider scholarships. In fact, the data regarding this policy are observed at the universities' level. Therefore, even if the DSU offices can discretionally modify their supply, in order to have a simultaneity bias, also the winning applications in each university have to increase. Ideally, to completely solve this problem we should observe an exogenous event or collect data referring to previous academic years. However, in the absence of these possibilities, we believe that the nature of our data is mostly unaffected by this endogeneity source.

Correlation between the error term and our regressors can arise also in the presence of unobserved heterogeneity in preferences and omitted variables. If students' preferences for DSU's policies and HEUs' characteristics are affected by some unobserved factor, we will have those observationally identical students will take different decisions according to elements for which we have not accounted for. We first address this issue by using a very rich set of controls variables on both HEUs' and hosting areas' characteristics. Second, as extensively explained in Section 3.5.2, the ML model provides various solutions to account for observed, unobserved and scale heterogeneity. Namely, the researcher can specify one or more parameters to be randomly distributed and correlated in order to have an individual set of parameters that will depend on students' characteristics and idiosyncratic preferences. In our case, with the LCM, we semi-parametrically approximate the continuous distribution of students' preferences using a discrete one. This permits to avoid assumptions on the functional form of students' individual preferences and to control for unobserved heterogeneity that depends also on unobserved factors. Therefore, these sources of endogeneity should be less of an issue in our case.

3.5.4 Empirical strategy

The first step of our empirical strategy concerns the estimation of a CL in order to have a preliminary understanding of how HEUs' and hosting areas' characteristics affect students' choices.

In this case, the utility that student n will obtain choosing HEU j is specified as:

$$U_{nj} = DSU_j\beta_{DSU} + HEU_j'\beta_{HEU} + AREA_j'\beta_{AREA} + d_{nj}'\beta_d + \epsilon_{nj} \tag{3.13}$$

where DSU_j denotes the services provided by DSU offices in HEU's hosting area, HEU_j includes HEUs' controls, $AREA_j$ includes HEU's hosting area controls, d_{nj} indicates the regressors that varies among alternatives and individuals, and ϵ_{nj} is the error term.

The vector DSU_j contains our main variable of interests: i. the number of scholarships weighted by the probability to obtain a scholarship; ii. the number of places in dormitories without scholarships weighted by the probability to obtain a place in a dormitory; iii. the number of places in dormitories with scholarships (student packages) weighted by the probability to obtain a place in a dormitory. The probabilities to obtain the services are computed as the ratio between the number of applications accepted by DSU offices and the number of received applications. As explained in Section 3.4.2, the indicators concerning dormitories and student packages vary over DSU offices while the one related to scholarships is computed considering the information available at the HEU's level. One important element to note is that we use expected indicators rather than absolute numbers. This is done to consider the information related to the ability of DSU offices to satisfy the demand for these services.

The variables included in vector HEU_j are used to control for the various dimensions of HEUs' attractiveness that can affect students' choices other than our variables of interest. We include in this vector the number of places in canteens and a dummy variable that takes value 1 if there is a college in the HEU's hosting area. Moreover, given that universities can provide scholarships and places in dormitories outside the DSU program, we include in HEU_j also the number of non-DSU scholarships and the number of places in dormitories provided outside the DSU program weighted by the probability to obtain a non-DSU place in a dormitory. The last group of variables included in HEU_j are related to the various dimension of HEU's attractiveness that have been outlined in the previous literature summarized in Section 3.2. In particular, we control for the dimension and the quality of HEUs using: the number of excellence departments; the number of professors and researchers (academics) employed by the HEU; the share of foreign academics; the number of members of administrative staff; the number of academics employed in the field of study considered; the amount of public funding received by the HEU. Furthermore, we control for the effect of tuition fees and enrollment costs using the average tuition fee computed as the total students' contribution divided by the number of enrolled students.

Given the role highlighted in the previous literature of hosting areas' characteristics such as labor market conditions or life costs, we have included in vector $AREA_j$ the information relative to: the average unemployment rate between 2011 and 2013 in HEU's hosting province; the average housing purchase price per square meter in 2013 in hosting provinces; the GDP in HEU's hosting region in 2013.

Finally, the variables contained in d_{nj} are: a quadratic polynomial of the distance between student's city of residence and HEU's hosting city; a dummy variable that indicates if the HEU is located in student's province of residence; a dummy variable that indicates if the HEU is located in student's region of residence. These variables are used to control for student's cost of migration.

Table 3.6 presents the list of variables used in estimation along with their definition. The results related to the CL estimates are presented in Section 3.6.1 below.

The second step of our estimation strategy regards the estimation of the LCM outlined in

Section 3.5.2. In this case the utility of student n in latent class q is the defined as:

$$U_{nj|q} = DSU_j\beta_{DSU|q} + HEU_j'\beta_{HEU|q} + AREA_j'\beta_{AREA|q} + d_{nj}'\beta_{d|q} + \epsilon_{nj|q} \tag{3.14}$$

Eq. (3.14) differs from Eq. (3.13) for the presence of the subscript q in all the coefficients. This indicates that we are estimating a different utility function for each latent class q identified. These parameters are then used to estimate a set of individual coefficients on the basis of the posterior class membership probability defined in (3.11).

Recalling Eq. (3.9), the unconditional class membership probability is defined as:

$$H_{nq} = \frac{exp(z_n'\gamma_q)}{\sum_{q=1}^{Q} exp(z_n'\gamma_q)} \tag{3.15}$$

where the vector z_n contains the set of individual characteristics that we use to determine the probability of class assignment. In particular, z_n contains a set of individual characteristics and a set of variables that gives information on the student's region or province of residence. The first set of variables contains: a constant; one dummy that takes value 1 if the student resides in a northern or central region of Italy; student's high school diploma grade; a dummy that takes value 1 if the student is female; one dummy that takes value 1 if student's city of residence hosts at least one HEU. These variables are exploited to understand how individual characteristics shape students' preferences. The second set of variables contains: the average unemployment rate between 2011 and 2013 in students' province of residence; the GDP of students' region of residence in 2013; the average housing purchase price per square meter in student's province of residence. These variables are used in order to partially control for students' socio-economic background.

Table 3.6 presents the list of variables used in estimation along with their definition. The results of LCM estimates are presented in Section 3.6.2 below.

Since the utilities estimated using the discrete choice approach presented are identified only up to a constant, the coefficients can be interpreted only in respect of their relative magnitude and sign. Therefore, to ease interpretation, we present the results in terms of semi-elasticities and willingness to travel (WTT).

The semi-elasticities are defined as the percentage change in the probability that student n

Table 3.6: Definitions of variables used in estimation

Variable	Definition
Characteristics of Higher Education Units	
E(Scholarship)	Number of scholarships weighted by the probability to obtain a scholarship.
E(Dormitory)	Number of places in dormitories without scholarship weighted by the probability to obtain a place in a dormitory.
E(Student Package)	Number of places in dormitories with scholarships weighted by the probability to obtain a place in a dormitory.
Places in Canteen	Number of places in canteens.
College	1 if a college serves the HEU
non-DSU Scholarship	Number of scholarships provided outside the DSU program.
E(non-DSU Dormitory)	Number of places in dormitories provided outside the DSU program weighted by the probability to obtain a non-DSU place in a dormitory.
Excellence Departments	Number of department of excellence.
Academics	Number of professors and researchers employed by the HEU.
Share of Intern. Academics	Share of foreigner professors and researchers.
Administrative staff	Number of administrative staff employed by the HEU.
Field of study Academics	Number of professors and researchers employed in the field of study considered.
Public funding (Mill.)	Amount of public funding received by the HEU in millions of Euro.
Average contribution	Average tuition fee computed as the total students' contribution divided by the number of enrolled students.
Distance	Distance between student's city of residence and HEU's hosting city.
Distance^2	Distance between student's city of residence and HEU's hosting city squared.
HEU in province	1 if the HEU is in the student's province of residence.
HEU in region	1 if the HEU is in the student's region of residence.
Unemployment	Average provincial unemployment rate between 2011 and 2013.
Housing price	Average provincial housing purchase price per square meter.
Regional GDP	Regional GDP.
Student's individual characteristics	
Diploma Grade	High school diploma grade.
CentreNorth	1 if the student resides in a central or northern region of Italy
Housing price in residence	Average housing purchase price per square meter in student's province of residence
Unemployment in residence	Average unemployment rate between 2011 and 2013 in student's province of residence.
Regional GDP in residence	GDP of student's region of residence
HEU in residence	1 if student's city of residence hosts one HEU.
Female	1 if student is female

The table reports the definitions of the variables used in estimation. The first panel contains the definitions of student's utility determinants. The second panel contains informations on the student's characteristics used to explore the existence of heterogeneity in students' preferences.

chooses alternative j when the service indicator in j increases by 1%. In the LCM model, the individual semi-elasticities with respect to the regressor x_j are computed as follows:

$$\varepsilon_{nj} = \sum_{q=1}^{Q} \hat{H}_{q|n} \varepsilon_{njq} = \sum_{q=1}^{Q} \hat{H}_{q|n} x_j (1 - P_{njq}) \beta_q \tag{3.16}$$

where $\hat{H}_{q|n}$ is the posterior probability of individual n to belong to class q computed using Eq. (3.11), P_{njq} is the probability for student n to choose alternative j given the class q computed using Eq. (3.8), and ε_{nq} is the semi-elasticity of the individual n for the latent class q. As we can note, Eq. (3.16) indicates that individual semi-elasticities are computed as the average of each latent class semi-elasticity weighted by individuals posterior class membership probabilities. This feature allows us to have individual estimates for semi-elasticities that will depend on the entire vector of individual characteristics z_n.

The WTT is defined as the additional number of kilometers that student n is willing to travel for a 1% increase in one of the service indicators. The WTT for a student n in the latent class q for one of the DSU services is computed as:

$$WTT_n = -\frac{\partial U_{nj} / \partial DSU_j}{\partial U_{nj} / \partial d_{nj}} = -\frac{\beta_{DSU,n} \times \Delta DSU_j}{2\beta_{d2,n} dist_{nj} + \beta_{d1,n}} \tag{3.17}$$

where ΔDSU_j denotes the 1% change in DSU service indicator and $\beta_{DSU,n}$, $\beta_{d1,n}$, $\beta_{d2,n}$, indicate, respectively, the individual coefficients associated with the DSU indicator considered and the linear and quadratic terms of the polynomial of distance. Namely, the WTT measures the marginal rate of substitution between DSU's services and distance. This is given by the ratio between student's marginal utility for the service over her marginal utility for the distance. Each WTT estimates will be based on the individual set of parameters obtained through Eq. (3.12).

The results related to these two measures of students' sensitivity are visually explored through non-parametric regressions to explore the existence of heterogeneity between different groups of students. In particular, for each variable of interest, we have estimated a local polynomial regression to estimate the relationships existing between students' sensitivity to DSU's policies and their characteristics (e.g. distance traveled and high school diploma grade). Local polynomial regressions are techniques that permit to estimate the relationship between two variables y and x without assuming its functional form. For a given point x_0, the relationship is estimated by regressing the realizations of y on a constant and a polynomial of the difference between x_0 and one x in its neighborhood. The width of this neighborhood is chosen by deciding a bandwidth. Larger bandwidths permit more smoothing but less resolution, whereas smaller ones give more resolution but higher variability in the results. In our case, we have chosen the asymptotic optimal bandwidth provided in Fan and Gijbels (1996). This bandwidth is chosen to solve the trade-off between resolution and smoothing by minimizing the conditional mean integrated square error of the regression. Another element to choose is the degree of the polynomial. After various tests with higher degrees we have opted for a degree 3 polynomial.[17]

3.6 Results

3.6.1 Baseline: Conditional Logit estimates

Table 3.7 reports CL estimates of the utility function defined in Eq.3.13 in Section 3.5.4 for each field of study considered.

Given that utility functions are identified only up to a constant, we cannot compare the magnitude of coefficients across different specifications. Nevertheless, we can infer the effects of universities' attributes on students' choices by comparing coefficients' signs and relative magnitude in each field. By applying this logic, we can highlight various interesting results.

Since coefficients' signs change across fields of study, we have found evidence of the existence of heterogeneity in students' preferences among fields of study. If we consider our variables of interest, we can note that DSU's policies have different effects depending on the field of study. Indeed, the effect of $E(Scholarships)$ is positive and significant in 5 out of 11 fields considered, whereas $E(Dormitory)$ and $E(StudentPackage)$ have a positive significant effect in 7 fields. These results suggest that policies that provide places in a dormitory are more effective in attracting students. Moreover, if we look at coefficients' relative magnitude, we can see that these policies have, in most of the cases, much stronger effects than the ones associated with scholarships. This element suggests that in-kind policies play a major role in attracting students. For example, the effect of one additional expected student package in Engineering is

[17] See Fan and Gijbels (1996) for details on the local polynomial regression approach.

almost 8 times the negative effect of one additional expected scholarship. These results can be related to the fact that, although scholarships can reduce students' cost of living, they do not cover housing and accommodations costs related, for example, to the research of an apartment.

We have evidence of heterogeneity in preferences even considering places in canteens and colleges. In fact, places in canteens have a positive, although smaller compared with other variables, in 5 of the fields considered while colleges have a stronger positive effect in 7 fields. Since colleges provide places in their dormitories to particular kinds of students, this result confirms the importance of in-kind policies.

Concerning the effect of non-DSU policies we can note that, in the majority of the fields, these policies have a negative effect on students' choice probabilities that, in general, is stronger than the one of DSU's policies. Moreover, signs of coefficients associated with non-DSU policies are in general different from those of our variable of interest. This element suggests that these policies are a poor substitute for DSU's policies.

Turning on the effect of the HEU's attributes we can remark some interesting elements. The number of excellence department is positive in the majority of fields, this way suggesting that HEU's quality of research is an important determinant of students' utility functions. Concerning the effect of variables related to the academic staff, we can see that the number of academics has always a negative or non-significant effect on choice probabilities whereas the number of academics employed in the specific field of study has a positive effect in all the fields considered. This element suggests that students are more interested in the staff employed in their field than on the number of academics in general. As for public fundings and average students' contributions we can see that, as expected, students are more attracted by universities with more resources and that require them a lower contribution in terms of taxes.

With respect to the effect of variables related to HEUs' hosting areas, we can see that, as expected, students tend to choose universities in their region or province of residence and their utility is negatively affected by the distance between the university and their residence. Moreover, our results suggest that students prefer universities in areas with lower unemployment and higher GDP and housing prices. These results indicate that socio-economic conditions of hosting areas are an important determinant of the demand for education in one specific HEU.

Although these results are interesting, they are only a partial picture of the phenomenon.

Table 3.7a: Conditional Logit Estimates

	Chemistry & Pharmacy	Business & Statistics	Life & Natural sciences	Law	Engineering	Education
E(Scholarship)/100	0.030***	-0.009***	0.011***	-0.016***	-0.027***	0.027***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
E(Dormitory)/100	0.111***	0.028***	-0.044***	0.132***	0.153***	0.166***
	(0.015)	(0.009)	(0.013)	(0.012)	(0.010)	(0.058)
E(Student Package)/100	0.109***	0.025***	0.126***	0.043***	0.214***	-0.076***
	(0.014)	(0.006)	(0.010)	(0.007)	(0.008)	(0.026)
Places in Canteen/100	-0.008***	0.029***	0.008***	0.015***	-0.003***	0.007***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
College	-0.039	0.168***	-0.314***	0.092***	0.820***	-0.009
	(0.043)	(0.019)	(0.033)	(0.028)	(0.023)	(0.059)
non-DSU Scholarship/100	-0.134***	-0.072***	-0.019***	-0.0002	0.144***	-0.012
	(0.009)	(0.004)	(0.007)	(0.0064)	(0.006)	(0.016)
E(non-DSU Dormitory)/100	-1.909***	0.180***	-0.530***	0.589***	-0.235***	0.489***
	(0.100)	(0.019)	(0.058)	(0.026)	(0.012)	(0.100)
Excellence Departments	-0.290***	0.145***	0.234***	0.219***	0.109***	-0.043
	(0.028)	(0.010)	(0.016)	(0.015)	(0.017)	(0.041)
Academics/100	-0.090***	0.004	-0.242***	-0.101***	-0.147***	-0.123***
	(0.031)	(0.008)	(0.014)	(0.011)	(0.011)	(0.037)
Share of Intern. Academics	-0.468***	0.034***	-0.062***	0.096***	-0.201***	-0.621***
	(0.034)	(0.006)	(0.018)	(0.011)	(0.011)	(0.035)
Administrative staff	-0.157***	-0.018***	0.013*	0.078***	0.168***	-0.005
	(0.014)	(0.005)	(0.008)	(0.006)	(0.006)	(0.022)
Field of study Academics/100	2.107***	0.818***	1.057***	0.693***	0.141***	0.447***
	(0.109)	(0.027)	(0.048)	(0.044)	(0.016)	(0.127)
Public funding (Mill.)	0.011***	0.0005	0.007***	0.003***	-0.001**	-0.0006
	(0.003)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.0024)
Average contribution	0.063***	-0.007***	-0.017***	-0.016***	-0.094***	-0.062***
	(0.010)	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)
Distance	-0.022***	-0.019***	-0.021***	-0.018***	-0.018***	-0.031***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Distance^2/100	0.002***	0.001***	0.002***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HEU in province	1.331***	1.599***	1.266***	1.847***	1.602***	1.183***
	(0.043)	(0.019)	(0.032)	(0.028)	(0.020)	(0.054)
HEU in region	1.117***	1.470***	1.269***	1.344***	1.504***	1.043***
	(0.047)	(0.029)	(0.039)	(0.038)	(0.026)	(0.061)
Unemployment	-0.100***	0.034***	-0.065***	-0.041***	-0.043***	-0.273***
	(0.012)	(0.004)	(0.007)	(0.006)	(0.005)	(0.015)
Housing price	0.049***	0.018***	0.018***	0.115***	0.090***	0.166***
	(0.008)	(0.003)	(0.005)	(0.004)	(0.003)	(0.010)
Regional GDP	0.100***	0.136***	0.053***	0.122***	0.069***	-0.0007
	(0.009)	(0.004)	(0.006)	(0.005)	(0.004)	(0.0097)
Observations	376488	2478941	724128	1355184	2022936	279552
Pseudo R^2	0.65	0.56	0.60	0.59	0.59	0.71
Log Likelihood	-11821.1	-59900.4	-20681.1	-32732.1	-55065.4	-7106.7

Notes: Conditional Logit regression by field of study estimated on the sample of Italian student enrolled for the first time in academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Variable definitions are reported in Table 3.6.

Table 3.7b: Conditional Logit Estimates

	Humanities	Languages	Social & Political sciences	Psychology	Math. & Physical sciences
E(Scholarship)/100	-0.023***	0.00009	-0.007***	0.018***	0.021***
	(0.001)	(0.00099)	(0.001)	(0.002)	(0.002)
E(Dormitory)/100	-0.037***	-0.025*	0.090***	0.209***	-0.050***
	(0.013)	(0.013)	(0.012)	(0.028)	(0.019)
E(Student Package)/100	0.035***	-0.159***	-0.008	-0.262***	0.218***
	(0.009)	(0.008)	(0.008)	(0.016)	(0.012)
Places in Canteen/100	0.002	-0.002**	0.018***	-0.012***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
College	0.150***	0.240***	0.289***	-0.405***	0.210***
	(0.034)	(0.026)	(0.025)	(0.056)	(0.045)
non-DSU Scholarship/100	0.125***	0.012*	-0.025***	0.104***	-0.128***
	(0.007)	(0.006)	(0.006)	(0.013)	(0.010)
E(non-DSU Dormitory)/100	0.252***	-0.262***	-0.363***	-1.241***	-0.331***
	(0.055)	(0.046)	(0.029)	(0.084)	(0.076)
Excellence Departments	-0.214***	-0.013	0.474***	-0.182***	0.171***
	(0.018)	(0.034)	(0.033)	(0.069)	(0.031)
Academics/100	-0.095***	-0.071***	-0.097***	0.006	-0.028
	(0.012)	(0.011)	(0.012)	(0.038)	(0.021)
Share of Intern. Academics	0.079***	-0.033***	0.016*	0.422***	-0.094***
	(0.015)	(0.012)	(0.009)	(0.036)	(0.021)
Administrative staff	0.064***	0.091***	-0.035***	-0.178***	-0.094***
	(0.008)	(0.008)	(0.007)	(0.016)	(0.011)
Field of study Academics/100	0.964***	1.208***	1.551***	1.265***	1.511***
	(0.040)	(0.034)	(0.085)	(0.131)	(0.074)
Public funding (Mill.)	0.004***	-0.006***	0.011***	0.008***	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0012)
Average contribution	-0.029***	-0.031***	0.014***	0.010***	0.010
	(0.002)	(0.002)	(0.001)	(0.002)	(0.008)
Distance	-0.019***	-0.021***	-0.021***	-0.020***	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance^2/100	0.002***	0.002***	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HEU in province	1.169***	0.906***	1.131***	0.912***	1.530***
	(0.032)	(0.028)	(0.026)	(0.058)	(0.046)
HEU in region	1.368***	1.017***	1.053***	0.935***	1.366***
	(0.038)	(0.033)	(0.032)	(0.060)	(0.052)
Unemployment	-0.107***	-0.221***	-0.108***	-0.262***	-0.155***
	(0.007)	(0.008)	(0.007)	(0.013)	(0.011)
Housing price	0.117***	0.095***	0.028***	0.078***	0.081***
	(0.005)	(0.004)	(0.004)	(0.010)	(0.006)
Regional GDP	0.013**	-0.055***	0.056***	-0.163***	-0.030***
	(0.006)	(0.005)	(0.005)	(0.011)	(0.009)
Observations	880840	845104	1440947	172391	422577
Pseudo R^2	0.61	0.54	0.59	0.59	0.65
Log Likelihood	-23362.1	-29312.0	-35075.5	-7774.8	-11958.7

Notes: Conditional Logit regression by field of study estimated on the sample of Italian student enrolled for the first time in academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Variable definitions are reported in Table 3.6.

As explained in section 3.5.1, the CL model is not able to capture random heterogeneity in preferences that can be important in this context. Moreover, these results do not give any information on the effect of these variables on the utilities of more narrowly defined groups of students. For example, if we want to know the effect of scholarships on female students with high Diploma Grades that reside in a southern region we should estimate the model with three sets of interaction terms and with all their combinations. In Tables 3A.1 and 3A.2 in Appendix we have reported the results related to a specification in which universities' attributes are interacted with all individuals' observed characteristics. As we can see, besides the issues related to unobserved heterogeneity in preferences, the results of this approach are very hard to interpret. Indeed, we should combine all the coefficients related to interaction terms in order to have an understandable estimate for specific groups of students.

To overcome these issues and shed some light on understanding how these elements affect students' utility in the next section we apply the LCM outlined in Section 3.5.2.

3.6.2 Latent Class Logit estimates

Table 3.8 shows the results of LCM estimates of the utility function defined in Eq. (3.14) for each field of study. For each latent class identified we report two vectors of coefficients. The first indicates the random utility parameters that enter in student's utility function. The second indicates the parameters that enter in the class membership probability model. This second vector informs on the contribution that individual characteristics give on the probability of student n to belong to the class q. In order to have an average estimate of students' preferences, we report also the mean parameter computed by weighting each class-specific parameter for the average class membership probability.

For each field of study, we have estimated the model considering specifications with from 2 to 5 latent classes. Then, following the suggestion of Greene and Hensher (2003) and Hole (2008), we have chosen the model on the basis of Akaike (AIC) and Bayesian (BIC) information criteria and convergence results. In particular, we have chosen the specifications that reports the lower values for AIC and BIC and that identify statistically significant differences between the class-specific vectors of coefficients. With this strategy, we have chosen a specification with 2 latent classes for all the fields considered except for Engineering for which we have estimated a 4-class model. For each class, we report the average class membership probability that can be used as a measure of the importance of the specific latent class in the sample. Even though these values can be small in some cases, it is worth remembering that the weight of these classes in computing the distribution of individual coefficients can be still important for some individuals.

Table 3.8a: Latent Class Logit results by field of study

	Chemistry & Pharmacy			Business & Statistics		
	Class1	*Class2*	*Mean*	*Class1*	*Class2*	*Mean*
Random Utility Par. β						
E(Scholarship)/100	0.075***	0.015***	0.048	0.013***	-0.029***	0.002
	(0.007)	(0.003)		(0.002)	(0.002)	
E(Dormitory)/100	0.166***	0.170***	0.168	0.124***	-0.077**	0.068
	(0.051)	(0.026)		(0.013)	(0.031)	
E(Student Package)/100	0.709***	0.006	0.389	0.002	0.043***	0.013
	(0.062)	(0.019)		(0.010)	(0.013)	
Places in Canteen/100	-0.007	-0.022***	-0.014	0.033***	0.034***	0.033
	(0.007)	(0.003)		(0.002)	(0.002)	
College	0.041	0.118	0.076	-0.027	0.614***	0.150
	(0.171)	(0.075)		(0.030)	(0.057)	
non-DSU Scholarship/100	-0.432***	0.010	-0.230	-0.123***	0.065***	-0.071
	(0.030)	(0.016)		(0.008)	(0.011)	
E(non-DSU Dormitory)/100	-4.173***	-1.221***	-2.827	-0.030	0.091***	0.003
	(0.317)	(0.159)		(0.057)	(0.035)	
Excellence Departments	-1.141***	-0.004	-0.623	0.079***	0.283***	0.135
	(0.113)	(0.050)		(0.016)	(0.027)	
Academics/100	0.984***	-0.288***	0.404	0.229***	-0.295***	0.084
	(0.112)	(0.050)		(0.014)	(0.024)	
Share of Intern. Academics	-0.449***	-0.539***	-0.490	0.050***	0.130***	0.072
	(0.087)	(0.067)		(0.015)	(0.016)	
Administrative staff	-0.523***	-0.032	-0.299	-0.101***	0.271***	0.002
	(0.048)	(0.024)		(0.011)	(0.017)	
Field of study Academics/100	3.209***	1.319***	2.347	0.645***	0.405***	0.578
	(0.380)	(0.191)		(0.046)	(0.081)	
Public funding (Mill.)	-0.044***	0.017***	-0.016	-0.012***	0.004***	-0.007
	(0.009)	(0.004)		(0.001)	(0.001)	
Average contribution	0.035	0.003	0.020	-0.069***	0.022***	-0.044
	(0.029)	(0.016)		(0.003)	(0.002)	
HEU in province	-0.283**	2.095***	0.802	0.436***	2.894***	1.117
	(0.126)	(0.098)		(0.033)	(0.094)	
HEU in region	0.663***	1.278***	0.943	0.832***	0.928***	0.859
	(0.125)	(0.104)		(0.039)	(0.085)	
Unemployment	0.428***	-0.273***	0.109	0.127***	-0.033***	0.083
	(0.044)	(0.021)		(0.008)	(0.011)	
Distance	-0.076***	-0.013***	-0.047	-0.055***	-0.006***	-0.041
	(0.003)	(0.001)		(0.001)	(0.000)	
Distance^2/100	0.006***	0.0007***	0.003	0.004***	0.0004***	0.003
	(0.000)	(0.0001)		(0.000)	(0.0000)	
Housing price	-0.054**	0.128***	0.029	0.031***	0.005	0.024
	(0.024)	(0.014)		(0.004)	(0.006)	
Regional GDP	0.085***	0.016	0.053	0.063***	0.068***	0.065
	(0.024)	(0.015)		(0.007)	(0.008)	
Class Probability Par. θ						
Const.	-1.361**	Fixed		4.353***	Fixed	
	(0.656)	Fixed		(0.289)	Fixed	
Diploma Grade	0.010**	Fixed		-0.053***	Fixed	
	(0.004)	Fixed		(0.002)	Fixed	
CentreNorth	1.568***	Fixed		0.748***	Fixed	
	(0.268)	Fixed		(0.115)	Fixed	
HEU in residence	0.092	Fixed		-0.614***	Fixed	
	(0.170)	Fixed		(0.047)	Fixed	
Housing price in residence	0.033**	Fixed		0.022***	Fixed	
	(0.013)	Fixed		(0.006)	Fixed	
Unemployment in residence	0.027	Fixed		-0.003	Fixed	
	(0.021)	Fixed		(0.009)	Fixed	
Regional GDP in residence	-0.048**	Fixed		0.008	Fixed	
	(0.021)	Fixed		(0.009)	Fixed	
Female	0.330***	Fixed		0.341***	Fixed	
	(0.091)	Fixed		(0.038)	Fixed	
Class membership prob.	0.544	0.456		0.723	0.277	
BIC/N	2.520			3.426		
Mc Fadden Pseudo R^2	0.670			0.610		
AIC/N	2.480			3.412		
Log Likelihood	-11064.9			-53490.2		
N	8964			31379		
N. Classes	2			2		

Notes: Latent Class Logit regressions estimated on the sample of Italian students enrolled for the first time in the academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For each field, the table reports the set of class-specific random utility parameters (β) and the class membership probability parameters θ. The mean parameter is computed as the average of class-specific parameter weighted for the class membership probability. Variable definitions are reported in Table 3.6.

Table 3.8b: Latent Class Logit results by field of study

	Life & Natural sciences			Law		
	Class1	*Class2*	*Mean*	*Class1*	*Class2*	*Mean*
Random Utility Par. β						
E(Scholarship)/100	0.010**	0.015***	0.012	-0.023***	-0.028***	-0.025
	(0.004)	(0.004)		(0.003)	(0.002)	
E(Dormitory)/100	-0.090***	0.111***	-0.041	0.184***	-0.041	0.108
	(0.024)	(0.027)		(0.027)	(0.034)	
E(Student Package)/100	0.038*	0.173***	0.071	0.059***	0.104***	0.074
	(0.020)	(0.020)		(0.021)	(0.015)	
Places in Canteen/100	0.031***	-0.005**	0.022	0.030***	0.010***	0.024
	(0.004)	(0.003)		(0.003)	(0.002)	
College	-0.094	-0.911***	-0.295	0.335***	0.084	0.251
	(0.081)	(0.106)		(0.057)	(0.070)	
non-DSU Scholarship/100	0.010	0.019	0.012	-0.096***	0.131***	-0.020
	(0.012)	(0.029)		(0.014)	(0.015)	
E(non-DSU Dormitory)/100	0.021	-1.403***	-0.329	0.906***	0.538***	0.782
	(0.113)	(0.371)		(0.106)	(0.053)	
Excellence Departments	0.213***	0.160***	0.200	0.017	0.348***	0.129
	(0.041)	(0.034)		(0.038)	(0.036)	
Academics/100	-0.151***	-0.277***	-0.182	-0.439***	0.072***	-0.267
	(0.027)	(0.042)		(0.034)	(0.025)	
Share of Intern. Academics	0.024	-0.252***	-0.044	-0.220***	0.183***	-0.084
	(0.056)	(0.053)		(0.046)	(0.020)	
Administrative staff	0.017	-0.030	0.006	0.044***	0.125***	0.071
	(0.015)	(0.036)		(0.012)	(0.016)	
Field of study Academics/100	0.955***	1.212***	1.018	1.434***	-0.102	0.917
	(0.105)	(0.116)		(0.098)	(0.110)	
Public funding (Mill.)	0.002	0.010***	0.004	0.028***	-0.008***	0.016
	(0.003)	(0.002)		(0.003)	(0.001)	
Average contribution	-0.028***	0.019***	-0.017	-0.079***	0.006**	-0.050
	(0.008)	(0.007)		(0.009)	(0.003)	
HEU in province	0.796***	0.673	0.766	1.115***	1.599***	1.278
	(0.115)	(0.473)		(0.057)	(0.107)	
HEU in region	0.510***	2.149***	0.914	0.675***	1.287***	0.881
	(0.168)	(0.112)		(0.082)	(0.079)	
Unemployment	0.029**	-0.135***	-0.011	-0.067***	0.047***	-0.029
	(0.014)	(0.019)		(0.013)	(0.014)	
Distance	-0.048***	-0.008***	-0.038	-0.059***	-0.010***	-0.042
	(0.006)	(0.001)		(0.002)	(0.000)	
Distance^2/100	0.004***	0.0006***	0.003	0.005***	0.0006***	0.003
	(0.000)	(0.0001)		(0.000)	(0.0000)	
Housing price	-0.029***	-0.0004	-0.022	0.061***	0.177***	0.100
	(0.010)	(0.0188)		(0.010)	(0.008)	
Regional GDP	0.013	0.015	0.014	0.016	0.111***	0.048
	(0.013)	(0.022)		(0.013)	(0.011)	
Class Probability Par. θ						
Const.	-5.181***	Fixed		2.243***	Fixed	
	(0.880)	Fixed		(0.333)	Fixed	
Diploma Grade	0.008**	Fixed		-0.032***	Fixed	
	(0.004)	Fixed		(0.002)	Fixed	
CentreNorth	-1.459***	Fixed		-0.096	Fixed	
	(0.430)	Fixed		(0.141)	Fixed	
HEU in residence	0.168	Fixed		-0.0009	Fixed	
	(0.315)	Fixed		(0.0605)	Fixed	
Housing price in residence	0.248***	Fixed		0.068***	Fixed	
	(0.047)	Fixed		(0.009)	Fixed	
Unemployment in residence	0.027	Fixed		-0.005	Fixed	
	(0.022)	Fixed		(0.012)	Fixed	
Regional GDP in residence	0.166***	Fixed		0.009	Fixed	
	(0.048)	Fixed		(0.011)	Fixed	
Female	-0.303***	Fixed		0.287***	Fixed	
	(0.113)	Fixed		(0.048)		
Class membership prob.	0.754	0.246		0.663	0.337	
BIC/N	3.131			3.257		
Mc Fadden Pseudo R^2	0.617			0.622		
AIC/N	3.102			3.236		
Log Likelihood	-19655.0			-30405.3		
N	12704			18822		
N. Classes	2					

Notes: Latent Class Logit regressions estimated on the sample of Italian students enrolled for the first time in the academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For each field, the table reports the set of class-specific random utility parameters (β) and the class membership probability parameters θ. The mean parameter is computed as the average of class-specific parameter weighted for the class membership probability. Variable definitions are reported in Table 3.6..

Table 3.8c: Latent Class Logit results by field of study

	Humanities			Education		
	*Class*1	*Class*2	*Mean*	*Class*1	*Class*2	*Mean*
Random Utility Par. β						
E(Scholarship)/100	-0.039***	-0.017***	-0.030	0.043***	0.022***	0.038
	(0.003)	(0.003)		(0.006)	(0.004)	
E(Dormitory)/100	-0.166***	0.060*	-0.070	0.404***	0.233***	0.365
	(0.033)	(0.034)		(0.144)	(0.075)	
E(Student Package)/100	0.187***	-0.007	0.105	0.041	-0.115***	0.005
	(0.024)	(0.020)		(0.050)	(0.044)	
Places in Canteen/100	0.017***	-0.021***	0.0008	0.026***	-0.0006	0.020
	(0.004)	(0.003)		(0.004)	(0.0048)	
College	-0.008	1.508***	0.633	0.945***	-0.886***	0.528
	(0.074)	(0.114)		(0.107)	(0.132)	
non-DSU Scholarship/100	0.050***	0.184***	0.106	-0.097***	0.123***	-0.047
	(0.019)	(0.013)		(0.029)	(0.030)	
E(non-DSU Dormitory)/100	0.888***	-0.422**	0.334	1.850***	-0.351**	1.348
	(0.122)	(0.203)		(0.196)	(0.166)	
Excellence Departments	-0.591***	0.053	-0.318	-0.586***	0.273***	-0.390
	(0.043)	(0.042)		(0.087)	(0.093)	
Academics/100	0.210***	-0.194***	0.039	-0.088	-0.054	-0.080
	(0.035)	(0.037)		(0.075)	(0.071)	
Share of Intern. Academics	-0.032	0.084**	0.017	-0.642***	-0.534***	-0.618
	(0.044)	(0.034)		(0.063)	(0.088)	
Administrative staff	0.064***	0.076**	0.069	-0.198***	-0.033	-0.160
	(0.018)	(0.033)		(0.042)	(0.040)	
Field of study Academics/100	1.194***	1.442***	1.299	0.949***	-0.720**	0.568
	(0.105)	(0.099)		(0.249)	(0.286)	
Public funding (Mill.)	-0.017***	0.006***	-0.007	0.009*	0.004	0.008
	(0.002)	(0.001)		(0.005)	(0.005)	
Average contribution	-0.140***	-0.006	-0.083	-0.083***	-0.041***	-0.073
	(0.011)	(0.004)		(0.008)	(0.012)	
HEU in province	0.592***	1.035***	0.780	0.466***	1.317***	0.660
	(0.070)	(0.097)		(0.075)	(0.136)	
HEU in region	0.927***	1.423***	1.137	0.718***	1.249***	0.839
	(0.088)	(0.074)		(0.092)	(0.160)	
Unemployment	0.067***	-0.286***	-0.082	0.083***	-0.583***	-0.069
	(0.016)	(0.015)		(0.025)	(0.041)	
Distance	-0.055***	-0.011***	-0.037	-0.053***	-0.026***	-0.047
	(0.002)	(0.000)		(0.001)	(0.001)	
Distance^2/100	0.004***	0.0008***	0.003	0.004***	0.001***	0.003
	(0.000)	(0.0000)		(0.000)	(0.000)	
Housing price	0.039***	0.289***	0.144	0.056***	0.113***	0.069
	(0.014)	(0.013)		(0.017)	(0.031)	
Regional GDP	-0.003	-0.132***	-0.057	-0.018	-0.003	-0.015
	(0.014)	(0.014)		(0.019)	(0.017)	
Class Probability Par. θ						
Const.	1.562***	Fixed		-6.187***	Fixed	
	(0.395)	Fixed		(1.613)	Fixed	
Diploma Grade	-0.008***	Fixed		-0.007	Fixed	
	(0.002)	Fixed		(0.010)	Fixed	
CentreNorth	0.376**	Fixed		-4.741***	Fixed	
	(0.155)	Fixed		(0.987)	Fixed	
HEU in residence	-0.469***	Fixed		0.895*	Fixed	
	(0.076)	Fixed		(0.498)	Fixed	
Housing price in residence	0.043***	Fixed		0.676***	Fixed	
	(0.010)	Fixed		(0.083)	Fixed	
Unemployment in residence	0.023*	Fixed		-0.382***	Fixed	
	(0.013)	Fixed		(0.084)	Fixed	
Regional GDP in residence	-0.068***	Fixed		0.330***	Fixed	
	(0.013)	Fixed		(0.072)	Fixed	
Female	0.175***	Fixed		1.504***	Fixed	
	(0.059)	Fixed		(0.466)	Fixed	
Class membership prob.	0.577	0.423		0.772	0.228	
BIC/N	3.050			2.017		
Mc Fadden Pseudo R^2	0.633			0.739		
AIC/N	3.024			1.965		
Log Likelihood	-21783.8			-6490.8		
N	14440			6656		
N. Classes	2			2		

Notes: Latent Class Logit regressions estimated on the sample of Italian students enrolled for the first time in the academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For each field, the table reports the set of class-specific random utility parameters (β) and the class membership probability parameters θ. The mean parameter is computed as the average of class-specific parameter weighted for the class membership probability. Variable definitions are reported in Table 3.6.

Table 3.8d: Latent Class Logit results by field of study

	Math. & Physical sciences			Languages		
	Class1	*Class2*	*Mean*	*Class1*	*Class2*	*Mean*
Random Utility Par. β						
E(Scholarship)/100	0.016***	0.012***	0.014	0.016***	-0.025***	-0.007
	(0.005)	(0.004)		(0.004)	(0.002)	
E(Dormitory)/100	-0.055	0.033	-0.018	0.141***	-0.010	0.054
	(0.048)	(0.037)		(0.037)	(0.026)	
E(Student Package)/100	0.351***	0.153***	0.267	-0.462***	-0.128***	-0.269
	(0.040)	(0.024)		(0.046)	(0.012)	
Places in Canteen/100	0.015**	-0.011***	0.004	-0.025***	0.005***	-0.008
	(0.006)	(0.003)		(0.004)	(0.002)	
College	-0.251**	0.847***	0.213	0.147	0.207***	0.182
	(0.125)	(0.112)		(0.092)	(0.048)	
non-DSU Scholarship/100	-0.253***	-0.010	-0.151	-0.046**	0.086***	0.030
	(0.025)	(0.023)		(0.020)	(0.012)	
E(non-DSU Dormitory)/100	0.315	-0.412**	0.009	0.505***	0.028	0.230
	(0.205)	(0.161)		(0.187)	(0.077)	
Excellence Departments	0.443***	0.112	0.303	-0.824***	-0.210***	-0.470
	(0.078)	(0.073)		(0.115)	(0.060)	
Academics/100	0.422***	-0.204***	0.158	-0.050	-0.095***	-0.076
	(0.069)	(0.038)		(0.038)	(0.021)	
Share of Intern. Academics	-0.022	-0.100**	-0.055	-1.097***	0.194***	-0.352
	(0.060)	(0.041)		(0.091)	(0.020)	
Administrative staff	-0.088***	-0.078***	-0.084	0.038	0.121***	0.086
	(0.027)	(0.028)		(0.030)	(0.014)	
Field of study Academics/100	1.070***	1.497***	1.250	1.051***	1.541***	1.334
	(0.190)	(0.171)		(0.120)	(0.065)	
Public funding (Mill.)	-0.030***	0.013***	-0.012	-0.003**	-0.004***	-0.004
	(0.004)	(0.003)		(0.001)	(0.001)	
Average contribution	-0.142***	0.053***	-0.060	-0.056***	-0.016***	-0.033
	(0.023)	(0.015)		(0.005)	(0.002)	
HEU in province	0.412***	2.074***	1.114	-0.100	0.917***	0.487
	(0.124)	(0.144)		(0.091)	(0.056)	
HEU in region	1.714***	1.491***	1.619	0.228***	1.098***	0.730
	(0.151)	(0.106)		(0.086)	(0.054)	
Unemployment	-0.046*	-0.157***	-0.093	-0.491***	-0.184***	-0.314
	(0.028)	(0.028)		(0.042)	(0.013)	
Distance	-0.072***	-0.013***	-0.047	-0.075***	-0.015***	-0.040
	(0.003)	(0.001)		(0.003)	(0.000)	
Distance^2/100	0.005***	0.001***	0.004	0.006***	0.001***	0.003
	(0.000)	(0.000)		(0.000)	(0.000)	
Housing price	0.101***	0.141***	0.118	0.107***	0.153***	0.134
	(0.016)	(0.013)		(0.015)	(0.007)	
Regional GDP	-0.234***	-0.072***	-0.166	-0.164***	-0.066***	-0.108
	(0.031)	(0.022)		(0.020)	(0.010)	
Class Probability Par. θ						
Const.	2.399***	Fixed		0.926**	Fixed	
	(0.640)	Fixed		(0.429)	Fixed	
Diploma Grade	-0.025***	Fixed		-0.033***	Fixed	
	(0.004)	Fixed		(0.003)	Fixed	
CentreNorth	-0.114	Fixed		1.534***	Fixed	
	(0.244)	Fixed		(0.188)	Fixed	
HEU in residence	-0.222	Fixed		-0.217**	Fixed	
	(0.147)	Fixed		(0.100)	Fixed	
Housing price in residence	0.009	Fixed		-0.067***	Fixed	
	(0.016)	Fixed		(0.010)	Fixed	
Unemployment in residence	-0.024	Fixed		0.032**	Fixed	
	(0.022)	Fixed		(0.015)	Fixed	
Regional GDP in residence	0.010	Fixed		0.030**	Fixed	
	(0.021)	Fixed		(0.012)	Fixed	
Female	-0.121	Fixed		0.046	Fixed	
	(0.091)	Fixed		(0.077)	Fixed	
Class membership prob.	0.578	0.422		0.423	0.577	
BIC/N	2.537			3.455		
Mc Fadden Pseudo R^2	0.677			0.567		
AIC/N	2.498			3.431		
Log Likelihood	-11178.3			-27831.3		
N	8991			16252		
N. Classes	2			2		

Notes: Latent Class Logit regressions estimated on the sample of Italian students enrolled for the first time in the academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For each field, the table reports the set of class-specific random utility parameters (β) and the class membership probability parameters θ. The mean parameter is computed as the average of class-specific parameter weighted for the class membership probability. Variable definitions are reported in Table 3.6.

Table 3.8e: Latent Class Logit results by field of study

	Social & Political sciences			Psychology		
	*Class*1	*Class*2	*Mean*	*Class*1	*Class*2	*Mean*
Random Utility Par. β						
E(Scholarship)/100	-0.033***	0.014***	-0.016	0.093***	-0.010***	0.021
	(0.002)	(0.002)		(0.017)	(0.004)	
E(Dormitory)/100	0.151***	-0.044	0.083	2.301***	0.131***	0.787
	(0.022)	(0.046)		(0.475)	(0.043)	
E(Student Package)/100	0.026	0.013	0.021	-1.735***	-0.335***	-0.758
	(0.019)	(0.016)		(0.375)	(0.027)	
Places in Canteen/100	0.034***	-0.002	0.021	-0.033*	-0.011***	-0.018
	(0.003)	(0.002)		(0.017)	(0.004)	
College	0.269***	0.453***	0.333	-0.256	0.291***	0.126
	(0.050)	(0.064)		(0.571)	(0.096)	
non-DSU Scholarship/100	0.024*	-0.088***	-0.016	-1.176***	0.278***	-0.161
	(0.012)	(0.013)		(0.317)	(0.028)	
E(non-DSU Dormitory)/100	0.219**	-1.105***	-0.243	-6.482***	0.215	-1.807
	(0.092)	(0.049)		(1.032)	(0.168)	
Excellence Departments	-0.024	1.022***	0.341	2.456**	-0.086	0.682
	(0.081)	(0.078)		(1.024)	(0.090)	
Academics/100	-0.327***	0.228***	-0.133	0.054	0.134**	0.110
	(0.032)	(0.033)		(0.186)	(0.056)	
Share of Intern. Academics	-0.227***	0.146***	-0.097	0.805***	0.553***	0.629
	(0.031)	(0.018)		(0.221)	(0.062)	
Administrative staff	0.035**	-0.207***	-0.050	-0.609***	-0.124***	-0.270
	(0.015)	(0.022)		(0.093)	(0.026)	
Field of study Academics/100	2.578***	1.419***	2.173	0.879	0.992***	0.958
	(0.207)	(0.211)		(0.732)	(0.173)	
Public funding (Mill.)	0.023***	0.0002	0.015	0.028***	0.0008	0.009
	(0.002)	(0.0017)		(0.009)	(0.0022)	
Average contribution	-0.068***	0.068***	-0.020	0.037***	-0.015***	0.0010
	(0.006)	(0.003)		(0.008)	(0.005)	
HEU in province	0.245***	1.398***	0.648	1.368***	0.723***	0.918
	(0.054)	(0.085)		(0.340)	(0.108)	
HEU in region	0.527***	1.139***	0.740	3.452***	0.946***	1.703
	(0.065)	(0.070)		(0.799)	(0.082)	
Unemployment	-0.038***	-0.158***	-0.080	-0.946***	-0.409***	-0.571
	(0.013)	(0.017)		(0.214)	(0.031)	
Distance	-0.054***	-0.011***	-0.039	-0.048***	-0.021***	-0.029
	(0.001)	(0.000)		(0.010)	(0.001)	
Distance^2/100	0.004***	0.0006***	0.003	0.003***	0.002***	0.002
	(0.000)	(0.0000)		(0.001)	(0.000)	
Housing price	0.023***	0.061***	0.036	0.426***	0.133***	0.221
	(0.009)	(0.008)		(0.077)	(0.017)	
Regional GDP	0.082***	-0.060***	0.033	-0.337***	-0.302***	-0.312
	(0.011)	(0.014)		(0.091)	(0.024)	
Class Probability Par. θ						
Const.	0.320	Fixed		4.946***	Fixed	
	(0.358)	Fixed		(0.905)	Fixed	
Diploma Grade	-0.023***	Fixed		-0.065***	Fixed	
	(0.002)	Fixed		(0.006)	Fixed	
CentreNorth	0.147	Fixed		-0.813*	Fixed	
	(0.167)	Fixed		(0.448)	Fixed	
HEU in residence	-0.194***	Fixed		0.142	Fixed	
	(0.059)	Fixed		(0.176)	Fixed	
Housing price in residence	0.061***	Fixed		-0.078***	Fixed	
	(0.008)	Fixed		(0.023)	Fixed	
Unemployment in residence	0.078***	Fixed		-0.027	Fixed	
	(0.013)	Fixed		(0.028)	Fixed	
Regional GDP in residence	0.018	Fixed		0.010	Fixed	
	(0.012)	Fixed		(0.033)	Fixed	
Female	0.032	Fixed		0.904***	Fixed	
	(0.051)	Fixed		(0.156)	Fixed	
Class membership prob.	0.651	0.349		0.302	0.698	
BIC/N	3.418			2.726		
Mc Fadden Pseudo R^2	0.605			0.614		
AIC/N	3.398			2.667		
Log Likelihood	-33488.1			-7364.6		
N	19739			5561		
N. Classes	2			2		

Notes: Latent Class Logit regressions estimated on the sample of Italian students enrolled for the first time in the academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For each field, the table reports the set of class-specific random utility parameters (β) and the class membership probability parameters θ. The mean parameter is computed as the average of class-specific parameter weighted for the class membership probability. Variable definitions are reported in Table 3.6.

Table 3.8f: Latent Class Logit results by field of study

	Engineering				
	Class1	*Class2*	*Class3*	*Class4*	*Mean*
Random Utility Par. β					
E(Scholarship)/100	-0.066***	-0.045***	0.023***	-1.409***	-0.024
	(0.008)	(0.006)	(0.004)	(0.018)	
E(Dormitory)/100	2.438***	1.532***	0.523***	3.143***	1.154
	(0.141)	(0.070)	(0.023)	(0.153)	
E(Student Package)/100	-0.075	0.866***	0.095***	14.398***	0.393
	(0.078)	(0.063)	(0.018)	(0.095)	
Places in Canteen/100	-0.103***	-0.079***	-0.018***	-0.087***	-0.050
	(0.013)	(0.005)	(0.002)	(0.008)	
College	-5.841***	4.006***	1.445***	15.830***	0.919
	(0.332)	(0.181)	(0.051)	(0.256)	
non-DSU Scholarship/100	0.196***	0.688***	-0.113***	3.102***	0.179
	(0.064)	(0.049)	(0.014)	(0.064)	
E(non-DSU Dormitory)/100	1.367***	-0.132**	0.064	-3.629***	0.216
	(0.191)	(0.062)	(0.039)	(0.306)	
Excellence Departments	-0.852***	-0.659***	1.007***	2.314***	0.251
	(0.192)	(0.118)	(0.048)	(0.198)	
Academics/100	0.173	0.413***	0.026	-1.550***	0.139
	(0.153)	(0.069)	(0.019)	(0.117)	
Share of Intern. Academics	-0.101	-0.323**	-0.897***	0.281	-0.593
	(0.094)	(0.145)	(0.029)	(0.242)	
Administrative staff	0.227***	0.305***	-0.176***	-2.356***	0.002
	(0.036)	(0.066)	(0.020)	(0.055)	
Field of study Academics/100	0.942***	1.778***	-0.362***	-7.464***	0.364
	(0.213)	(0.126)	(0.045)	(0.280)	
Public funding (Mill.)	-0.015*	-0.057***	0.004***	0.387***	-0.012
	(0.009)	(0.007)	(0.001)	(0.010)	
Average contribution	0.029***	-0.669***	-0.400***	0.706***	-0.382
	(0.007)	(0.027)	(0.009)	(0.011)	
HEU in province	0.941***	1.370***	1.509***	5.863	1.409
	(0.103)	(0.082)	(0.032)	(5.902)	
HEU in region	1.952***	1.523***	1.606***	17.108***	1.787
	(0.315)	(0.088)	(0.045)	(0.450)	
Unemployment	0.559***	-0.345***	-0.412***	4.579***	-0.174
	(0.037)	(0.054)	(0.015)	(0.054)	
Distance	-0.114***	-0.014***	-0.024***	-0.008***	-0.038
	(0.006)	(0.001)	(0.000)	(0.002)	
Distance^2/100	0.008**	0.0009***	0.002***	0.003***	0.003
	(0.003)	(0.0000)	(0.000)	(0.000)	
Housing price	0.075**	0.498***	0.234***	0.425***	0.275
	(0.036)	(0.024)	(0.007)	(0.044)	
Regional GDP	-0.026	-0.235***	0.038***	2.579***	-0.022
	(0.035)	(0.045)	(0.009)	(0.038)	
Class Probability Par. θ					
Const.	-2.126	-5.361***	7.686***	Fixed	
	(1.433)	(1.391)	(1.423)	Fixed	
Diploma Grade	0.0001	0.067***	-0.034***	Fixed	
	(0.0084)	(0.008)	(0.009)	Fixed	
CentreNorth	-1.849***	-1.042**	0.332	Fixed	
	(0.553)	(0.500)	(0.509)	Fixed	
HEU in residence	1.413***	1.255***	2.118***	Fixed	
	(0.331)	(0.329)	(0.330)	Fixed	
Housing price in residence	0.565***	0.508***	0.541***	Fixed	
	(0.045)	(0.045)	(0.045)	Fixed	
Unemployment in residence	0.054	-0.025	-0.244***	Fixed	
	(0.037)	(0.036)	(0.039)	Fixed	
Regional GDP in residence	0.080*	0.047	-0.070	Fixed	
	(0.047)	(0.043)	(0.044)	Fixed	
Female	-2.761***	-2.803***	-3.327***	Fixed	
	(0.204)	(0.203)	(0.207)	Fixed	
Class membership prob.	0.181	0.259	0.551	0.009	
BIC/N	3.052				
Mc Fadden Pseudo R^2	0.634				
AIC/N	3.024				
Log Likelihood	-49222.9				
N	32628				
N. Classes	4				

Notes: Latent Class Logit regressions estimated on the sample of Italian students enrolled for the first time in the academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For each field, the table reports the set of class-specific random utility parameters (β) and the class membership probability parameters θ. The mean parameter is computed as the average of class-specific parameter weighted for the class membership probability. Variable definitions are reported in Table 3.6.

These results confirm the heterogeneity in students' preferences based on the field of study chosen. Moreover, LCM's estimates suggest that there is substantial heterogeneity between different groups of students that depends upon students' characteristics. Indeed, the sign and the relative magnitude of random utility parameters change on the basis of the latent class estimated.

Focusing on the effect DSU's policies we can see that $E(Scholarship)$ has a positive coefficient in 6 fields considered while $E(Dormitory)$ and $E(StudentPackage)$ have, respectively, positive coefficients in 8 of the fields considered.[18] Moreover, the relative magnitude of the coefficients associated with places in-kind policies is most of the cases much higher than the one associated with $E(Scholarships)$. These results confirm our interpretation of CL results about the importance of places in dormitories and student packages in reducing substantially the costs sustained by students. Interestingly, we have that the effect of these policies changes among classes on the basis of individual characteristics. For example, considering Business & Statistics the estimated coefficient of $E(Dormitory)$ is positive for 72.3% of students whereas is negative for the remaining 27.7%. Moreover, if we consider the individual characteristics, we can note that this parameter is more likely to be positive if the student is female, resides in a region in the Centre-North and does not have an HEU in her city of residence. In the next section, we present a further interpretation of the relationship between our main variable of interest and individual characteristics of students. In this section, we focus on the average effect of the various determinants of students' utility analyzed.

With regards to non-DSU policies we can note that, differently from the CL estimates, LCM results indicate that the $E(non-DSUDormitory)$ have a positive effect in the majority of the field considered. However, $non-DSUScholarships$ have still a negative effect in 7 of 11 fields. Another difference between CL and LCM is related to the effect of colleges. Indeed, although the effect is heterogeneous among classes, we have that the presence of one college has a positive effect in all the fields considered except for Life & Natural Sciences.

With relationship to the other determinants of students' utility, we can highlight some interesting elements. Differently from the CL, the LCM estimates a positive and heterogeneous effect of the number of academics in 6 fields. However, the number of academics employed in the specific field is still more important than the general one and has a positive and very strong

[18]The coefficients related to $E(StudentPackage)$ in Social & Political sciences is not significant in both classes identified

effect in all the fields considered. Moreover, the results regarding the number of departments of excellence and the average contribution are confirmed: students tend to prefer universities with a higher quality of research and lower average contributions.

Concerning hosting areas' characteristics we have that LCM's results are, in general, in line with the one presented in the previous section. In particular, we have that students prefer HEUs located in their region or their province of residence or HEUs closer to their residence. Moreover, we can see that, in general, students prefer to locate in areas with a higher housing price, a lower unemployment rate, and a higher GDP. These elements confirm that students tend to locate in areas with better socio-economic conditions.

In the next sections, we further explore the effect of our main variable of interest exploiting the individual distribution of parameters to better understand the effect of these policies on specific groups of students.

Semi-elasticity results

Table 3.9 shows the results regarding the sensitivity of students' choice probabilities to DSU's indicators in terms of semi-elasticities computed according to Eq. (3.16) by considering the individual distribution of parameters. Each semi-elasticity measures the percentage change in students' choice probabilities caused by a 1% increase in the service indicator.

The results in Table 3.9 confirm the presence of heterogeneity in preferences that depend on the field of study chosen. Moreover, if we consider the average effect we can see that the results of CL and LCM are confirmed: only places in dormitories and student packages have a positive effect on students' choices probabilities. Indeed, a 1% increase in $E(Scholarship)$ is associated with an average decrease in choice probabilities of -0.125%. Another element to note is that the figures in the row *Average* are computed on the basis of the distribution of individual parameters using the entire sample of students. Therefore, although the results are heterogeneous in each field, these elasticities can be used to infer the behavioral response of the majority of students in our sample.

Given the individual distribution of parameters, we can explore how the effects of these policies change on the basis of individual characteristics. In this respect, Figure 3.1 reports the results of non parametric regressions between individual semi-elasticities and the percentile

Table 3.9: **Average semi-elasticities to DSU policies**

	Expected Scholarships	Expected Places in Dormitory	Expected Student Packages
Average	-0.125	0.176	0.163
Social & Political sciences	-0.203	0.036	0.034
Psychology	0.310	0.430	-0.984
Math. & Physical sciences	0.199	-0.003	0.389
Life & Natural sciences	0.141	-0.006	0.116
Law	-0.388	0.048	0.122
Languages	-0.124	0.043	-0.395
Humanities	-0.564	-0.024	0.179
Engineering	-0.415	0.716	0.756
Education	0.399	0.156	0.009
Chemistry & Pharmacy	0.573	0.073	0.502
Business & Statistics	-0.002	0.055	0.025

Notes: The table reports the average individual semi-elasticities computed using the parameters estimated with the Latent Class Logit model by field of study. Columns 1, 2 and 3 report the semi-elasticities with respect to a 1% increase in, respectively, Expected Scholarships, Expected Places in Dormitories and Expected Student Packages. Each semi-elasticity is computed according to formula (3.16).

distribution of high school diploma grades for female and male students. Figures 3A.1-3A.3 in the Appendix report the results of this exercise for each field of study considered.

The results in Figure 3.1 evidences a clear path. Indeed, the effect of these policies is always stronger in absolute terms for students with higher diploma grades. Moreover, we can note that male students are, on average, more interested in these policies. In fact, even though the semi-elasticities for scholarships are always negative, we can see that the effect is weaker for these students. This element is even clearer if we consider places in dormitories.

These results are very interesting. In fact, while confirming the positive effect of in-kind policies, these results highlight also that these policies are more effective in attracting students with better grades and, therefore, in increasing the average quality of students. For example, the semi-elasticity for students package range from 0.1 for male students at the bottom of diploma grades distribution to around 0.5 if we consider students at the top. Although there are differences in magnitude, this effect is confirmed for male and female students.

Willingness to travel results

In this section, we give a further interpretation of the results with respect to the effect of distance on students' utility and their willingness to travel (WTT). Table 3.10 reports the

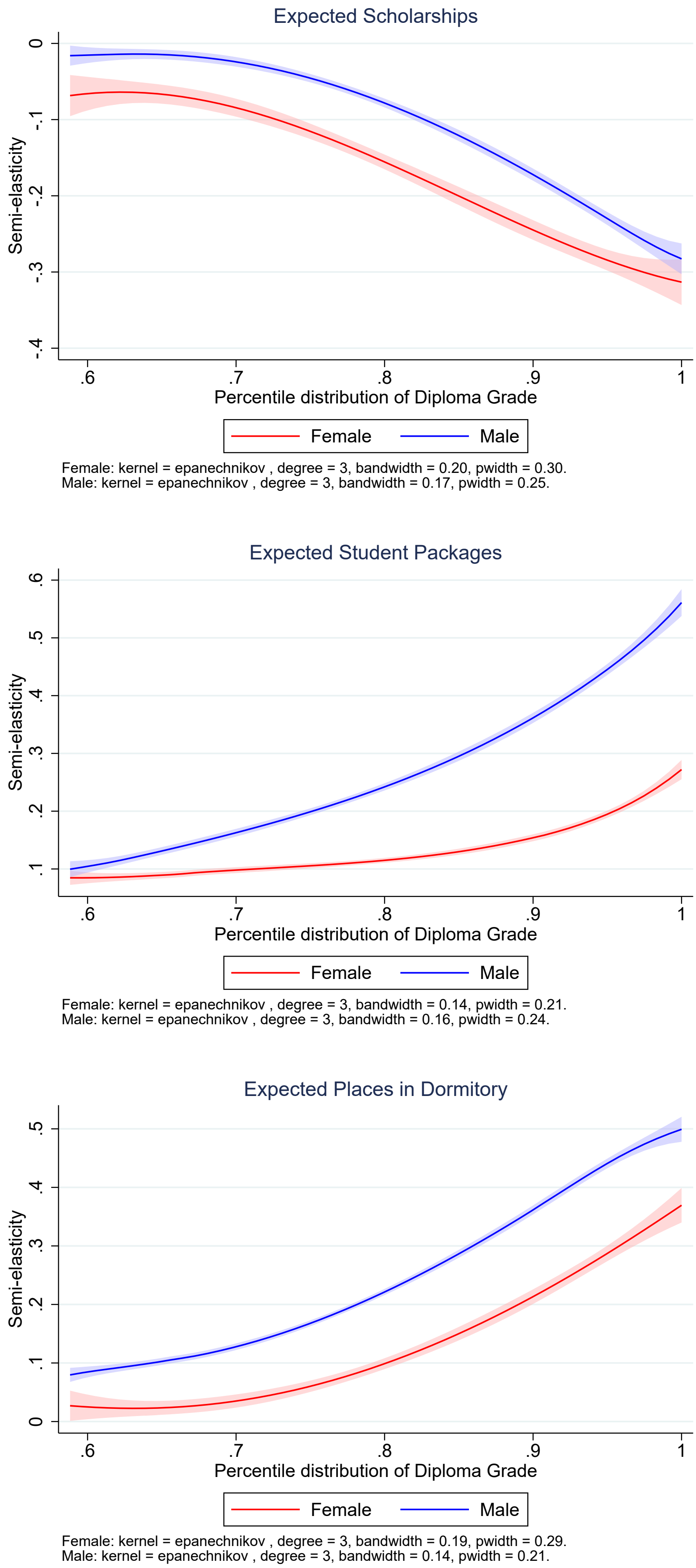


Figure 3.1: Individual semi-elasticities with respect to High School Diploma Grade

Notes: The figure reports the results of non parametric regressions between semi-elasticities with respect to DSU's policy indicators and the percentile distribution of high school diploma grade. The regressions are estimated considering the samples of male and female students. Semi-elasticities measure the percentage change in students' choices probabilities caused by a 1% increase in the DSU indicator. Each semi-elasticity is computed on the basis of the individual distribution of parameters estimated with the LCM. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

Table 3.10: Average willingness to travel for a 1% increase in DSU indicators

	Expected Scholarships	Expected Places in Dormitory	Expected Student Packages
Average	-0.1890	0.0474	0.0258
Social & Political sciences	0.0174	0.0249	0.0057
Psychology	0.1570	-0.6906	0.2536
Math. & Physical sciences	0.1089	0.1956	0.0004
Life & Natural sciences	0.1325	0.1200	0.0063
Law	-1.8494	0.7203	-0.0765
Languages	-0.2462	-0.2687	0.0077
Humanities	-0.2774	0.0670	-0.0045
Engineering	0.2300	-0.1501	0.0934
Education	0.2568	-0.0280	0.0992
Chemistry & Pharmacy	0.3905	0.2149	0.1004
Business & Statistics	-0.2255	0.0450	-0.0094

Notes: The table reports the average individual willingness to travel (WTT) computed according to the parameters estimated with the Latent Class Logit model by field of study. Each WTT measures the number of additional kilometers that the student is willing to travel from the chosen distance for a 1% increase in DSU indicators. Columns 1, 2 and 3 report the results with respect to, respectively, Expected Scholarships, Expected Places in Dormitories and Expected Student Packages. Each WTT is computed according to formula (3.17).

results regarding the average WTT of students for a 1% increase in DSU indicators. These measures are estimated according to the individual distribution of parameters using Eq. (3.17). Each WTT measures the additional number of kilometers that the student is willing to travel considering the chosen distance.

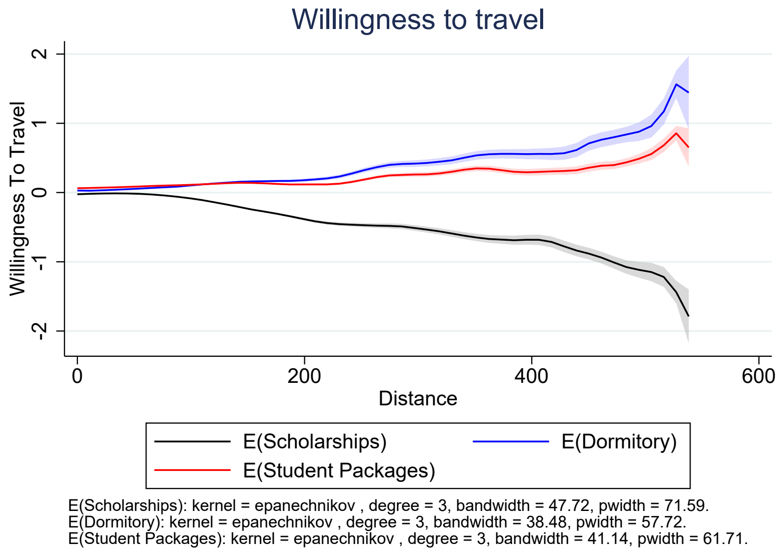
The figures in Table 3.10 confirm our previous results regarding the effect in terms of signs of our variables of interest. However, by comparing Tables 3.10 and 3.9 we can notice that the negative effect of $E(Scholarship)$ is stronger than the positive effect of $E(Dormitory)$ and $E(StudentPackage)$. This result is confirmed also by looking at the values for each field of study. For example, we have that the students' WTT for $E(StudentPackage)$ is lower than 0.001 (1 meter) in 5 fields considered. This result can be related to the disutility of distance. Indeed, the students that are more likely to be interested in these in-kind policies are those who have already traveled outside of their city to reach the university (out-of-site students). Therefore, given that the disutility of distance si increasing in the number of kilometers, we have that the ratio in Eq. (3.17) assumes lower values. This effect is clear if we look at Figure 3.2.

The first plot in Figure 3.2 reports the results of non parametric regressions estimated between individual WTT for DSU's indicators and the distance between students' city of residence and HEU's hosting city. The second plot reports the information regarding a non parametric regression of the estimated utility of distance. Figures 3A.4-3A.7 in Appendix report the results for each field of study considered. These plots are computed by using the individual distribution of parameters estimated with the LCM.

Results in Figure 3.2 confirm those of Table 3.10. Indeed, we can see that the effect of $E(Scholarship)$ is negative whereas those of $E(Dormitory)$ and $E(StudentPackage)$ are positive. Moreover, the effect related to $E(Dormitory)$ is stronger than the one of $E(StudentPackage)$ and the difference between their magnitude grows with the distance. Although the results for in-kind benefits are expected, the one related to scholarships is still counterintuitive. Indeed, the negative effect of this policy is stronger for students that have already traveled to reach their university. However, if we consider the absolute change in DSU indicators we can have a clearer picture. Indeed, as we can see from Table 3.1, a 1% increase in $E(Scholarship)$ indicate 25 additional scholarships whereas a 1% increase in $E(Dormitory)$ and $E(StudentPackage)$ means, respectively, 0.87 and 3.21 additional places. Therefore, if we consider the unitary effect we can see that, although negative, the effects related to $E(Scholarship)$ are much lower than those of in-kind benefits.

Figure 3.3 reports the result of non parametric regressions between individual WTT and distance by splitting the sample on the basis of students' macroregion of residence. The results of these regressions confirm those shown in Figure 3.2. Indeed, the effect related to $E(Dormitory)$ and $E(StudentPackage)$ is positive in all the sample considered. Moreover, we can see that the magnitude of WTTs associated with the former policy is stronger than those associated with $E(StudentPackage)$. With respect to the macroregion of residence, we can see that DSU's policies have a stronger effect on students in Centre-North. This difference increases with the number of kilometers traveled by the students.

Although the magnitude of the effects is small, these results indicate that in-kind policies can be more attractive for students who reside in Centre-North that have already traveled more than 200 kilometers. Therefore, these policies can be a useful tool to attract students that have already decided to move outside their region. However, the magnitude of the WTTs suggests that, to have a relevant effect on these students, DSU offices need to strongly increase their



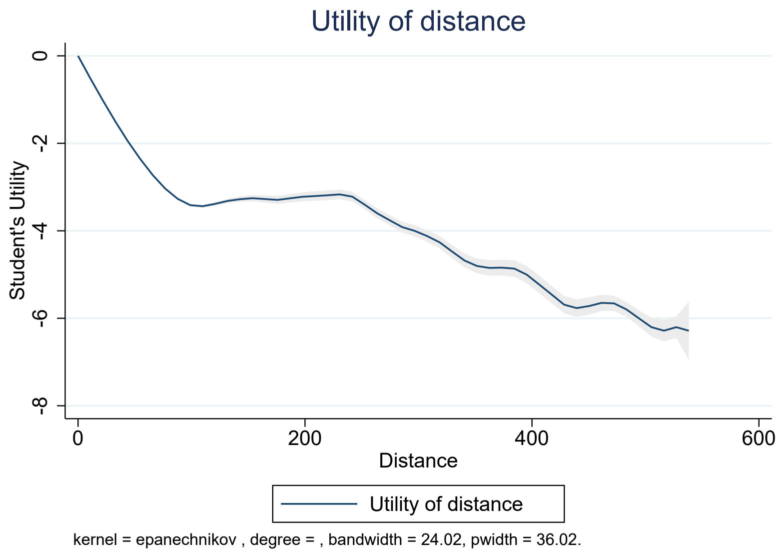


Figure 3.2: Individual willingness to travel and utility of distance

Notes: The first plot of the figure reports the result of a non parametric regression between individual WTT to DSU's policies indicators and the distance between students' city of residence and HEU's hosting city. The second plot reports the result of a non parametric regression between individual utility functions and the distance between students' city of residence and HEU's hosting city. Each regression is estimated using the individual distribution of parameters estimated through the LCM. Each WTT measures the number of additional kilometers that the student is willing to travel with respect to the chosen HEU for a 1% increase in DSU policy indicators. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

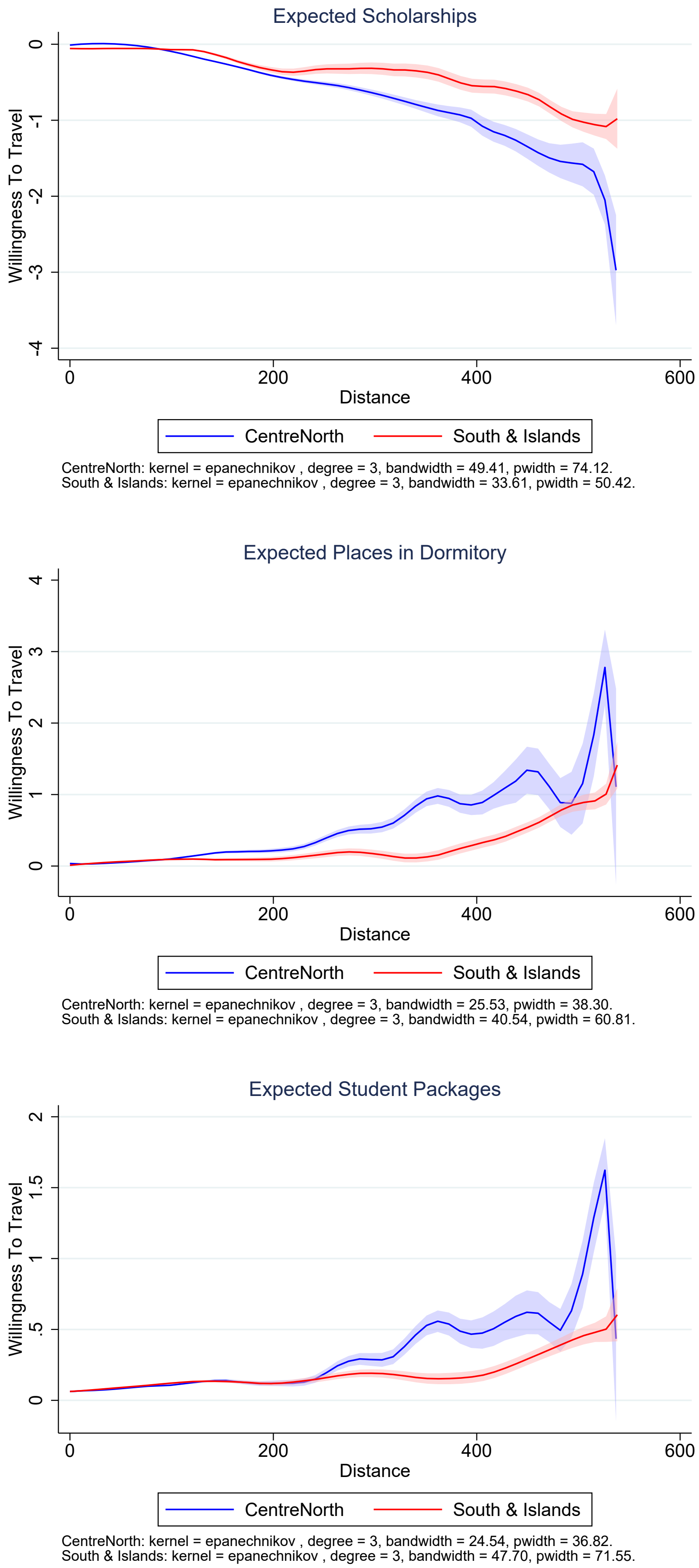


Figure 3.3: Individual willingness to travel by macroregion of residence

Notes: The figure reports, for each student's macroregion of residence, the result of a non parametric regression between individual WTT with respect to DSU's policy indicators and the distance between students' city of residence and HEU's hosting city. Each regression is estimated using the individual distribution of parameters estimated through the LCM. Each WTT measures the number of additional kilometers that the student is willing to travel with respect to the chosen HEU for a 1% increase in DSU's services supply. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

supply of in-kind benefits.

3.7 Conclusion

In this study, we have investigated the effect of financial and in-kind aid programs on the location decision process of Italian high school leavers that decide to enroll in an Italian university.

The phenomenon has been analyzed by using administrative data regarding the entire population of students enrolled in an Italian university in the academic year 2014-2015 for the first time. This data has been linked with a dataset containing detailed information regarding the financial and in-kind aid program called *Diritto allo studio universitario*. This unique dataset has permitted to separately consider the effects of the different services provided by the program.

The empirical analysis has been carried by accounting explicitly for the existence of heterogeneity in students' preferences. In particular, we have split the entire sample of Italian students according to their field of study in 11 groups: business & statistics, chemistry & pharmacy, education, engineering, humanities, languages, law, life & natural sciences, mathematical and physical sciences, psychology, social & political sciences. Moreover, we have taken advantage of a discrete choice Latent Class Logit model. This approach has permitted to explore the heterogeneity in students' preferences caused by differences in individual characteristics. This is the first work that considers this approach in modeling students' location choices.

The estimates have been exploited by computing students' willingness to travel measures and semi-elasticities, this way allowing for a better interpretation of Latent Class Logit results.

Our results provide clear evidence of the existence of heterogeneity in students' preferences regarding aid policies and university characteristics among different fields and with respect to their individual characteristics. This result calls for further investigation into students' preferences heterogeneity in order to have a better understanding of the elements that affect universities' attractiveness. In this way will be possible to target the policies to more sensitive groups and to have more effective instruments to improve universities' attractiveness.

With respect to the effect of financial and in-kind aid policies, our results suggest that scholarships alone are not an effective instrument in attracting more students at the destination universities. In fact, willingness to pay estimates indicate that students are almost insensitive or negatively affected by the number of expected scholarships. This result can be related to the fact that these policies are not able to cover the entire students' migration and locations costs. These results are confirmed by semi-elasticity results. In fact, we have found that choice probabilities are negatively affected by scholarships. Moreover, this effect is stronger for female students and students at the top of the diploma grade distribution.

Concerning places in dormitories with and without scholarships we have a different picture. In this case, we have found that in-kind policies have a positive effect on students choice probabilities. These results are confirmed both using semi-elasticities measures and WTT. However, the magnitude of WTTs suggest that DSUs offices should increase significantly their supply of in-kind services in order to attract students that reside in very distant areas. With respect to the results in terms of semi-elasticities we can highlight some interesting elements. First, the effect of in-kind policies is stronger for male students than for female students. Second, the effect of these policies increase when student's diploma grade increases. This last effect is even clearer if we consider student packages.

Therefore, this study has provided evidence on the effectiveness of financial and in-kind services in attracting high school leavers that decide to enroll in an Italian university. Our results suggest that scholarships alone are not enough but that they need to be provided along with places in dormitories to be effective. Moreover, this combination is stronger for students with better grades, this way suggesting that an increase in DSU's service supply can improve the average quality of the students in the area in which the services are provided.

3.7.1 Scope for future research

This study has provided evidence of the presence of heterogeneity in students' preferences. However, a better understanding of this phenomenon could be reached by considering more detailed information on students' individual characteristics and university characteristics. In particular, a better proxy of students' performances in high school could be useful to understand the effect of DSU policies on the average quality of students.

Moreover, one clear step forward in the understanding the determinants of students' location choices could be to model the possibility for students to opt-out from the Italian Higher Education system. These choices can be investigated by using accessible administrative data regarding Italian high school leavers in general and their family background.[19]

[19]e.g. see Dardanoni, Laudicella, and Li Donni (2018) that have investigated patients' hospital choices in the National Health Service system in England.

Appendix

3.A Appendix

Table 3A.1: Conditional Logit Estimates: Interactions with individual variables

	Chemistry & Pharmacy	Business & Statistics	Life & Natural sciences	Engineering	Law	Education
E(Scholarship)/100	0.005	0.065***	-0.003	-0.020	0.025*	0.005
	(0.018)	(0.009)	(0.016)	(0.013)	(0.013)	(0.042)
E(Scholarship)/100 × CentreNorth	-0.031	-0.040***	0.0008	-0.213***	-0.006	0.002
	(0.023)	(0.011)	(0.0191)	(0.028)	(0.017)	(0.049)
E(Scholarship)/100 × Female	0.017***	0.002	-0.002	0.0010	0.003	-0.019
	(0.004)	(0.002)	(0.003)	(0.0027)	(0.002)	(0.012)
E(Scholarship)/100 × Higher Unemp. in res.	0.025	-0.069***	0.0004	-0.016	-0.042***	0.046
	(0.017)	(0.009)	(0.0161)	(0.013)	(0.013)	(0.040)
E(Scholarship)/100 × Higher GDP in res.	0.040**	0.004	0.011	0.241***	-0.006	0.040
	(0.016)	(0.007)	(0.011)	(0.026)	(0.010)	(0.042)
E(Scholarship)/100 × Higher Housing Price in res.	-0.011	-0.009***	-0.013**	0.027***	-0.012***	0.004
	(0.008)	(0.003)	(0.006)	(0.005)	(0.003)	(0.017)
E(Scholarship)/100 × HEU in residence	0.012	-0.009***	0.010**	0.009***	-0.002	-0.003
	(0.008)	(0.002)	(0.004)	(0.003)	(0.003)	(0.014)
E(Scholarship)/100 × Grade: 76-85	0.005	-0.009***	0.003	-0.002	-0.008***	-0.0004
	(0.005)	(0.002)	(0.004)	(0.003)	(0.003)	(0.0069)
E(Scholarship)/100 × Grade: 86-95	0.006	-0.013***	0.005	-0.012***	-0.008***	-0.001
	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.009)
E(Scholarship)/100 × Grade: 96-102	0.005	-0.011***	0.010**	-0.015***	-0.018***	-0.044***
	(0.007)	(0.003)	(0.005)	(0.003)	(0.004)	(0.015)
E(Dormitory)/100	0.241	0.559***	0.176	0.606***	0.100	-0.619
	(0.208)	(0.110)	(0.141)	(0.101)	(0.187)	(1.098)
E(Dormitory)/100 × CentreNorth	-0.399	-0.498***	0.096	-0.965***	0.112	-0.115
	(0.283)	(0.123)	(0.171)	(0.154)	(0.231)	(1.109)
E(Dormitory)/100 × Female	0.122***	0.024	-0.009	-0.071***	0.001	-0.018
	(0.035)	(0.020)	(0.028)	(0.025)	(0.028)	(0.255)
E(Dormitory)/100 × Higher Unemp. in res.	0.100	-0.534***	-0.027	-0.431***	-0.007	0.381
	(0.203)	(0.108)	(0.139)	(0.099)	(0.185)	(1.065)
E(Dormitory)/100 × Higher GDP in res.	0.163	0.036	-0.315***	0.436***	-0.229	1.592**
	(0.199)	(0.072)	(0.103)	(0.128)	(0.139)	(0.623)
E(Dormitory)/100 × Higher Housing Price in res.	-0.012	-0.065***	-0.098***	0.101***	0.141***	0.209
	(0.045)	(0.023)	(0.038)	(0.033)	(0.034)	(0.315)
E(Dormitory)/100 × HEU in residence	0.153**	0.077***	-0.016	0.122***	0.136***	-0.539
	(0.068)	(0.027)	(0.042)	(0.031)	(0.038)	(0.339)
E(Dormitory)/100 × Grade: 76-85	-0.029	0.049**	-0.005	0.116***	0.052	0.401***
	(0.041)	(0.023)	(0.032)	(0.028)	(0.032)	(0.136)
E(Dormitory)/100 × Grade: 86-95	-0.025	0.039	0.028	0.163***	0.070*	0.484***
	(0.047)	(0.028)	(0.038)	(0.031)	(0.038)	(0.183)
E(Dormitory)/100 × Grade: 96-102	-0.052	0.047	0.082*	0.314***	0.166***	0.556**
	(0.053)	(0.033)	(0.043)	(0.032)	(0.044)	(0.284)
E(Student Pkg)/100	-0.278**	-0.221***	-0.131*	0.234***	0.113	-0.244
	(0.113)	(0.051)	(0.073)	(0.066)	(0.073)	(0.256)
E(Student Pkg)/100 × CentreNorth	0.470**	0.256***	0.549***	1.017***	0.063	0.832**
	(0.190)	(0.061)	(0.099)	(0.124)	(0.122)	(0.366)
E(Student Pkg)/100 × Female	-0.0002	0.018	-0.030	-0.034*	0.002	-0.185*
	(0.0314)	(0.012)	(0.021)	(0.019)	(0.016)	(0.105)
E(Student Pkg)/100 × Higher Unemp. in res.	0.360***	0.362***	0.344***	0.229***	-0.032	0.321
	(0.108)	(0.050)	(0.071)	(0.064)	(0.072)	(0.236)
E(Student Pkg)/100 × Higher GDP in res.	0.133	-0.059	-0.329***	-0.919***	-0.092	-0.385
	(0.161)	(0.043)	(0.077)	(0.110)	(0.101)	(0.352)
E(Student Pkg)/100 × Higher Housing Price in res.	-0.031	-0.069***	-0.145***	-0.392***	-0.045**	-0.116
	(0.037)	(0.020)	(0.043)	(0.025)	(0.020)	(0.134)
E(Student Pkg)/100 × HEU in residence	-0.029	-0.055***	0.042	-0.041*	-0.064***	0.165
	(0.064)	(0.014)	(0.030)	(0.023)	(0.021)	(0.129)
E(Student Pkg)/100 × Grade: 76-85	-0.026	-0.051***	-0.007	-0.026	0.018	0.023
	(0.037)	(0.014)	(0.024)	(0.021)	(0.019)	(0.060)
E(Student Pkg)/100 × Grade: 86-95	-0.045	-0.025	0.005	0.032	-0.016	-0.011
	(0.041)	(0.017)	(0.028)	(0.023)	(0.022)	(0.086)
E(Student Pkg)/100 × Grade: 96-102	-0.017	-0.040**	-0.056*	-0.006	-0.071***	-0.106
	(0.044)	(0.019)	(0.031)	(0.024)	(0.026)	(0.125)
Pl. in Canteen/100	0.018	0.055***	-0.031***	0.025***	0.004	0.061**
	(0.016)	(0.005)	(0.011)	(0.005)	(0.009)	(0.024)
Pl. in Canteen/100 × CentreNorth	-0.060***	-0.014**	0.013	-0.076***	-0.029**	-0.073**
	(0.021)	(0.007)	(0.013)	(0.008)	(0.013)	(0.031)
Pl. in Canteen/100 × Female	-0.002	-0.002	-0.001	-0.002	-0.00007	0.006
	(0.005)	(0.002)	(0.003)	(0.002)	(0.00247)	(0.010)

	Chemistry & Pharmacy	Business & Statistics	Life & Natural sciences	Engineering	Law	Education
Pl. in Canteen/100 × Higher Unemp. in res.	-0.033**	-0.004	0.035***	-0.009*	0.014	-0.080***
	(0.015)	(0.005)	(0.011)	(0.005)	(0.009)	(0.022)
Pl. in Canteen/100 × Higher GDP in res.	0.036**	-0.008	0.044***	0.014**	0.036***	0.034
	(0.015)	(0.005)	(0.008)	(0.007)	(0.009)	(0.027)
Pl. in Canteen/100 × Higher Housing Price in res.	-0.015**	0.0005	0.001	0.018***	-0.002	0.006
	(0.006)	(0.0025)	(0.005)	(0.003)	(0.003)	(0.012)
Pl. in Canteen/100 × HEU in residence	-0.018**	-0.015***	-0.004	-0.007***	-0.018***	0.014
	(0.009)	(0.003)	(0.005)	(0.003)	(0.003)	(0.012)
Pl. in Canteen/100 × Grade: 76-85	0.008	-0.001	-0.004	0.002	0.004	-0.0008
	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)	(0.0062)
Pl. in Canteen/100 × Grade: 86-95	0.009	-0.006**	-0.008*	0.005*	0.006*	0.007
	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.009)
Pl. in Canteen/100 × Grade: 96-102	0.014**	-0.005*	0.003	0.009***	0.003	0.005
	(0.007)	(0.003)	(0.005)	(0.003)	(0.004)	(0.016)
College	-1.058**	0.081	-1.405***	0.748***	0.067	-4.660***
	(0.465)	(0.151)	(0.277)	(0.162)	(0.332)	(0.723)
College × CentreNorth	0.223	0.309	0.382	1.660***	1.443***	5.269***
	(0.776)	(0.239)	(0.420)	(0.292)	(0.503)	(0.823)
College × Female	-0.424***	-0.026	-0.048	0.108**	-0.069	0.019
	(0.096)	(0.040)	(0.070)	(0.052)	(0.058)	(0.248)
College × Higher Unemp. in res.	0.847*	0.224	0.553**	-0.116	-0.530	3.506***
	(0.450)	(0.143)	(0.265)	(0.154)	(0.327)	(0.660)
College × Higher GDP in res.	1.501**	-0.737***	0.818**	-0.908***	-1.054***	0.113
	(0.640)	(0.202)	(0.337)	(0.261)	(0.386)	(0.843)
College × Higher Housing Price in res.	0.249**	0.258***	0.078	-0.336***	0.651***	-0.138
	(0.122)	(0.052)	(0.100)	(0.065)	(0.070)	(0.285)
College × HEU in residence	0.028	0.178***	-0.139	0.205***	-0.494***	0.868***
	(0.176)	(0.051)	(0.098)	(0.063)	(0.081)	(0.289)
College × Grade: 76-85	0.178	0.160***	0.043	0.049	0.042	-0.118
	(0.112)	(0.046)	(0.081)	(0.057)	(0.067)	(0.140)
College × Grade: 86-95	0.071	0.344***	0.476***	0.240***	0.118	0.148
	(0.128)	(0.057)	(0.095)	(0.064)	(0.079)	(0.200)
College × Grade: 96-102	0.277*	0.474***	0.572***	0.531***	0.230**	0.239
	(0.144)	(0.066)	(0.106)	(0.068)	(0.095)	(0.319)
non-DSU Scholar./100	-0.178*	-0.303***	-0.208***	0.078**	-0.236***	0.325**
	(0.108)	(0.037)	(0.065)	(0.039)	(0.072)	(0.159)
non-DSU Scholar./100 × CentreNorth	0.434***	-0.005	-0.029	0.296***	0.248***	0.034
	(0.134)	(0.045)	(0.073)	(0.071)	(0.092)	(0.201)
non-DSU Scholar./100 × Female	-0.121***	-0.030***	0.014	0.006	0.0006	0.047
	(0.021)	(0.010)	(0.015)	(0.013)	(0.0147)	(0.072)
non-DSU Scholar./100 × Higher Unemp. in res.	-0.058	0.247***	0.151**	0.122***	0.269***	-0.297**
	(0.104)	(0.035)	(0.062)	(0.035)	(0.071)	(0.138)
non-DSU Scholar./100 × Higher GDP in res.	-0.352***	0.124***	0.302***	-0.358***	-0.162***	-0.345*
	(0.086)	(0.032)	(0.041)	(0.064)	(0.060)	(0.197)
non-DSU Scholar./100 × Higher Housing Price in res.	0.045	0.024**	0.021	0.048**	0.103***	-0.117
	(0.028)	(0.012)	(0.022)	(0.020)	(0.020)	(0.075)
non-DSU Scholar./100 × HEU in residence	-0.078**	0.043***	-0.040**	-0.032**	-0.012	0.094
	(0.035)	(0.012)	(0.019)	(0.015)	(0.019)	(0.074)
non-DSU Scholar./100 × Grade: 76-85	-0.025	0.076***	-0.011	0.015	0.003	-0.053
	(0.024)	(0.011)	(0.017)	(0.015)	(0.017)	(0.040)
non-DSU Scholar./100 × Grade: 86-95	-0.017	0.154***	-0.021	0.029*	0.020	-0.0005
	(0.028)	(0.014)	(0.020)	(0.016)	(0.020)	(0.0590)
non-DSU Scholar./100 × Grade: 96-102	-0.004	0.156***	-0.026	0.012	0.040*	0.051
	(0.033)	(0.016)	(0.022)	(0.017)	(0.023)	(0.088)
E(non-DSU Dorm.)/100	0.480	0.324**	3.610***	-0.504***	0.490**	1.494
	(1.082)	(0.127)	(0.395)	(0.117)	(0.200)	(1.350)
E(non-DSU Dorm.)/100 × CentreNorth	-0.476	0.142	-4.681***	0.882***	-0.374	-1.161
	(1.437)	(0.154)	(0.589)	(0.171)	(0.272)	(1.443)
E(non-DSU Dorm.)/100 × Female	-0.675***	-0.065	-0.181	-0.034	0.008	1.270***
	(0.229)	(0.040)	(0.124)	(0.032)	(0.056)	(0.404)
E(non-DSU Dorm.)/100 × Higher Unemp. in res.	-2.636**	-0.064	-3.705***	-0.229**	-0.109	-2.836**
	(1.052)	(0.119)	(0.380)	(0.112)	(0.192)	(1.286)
E(non-DSU Dorm.)/100 × Higher GDP in res.	-1.719*	-0.660***	1.132**	-0.504***	0.210	-1.008
	(1.044)	(0.115)	(0.486)	(0.140)	(0.203)	(1.354)
E(non-DSU Dorm.)/100 × Higher Housing Price in res.	0.867**	0.479***	0.040	-0.075*	0.224***	1.848***
	(0.393)	(0.059)	(0.237)	(0.039)	(0.085)	(0.488)
E(non-DSU Dorm.)/100 × HEU in residence	-0.602	0.289***	-0.100	0.270***	0.220***	0.157
	(0.419)	(0.046)	(0.175)	(0.038)	(0.070)	(0.502)
E(non-DSU Dorm.)/100 × Grade: 76-85	-0.124	0.057	0.050	0.136***	0.173**	-0.076
	(0.270)	(0.048)	(0.147)	(0.039)	(0.069)	(0.220)
E(non-DSU Dorm.)/100 × Grade: 86-95	-0.082	-0.079	0.286*	0.227***	0.247***	0.065
	(0.301)	(0.054)	(0.162)	(0.042)	(0.079)	(0.301)
E(non-DSU Dorm.)/100 × Grade: 96-102	-0.512	-0.216***	0.308*	0.391***	0.373***	0.343
	(0.333)	(0.061)	(0.181)	(0.041)	(0.087)	(0.461)
Excellence Dept.	-0.905***	0.797***	1.060***	0.703***	0.390***	-0.751
	(0.301)	(0.093)	(0.147)	(0.151)	(0.125)	(0.716)
Excellence Dept. × CentreNorth	1.108***	-0.230**	-0.600***	2.467***	-0.018	0.004
	(0.377)	(0.105)	(0.162)	(0.293)	(0.136)	(0.705)
Excellence Dept. × Female	-0.298***	-0.036	-0.101***	-0.092**	-0.006	-0.303*
	(0.062)	(0.023)	(0.034)	(0.043)	(0.032)	(0.179)
Excellence Dept. × Higher Unemp. in res.	0.252	-0.322***	-1.004***	-0.724***	-0.112	1.455**
	(0.289)	(0.089)	(0.143)	(0.145)	(0.118)	(0.689)
Excellence Dept. × Higher GDP in res.	-0.652***	-0.408***	-0.388***	-2.585***	-0.206***	0.648
	(0.248)	(0.068)	(0.084)	(0.270)	(0.076)	(0.491)
Excellence Dept. × Higher Housing Price in res.	0.215**	-0.453***	-0.039	-0.290***	-0.172***	-0.131
	(0.085)	(0.030)	(0.046)	(0.059)	(0.046)	(0.203)
Excellence Dept. × HEU in residence	-0.122	-0.075***	-0.061	-0.002	0.518***	-0.556***
	(0.103)	(0.029)	(0.045)	(0.050)	(0.038)	(0.202)
Excellence Dept. × Grade: 76-85	0.023	-0.079***	0.127***	0.086*	0.005	0.205**
	(0.071)	(0.027)	(0.039)	(0.048)	(0.038)	(0.096)
Excellence Dept. × Grade: 86-95	0.125	-0.067**	0.228***	0.278***	0.041	0.012
	(0.086)	(0.033)	(0.046)	(0.054)	(0.046)	(0.135)
Excellence Dept. × Grade: 96-102	-0.007	-0.056	0.298***	0.316***	-0.011	0.365*
	(0.099)	(0.039)	(0.054)	(0.056)	(0.053)	(0.219)
Academics/100	0.255	0.120**	-0.194*	-0.528***	0.262**	0.667
	(0.326)	(0.061)	(0.107)	(0.064)	(0.124)	(0.469)
Academics/100 × CentreNorth	-0.223	0.028	-0.024	-0.607***	-0.474***	-0.281
	(0.419)	(0.080)	(0.130)	(0.109)	(0.153)	(0.466)
Academics/100 × Female	0.202***	0.003	-0.022	0.079***	0.007	-0.215
	(0.069)	(0.017)	(0.031)	(0.024)	(0.024)	(0.157)

	Chemistry & Pharmacy	Business & Statistics	Life & Natural sciences	Engineering	Law	Education
Academics/100 × Higher Unemp. in res.	-0.710**	-0.178***	-0.116	0.397***	-0.296**	-0.488
	(0.317)	(0.057)	(0.099)	(0.057)	(0.121)	(0.442)
Academics/100 × Higher GDP in res.	0.035	0.152**	0.161*	0.628***	0.301***	-0.158
	(0.299)	(0.063)	(0.090)	(0.101)	(0.101)	(0.330)
Academics/100 × Higher Housing Price in res.	-0.181	-0.064***	-0.009	0.351***	-0.111***	-0.284
	(0.121)	(0.023)	(0.045)	(0.038)	(0.031)	(0.176)
Academics/100 × HEU in residence	-0.202*	-0.088***	-0.098**	-0.165***	0.014	-0.028
	(0.119)	(0.021)	(0.039)	(0.026)	(0.031)	(0.199)
Academics/100 × Grade: 76-85	0.062	-0.016	0.042	-0.011	-0.048*	-0.061
	(0.082)	(0.021)	(0.038)	(0.027)	(0.029)	(0.092)
Academics/100 × Grade: 86-95	0.019	-0.034	0.007	-0.042	0.008	-0.062
	(0.092)	(0.025)	(0.043)	(0.030)	(0.034)	(0.134)
Academics/100 × Grade: 96-102	-0.054	-0.022	0.139***	-0.098***	-0.020	-0.079
	(0.098)	(0.029)	(0.042)	(0.031)	(0.039)	(0.221)
Share of Intern. Acad.	-0.434	-0.268***	-0.425**	0.047	-0.657***	-1.714***
	(0.486)	(0.054)	(0.177)	(0.096)	(0.107)	(0.297)
Share of Intern. Acad. × CentreNorth	-0.689	0.113*	0.425**	-0.526***	0.362***	0.851***
	(0.654)	(0.061)	(0.197)	(0.143)	(0.131)	(0.299)
Share of Intern. Acad. × Female	-0.255***	0.002	-0.071*	0.072**	-0.005	-0.110
	(0.075)	(0.013)	(0.042)	(0.033)	(0.023)	(0.146)
Share of Intern. Acad. × Higher Unemp. in res.	-0.067	0.143***	-0.034	-0.303***	0.517***	0.800***
	(0.475)	(0.051)	(0.168)	(0.090)	(0.104)	(0.220)
Share of Intern. Acad. × Higher GDP in res.	1.015**	-0.022	0.129	-0.013	0.122	0.830***
	(0.450)	(0.040)	(0.102)	(0.118)	(0.082)	(0.257)
Share of Intern. Acad. × Higher Housing Price in res.	-0.211**	0.040**	-0.124**	-0.053	0.075**	-0.666***
	(0.091)	(0.017)	(0.055)	(0.036)	(0.030)	(0.130)
Share of Intern. Acad. × HEU in residence	-0.408***	0.091***	0.157***	-0.136***	-0.017	0.349**
	(0.143)	(0.015)	(0.056)	(0.042)	(0.029)	(0.154)
Share of Intern. Acad. × Grade: 76-85	-0.055	0.157***	-0.038	-0.054	0.201***	0.003
	(0.085)	(0.016)	(0.048)	(0.034)	(0.031)	(0.085)
Share of Intern. Acad. × Grade: 86-95	-0.295***	0.261***	-0.001	-0.069*	0.286***	0.085
	(0.110)	(0.019)	(0.057)	(0.040)	(0.034)	(0.121)
Share of Intern. Acad. × Grade: 96-102	-0.178	0.360***	0.067	-0.041	0.406***	0.194
	(0.132)	(0.021)	(0.064)	(0.041)	(0.037)	(0.182)
Admin. staff	-0.250**	-0.147***	0.115*	-0.081*	-0.191***	-0.136
	(0.116)	(0.047)	(0.060)	(0.044)	(0.064)	(0.237)
Admin. staff × CentreNorth	0.216	0.066	-0.040	0.419***	0.269***	-0.022
	(0.135)	(0.063)	(0.075)	(0.099)	(0.093)	(0.237)
Admin. staff × Female	-0.097***	-0.006	-0.009	-0.023*	-0.003	0.172**
	(0.033)	(0.011)	(0.017)	(0.014)	(0.013)	(0.086)
Admin. staff × Higher Unemp. in res.	0.075	0.201***	-0.070	0.184***	0.229***	-0.121
	(0.109)	(0.046)	(0.056)	(0.042)	(0.063)	(0.214)
Admin. staff × Higher GDP in res.	-0.017	-0.192***	-0.122**	-0.303***	-0.172**	-0.364*
	(0.097)	(0.047)	(0.056)	(0.094)	(0.074)	(0.191)
Admin. staff × Higher Housing Price in res.	0.080*	0.044***	0.099***	0.028*	0.049***	0.121
	(0.046)	(0.015)	(0.024)	(0.016)	(0.018)	(0.099)
Admin. staff × HEU in residence	0.142**	0.064***	-0.029	0.084***	0.013	0.129
	(0.058)	(0.014)	(0.023)	(0.019)	(0.019)	(0.108)
Admin. staff × Grade: 76-85	-0.012	-0.0006	-0.037*	0.064***	0.052***	-0.106**
	(0.038)	(0.0130)	(0.019)	(0.016)	(0.016)	(0.051)
Admin. staff × Grade: 86-95	0.028	0.001	0.004	0.092***	0.061***	-0.149*
	(0.043)	(0.016)	(0.022)	(0.018)	(0.018)	(0.076)
Admin. staff × Grade: 96-102	-0.050	-0.022	-0.002	0.172***	0.105***	-0.029
	(0.047)	(0.018)	(0.024)	(0.018)	(0.021)	(0.115)
Field Academics/100	1.538*	-0.148	1.390***	-0.289***	1.345***	1.329
	(0.828)	(0.247)	(0.325)	(0.082)	(0.358)	(1.692)
Field Academics/100 × CentreNorth	-2.452**	1.073***	-0.802**	-0.937***	-0.535	-0.110
	(1.034)	(0.297)	(0.392)	(0.163)	(0.435)	(1.770)
Field Academics/100 × Female	0.269	0.103**	-0.065	-0.009	-0.080	0.111
	(0.214)	(0.048)	(0.074)	(0.020)	(0.093)	(0.422)
Field Academics/100 × Higher Unemp. in res.	0.236	0.649***	-0.602*	0.402***	-0.632*	-1.905
	(0.786)	(0.241)	(0.318)	(0.080)	(0.344)	(1.641)
Field Academics/100 × Higher GDP in res.	1.921***	-0.431**	0.318	1.010***	-0.168	-2.534**
	(0.742)	(0.206)	(0.249)	(0.148)	(0.296)	(1.112)
Field Academics/100 × Higher Housing Price in res.	-0.144	0.633***	-0.654***	0.171***	0.111	1.389***
	(0.325)	(0.059)	(0.122)	(0.027)	(0.135)	(0.470)
Field Academics/100 × HEU in residence	1.590***	0.031	0.391***	-0.044*	0.276**	0.218
	(0.389)	(0.058)	(0.099)	(0.025)	(0.122)	(0.477)
Field Academics/100 × Grade: 76-85	0.008	-0.044	-0.008	0.026	-0.106	-0.181
	(0.249)	(0.058)	(0.085)	(0.023)	(0.110)	(0.248)
Field Academics/100 × Grade: 86-95	0.377	-0.293***	0.036	-0.015	-0.343***	-0.361
	(0.284)	(0.068)	(0.101)	(0.026)	(0.127)	(0.352)
Field Academics/100 × Grade: 96-102	0.181	-0.511***	-0.100	0.017	-0.546***	-0.910
	(0.315)	(0.081)	(0.114)	(0.026)	(0.145)	(0.587)
Pub. funding (Mill.)	0.005	-0.003	-0.015*	0.044***	-0.008	-0.048
	(0.030)	(0.003)	(0.008)	(0.005)	(0.007)	(0.044)
Pub. funding (Mill.) × CentreNorth	0.003	-0.006*	0.019**	0.030***	0.013*	0.013
	(0.036)	(0.004)	(0.009)	(0.009)	(0.008)	(0.045)
Pub. funding (Mill.) × Female	-0.008	-0.0007	0.003	-0.002	0.00003	0.008
	(0.007)	(0.0008)	(0.002)	(0.002)	(0.00112)	(0.012)
Pub. funding (Mill.) × Higher Unemp. in res.	0.033	0.0001	0.026***	-0.040***	0.011	0.043
	(0.029)	(0.0033)	(0.007)	(0.005)	(0.007)	(0.043)
Pub. funding (Mill.) × Higher GDP in res.	-0.016	0.004*	-0.010	-0.053***	-0.006	0.060**
	(0.025)	(0.002)	(0.006)	(0.008)	(0.004)	(0.025)
Pub. funding (Mill.) × Higher Housing Price in res.	0.008	0.001	0.006**	-0.024***	0.005***	-0.0005
	(0.012)	(0.001)	(0.003)	(0.002)	(0.001)	(0.0117)
Pub. funding (Mill.) × HEU in residence	-0.007	0.003***	0.006**	0.005**	-0.002	-0.008
	(0.011)	(0.001)	(0.003)	(0.002)	(0.001)	(0.014)
Pub. funding (Mill.) × Grade: 76-85	-0.003	0.003***	0.0004	-0.004**	0.0005	0.014**
	(0.008)	(0.001)	(0.0026)	(0.002)	(0.0013)	(0.006)
Pub. funding (Mill.) × Grade: 86-95	-0.004	0.006***	-0.002	-0.004**	-0.003**	0.019**
	(0.009)	(0.001)	(0.003)	(0.002)	(0.002)	(0.009)
Pub. funding (Mill.) × Grade: 96-102	0.008	0.008***	-0.009***	-0.006***	-0.002	0.024
	(0.009)	(0.001)	(0.003)	(0.002)	(0.002)	(0.016)
Avg contribution	0.010	0.003	-0.055***	-0.009	0.021*	0.040
	(0.075)	(0.006)	(0.017)	(0.018)	(0.012)	(0.067)
Avg contribution × CentreNorth	-0.021	-0.008	0.003	-0.489***	-0.007	-0.088
	(0.084)	(0.007)	(0.024)	(0.041)	(0.014)	(0.063)
Avg contribution × Female	0.057**	-0.008***	0.020***	0.030***	-0.005*	-0.0004
	(0.022)	(0.002)	(0.005)	(0.006)	(0.003)	(0.0256)

	Chemistry & Pharmacy	Business & Statistics	Life & Natural sciences	Engineering	Law	Education
Avg contribution × Higher Unemp. in res.	0.092	-0.0003	0.032**	-0.079***	-0.008	-0.045
	(0.066)	(0.0057)	(0.016)	(0.018)	(0.011)	(0.061)
Avg contribution × Higher GDP in res.	-0.067	-0.001	0.00003	0.385***	-0.025***	0.014
	(0.054)	(0.005)	(0.01842)	(0.038)	(0.009)	(0.057)
Avg contribution × Higher Housing Price in res.	-0.060*	-0.018***	-0.005	-0.001	-0.019***	-0.049
	(0.033)	(0.002)	(0.006)	(0.012)	(0.003)	(0.030)
Avg contribution × HEU in residence	-0.036	0.0008	0.017***	0.038***	0.010***	-0.004
	(0.041)	(0.0019)	(0.005)	(0.009)	(0.003)	(0.022)
Avg contribution × Grade: 76-85	0.061**	0.005***	0.018***	-0.012**	-0.003	0.011
	(0.026)	(0.002)	(0.005)	(0.006)	(0.003)	(0.014)
Avg contribution × Grade: 86-95	0.083***	0.016***	0.014**	-0.061***	-0.004	0.019
	(0.030)	(0.002)	(0.006)	(0.010)	(0.003)	(0.021)
Avg contribution × Grade: 96-102	0.125***	0.023***	0.023***	-0.066***	-0.011***	0.009
	(0.035)	(0.003)	(0.006)	(0.010)	(0.004)	(0.041)
Distance	-0.016***	-0.022***	-0.005	-0.019***	-0.022***	-0.020**
	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)	(0.009)
Distance × CentreNorth	-0.012**	-0.006***	-0.022***	-0.0002	-0.018***	-0.013
	(0.005)	(0.002)	(0.004)	(0.0018)	(0.004)	(0.009)
Distance × Female	-0.001	-0.0007	0.001*	0.002***	-0.003***	-0.005**
	(0.001)	(0.0004)	(0.001)	(0.000)	(0.001)	(0.002)
Distance × Higher Unemp. in res.	-0.0004	0.002	-0.012***	0.001	0.002	-0.010
	(0.0043)	(0.002)	(0.003)	(0.001)	(0.003)	(0.008)
Distance × Higher GDP in res.	-0.007**	-0.007***	-0.006***	-0.016***	0.014***	-0.021***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.005)
Distance × Higher Housing Price in res.	-0.001	0.003***	-0.002	0.002***	-0.003***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Distance × HEU in residence	0.006***	0.008***	0.006***	0.005***	0.006***	0.010***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Distance × Grade: 76-85	-0.003***	0.003***	-0.0006	0.001**	0.002**	0.002
	(0.001)	(0.001)	(0.0008)	(0.001)	(0.001)	(0.001)
Distance × Grade: 86-95	-0.003**	0.005***	0.0008	0.003***	0.003***	0.003
	(0.001)	(0.001)	(0.0009)	(0.001)	(0.001)	(0.002)
Distance × Grade: 96-102	-0.002*	0.007***	-0.003**	0.004***	0.005***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
$Distance^2/100$	0.0009	0.001***	-0.0009**	0.001***	0.002***	0.0008
	(0.0007)	(0.000)	(0.0005)	(0.000)	(0.000)	(0.0013)
$Distance^2/100$ × CentreNorth	0.002***	0.002***	0.004***	0.0005**	0.003***	0.002*
	(0.001)	(0.000)	(0.001)	(0.0003)	(0.001)	(0.001)
$Distance^2/100$ × Female	0.0001	0.00005	-0.00006	-0.0002***	0.0002***	0.0005**
	(0.0001)	(0.00004)	(0.00007)	(0.0000)	(0.0001)	(0.0002)
$Distance^2/100$ × Higher Unemp. in res.	-0.0001	0.0002	0.002***	0.0004*	-0.0005	0.001
	(0.0007)	(0.0002)	(0.000)	(0.0002)	(0.0004)	(0.001)
$Distance^2/100$ × Higher GDP in res.	-0.0007	-0.0003	-0.0001	0.001***	-0.003***	0.0008
	(0.0005)	(0.0002)	(0.0003)	(0.000)	(0.000)	(0.0009)
$Distance^2/100$ × Higher Housing Price in res.	0.00009	-0.0002***	0.0001	-0.0002***	0.0005***	-0.0006**
	(0.00017)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0003)
$Distance^2/100$ × HEU in residence	-0.0006***	-0.0007***	-0.0005***	-0.0004***	-0.0005***	-0.0010***
	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
$Distance^2/100$ × Grade: 76-85	0.0003***	-0.0002***	0.00003	-0.0001**	-0.0001**	-0.0002*
	(0.0001)	(0.0000)	(0.00008)	(0.0001)	(0.0001)	(0.0001)
$Distance^2/100$ × Grade: 86-95	0.0003**	-0.0004***	-0.0001	-0.0002***	-0.0003***	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$Distance^2/100$ × Grade: 96-102	0.0003**	-0.0006***	0.0002*	-0.0004***	-0.0005***	-0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)
HEU in province	1.750***	1.913***	-154.308***	2.776***	1.560***	-15519.109***
	(0.128)	(0.137)	(0.090)	(0.146)	(0.357)	(0.231)
HEU in province × CentreNorth	-0.706***	-0.490***	155.179***	-1.516***	-1.299***	15519.981***
	(0.184)	(0.154)	(0.116)	(0.173)	(0.387)	(0.314)
HEU in province × Female	-0.423***	-0.023	-0.069	-0.089*	-0.208***	0.322
	(0.097)	(0.040)	(0.072)	(0.048)	(0.061)	(0.204)
HEU in province × Higher Unemp. in res.		-0.060	155.747	-1.126***	0.241	15518.998
		(0.129)	(0.000)	(0.139)	(0.351)	(0.000)
HEU in province × Higher GDP in res.	-0.328*	-0.445***	-0.133	-0.059	1.356***	-1.107***
	(0.191)	(0.094)	(0.125)	(0.109)	(0.169)	(0.309)
HEU in province × Higher Housing Price in res.	0.369***	0.067	-0.407***	-0.069	-0.098	0.319*
	(0.121)	(0.053)	(0.103)	(0.057)	(0.080)	(0.167)
HEU in province × HEU in residence	0.594***	0.693***	0.473***	0.514***	0.962***	0.437*
	(0.171)	(0.056)	(0.105)	(0.058)	(0.092)	(0.250)
HEU in province × Grade: 76-85	-0.187*	0.026	-0.043	-0.007	-0.085	0.162
	(0.112)	(0.047)	(0.081)	(0.052)	(0.071)	(0.128)
HEU in province × Grade: 86-95	-0.100	0.091	0.180*	0.108*	-0.166**	0.165
	(0.129)	(0.057)	(0.097)	(0.059)	(0.084)	(0.193)
HEU in province × Grade: 96-102	0.128	0.160**	-0.002	0.145**	-0.139	0.345
	(0.148)	(0.067)	(0.111)	(0.062)	(0.097)	(0.312)
HEU in region	0.852*	2.133***	4.189***	2.289***	2.781***	2.545***
	(0.486)	(0.178)	(0.383)	(0.171)	(0.271)	(0.608)
HEU in region × CentreNorth	0.882*	0.420*	-3.195***	-0.569***	0.195	-1.031*
	(0.520)	(0.237)	(0.399)	(0.191)	(0.406)	(0.547)
HEU in region × Female	-0.014	0.020	0.085	0.058	0.057	-0.146
	(0.103)	(0.058)	(0.085)	(0.064)	(0.078)	(0.245)
HEU in region × Higher Unemp. in res.	0.184	-0.419***	-2.830***	-0.129	-1.076***	-0.930*
	(0.468)	(0.161)	(0.370)	(0.149)	(0.255)	(0.531)
HEU in region × Higher GDP in res.	-1.046***	-1.876***	-0.067	-0.603***	-2.046***	-0.833**
	(0.232)	(0.177)	(0.155)	(0.130)	(0.317)	(0.345)
HEU in region × Higher Housing Price in res.	-0.017	0.466***	0.204*	-0.045	-0.428***	0.619***
	(0.139)	(0.073)	(0.117)	(0.076)	(0.096)	(0.206)
HEU in region × HEU in residence	0.308	-0.210***	0.317**	0.049	-0.701***	0.011
	(0.219)	(0.078)	(0.138)	(0.091)	(0.115)	(0.298)
HEU in region × Grade: 76-85	-0.070	0.166**	-0.031	0.015	0.160*	0.076
	(0.118)	(0.069)	(0.095)	(0.071)	(0.090)	(0.153)
HEU in region × Grade: 86-95	0.195	0.132	0.015	0.067	0.133	0.450*
	(0.139)	(0.082)	(0.116)	(0.079)	(0.105)	(0.236)
HEU in region × Grade: 96-102	0.239	0.094	-0.229*	0.041	0.074	0.062
	(0.155)	(0.097)	(0.131)	(0.083)	(0.125)	(0.364)
Unemployment	0.202**	0.210***	-0.221***	0.252***	-0.071	0.301
	(0.101)	(0.033)	(0.055)	(0.030)	(0.051)	(0.191)
Unemployment × CentreNorth	-0.643***	-0.325***	0.059	-0.308***	-0.410***	-0.574***
	(0.132)	(0.041)	(0.065)	(0.044)	(0.078)	(0.184)
Unemployment × Female	0.062**	0.016*	0.047***	-0.012	0.003	0.014

	Chemistry & Pharmacy	Business & Statistics	Life & Natural sciences	Engineering	Law	Education
	(0.025)	(0.009)	(0.016)	(0.012)	(0.013)	(0.053)
Unemployment × Higher Unemp. in res.	-0.307***	-0.181***	0.172***	-0.183***	0.0007	-0.868***
	(0.097)	(0.032)	(0.053)	(0.028)	(0.0495)	(0.183)
Unemployment × Higher GDP in res.	0.665***	0.312***	0.068	0.081**	0.553***	0.226*
	(0.092)	(0.028)	(0.045)	(0.038)	(0.062)	(0.119)
Unemployment × Higher Housing Price in res.	-0.248***	-0.040***	0.041*	-0.120***	-0.108***	0.005
	(0.031)	(0.012)	(0.022)	(0.016)	(0.018)	(0.043)
Unemployment × HEU in residence	-0.060	0.020*	0.102***	0.038***	0.074***	0.063
	(0.044)	(0.012)	(0.022)	(0.014)	(0.018)	(0.055)
Unemployment × Grade: 76-85	0.029	-0.005	-0.005	0.010	0.048***	0.074**
	(0.029)	(0.011)	(0.018)	(0.014)	(0.015)	(0.031)
Unemployment × Grade: 86-95	-0.039	-0.005	-0.048**	0.018	0.040**	0.052
	(0.033)	(0.013)	(0.021)	(0.015)	(0.018)	(0.046)
Unemployment × Grade: 96-102	0.040	-0.013	-0.075***	-0.011	0.006	0.058
	(0.037)	(0.015)	(0.025)	(0.015)	(0.021)	(0.074)
Housing price	0.004	0.095***	0.173***	0.108***	0.111***	-0.449***
	(0.070)	(0.017)	(0.046)	(0.019)	(0.038)	(0.134)
Housing price × CentreNorth	0.062	-0.088***	-0.165***	0.262***	0.260***	0.347**
	(0.087)	(0.023)	(0.056)	(0.029)	(0.056)	(0.138)
Housing price × Female	0.007	-0.002	-0.019*	-0.006	0.014	0.066
	(0.017)	(0.005)	(0.011)	(0.007)	(0.009)	(0.042)
Housing price × Higher Unemp. in res.	0.037	-0.073***	-0.116***	-0.079***	0.022	0.693***
	(0.066)	(0.016)	(0.044)	(0.018)	(0.037)	(0.126)
Housing price × Higher GDP in res.	-0.052	0.057***	-0.054	-0.100***	-0.282***	0.025
	(0.058)	(0.019)	(0.037)	(0.024)	(0.043)	(0.108)
Housing price × Higher Housing Price in res.	0.121***	-0.060***	0.049***	-0.052***	0.091***	0.063*
	(0.024)	(0.007)	(0.017)	(0.008)	(0.013)	(0.036)
Housing price × HEU in residence	0.011	0.025***	-0.056***	0.024***	0.012	-0.079
	(0.031)	(0.007)	(0.016)	(0.008)	(0.013)	(0.051)
Housing price × Grade: 76-85	-0.016	-0.005	0.009	0.005	-0.0008	-0.030
	(0.020)	(0.006)	(0.013)	(0.008)	(0.0110)	(0.023)
Housing price × Grade: 86-95	-0.008	-0.013*	0.035**	0.012	0.014	-0.054
	(0.023)	(0.008)	(0.016)	(0.009)	(0.013)	(0.035)
Housing price × Grade: 96-102	-0.055**	-0.047***	0.041**	0.019**	0.028*	-0.079
	(0.027)	(0.009)	(0.018)	(0.009)	(0.015)	(0.057)
Regional GDP	0.196**	0.158***	-0.097*	0.107***	0.006	0.353***
	(0.093)	(0.022)	(0.050)	(0.022)	(0.038)	(0.104)
Regional GDP × CentreNorth	-0.245**	-0.004	0.175***	0.298***	-0.157**	-0.408***
	(0.113)	(0.032)	(0.056)	(0.045)	(0.062)	(0.112)
Regional GDP × Female	0.029	0.004	0.007	-0.022**	-0.001	-0.010
	(0.019)	(0.008)	(0.013)	(0.010)	(0.011)	(0.040)
Regional GDP × Higher Unemp. in res.	-0.027	-0.032	0.185***	-0.021	0.102***	-0.423***
	(0.090)	(0.021)	(0.049)	(0.020)	(0.037)	(0.095)
Regional GDP × Higher GDP in res.	0.185***	0.010	-0.103***	-0.283***	0.293***	0.082
	(0.069)	(0.026)	(0.032)	(0.042)	(0.051)	(0.085)
Regional GDP × Higher Housing Price in res.	-0.197***	-0.073***	-0.038**	-0.130***	-0.086***	-0.103***
	(0.024)	(0.010)	(0.019)	(0.012)	(0.015)	(0.040)
Regional GDP × HEU in residence	-0.059*	-0.041***	-0.012	-0.019	-0.025*	-0.133***
	(0.035)	(0.010)	(0.019)	(0.012)	(0.015)	(0.050)
Regional GDP × Grade: 76-85	0.019	0.006	-0.008	0.002	0.036***	0.030
	(0.022)	(0.009)	(0.015)	(0.011)	(0.013)	(0.023)
Regional GDP × Grade: 86-95	-0.011	-0.021*	-0.025	0.009	0.017	0.0006
	(0.026)	(0.011)	(0.018)	(0.012)	(0.015)	(0.0363)
Regional GDP × Grade: 96-102	-0.015	-0.017	-0.037*	-0.028**	0.012	0.027
	(0.029)	(0.013)	(0.020)	(0.013)	(0.018)	(0.057)
Observations	376488	2478941	724128	2022936	1355184	279552
Pseudo R^2	0.67	0.60	0.54	0.63	0.62	-37.91
Log Likelihood	-10894.7	-54458.5	-23755.8	-49197.1	-30504.9	-968117.7

Notes: Conditional Logit regression by fields of study estimated on the sample of Italian students enrolled for the first time in the academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All the variables referring to HEUs' and areas' characteristics are interacted with individual variables. Variable definitions are reported in Table 3.6. In particular, Higher unemp. in res. indicates students that reside in provinces with an unemployment rate higher than the average; Higher GDP in res. takes value 1 if the student lives in a region with a GDP higher than the average GDP; Higher Housing Price indicates students that reside in provinces with a housing price higher than the national average; Grade: 76-85, Grade: 86-95, and Grade: 96-102 indicate students that have obtained a high school diploma with a final grade in the specified bracket.

Table 3A.2: Conditional Logit Estimates: Interactions with individual variables

	Humanities	Languages	Social & Political sciences	Psychology	Math. & Physical sciences
E(Scholarship)/100	-0.010	0.026**	0.007	0.067***	0.007
	(0.014)	(0.010)	(0.011)	(0.022)	(0.016)
E(Scholarship)/100 × CentreNorth	-0.026*	-0.005	-0.007	-0.062*	-0.006
	(0.016)	(0.015)	(0.013)	(0.032)	(0.019)
E(Scholarship)/100 × Female	0.000002	-0.002	0.010***	0.017***	-0.003
	(0.002417)	(0.003)	(0.002)	(0.006)	(0.004)
E(Scholarship)/100 × Higher Unemp. in res.	-0.010	-0.013	-0.012	-0.028	0.001
	(0.014)	(0.010)	(0.010)	(0.021)	(0.016)
E(Scholarship)/100 × Higher GDP in res.	0.033***	0.023*	0.018**	0.015	0.041***
	(0.008)	(0.014)	(0.009)	(0.026)	(0.013)
E(Scholarship)/100 × Higher Housing Price in res.	-0.013***	-0.023***	-0.025***	-0.009	-0.005
	(0.003)	(0.003)	(0.003)	(0.009)	(0.005)
E(Scholarship)/100 × HEU in residence	0.0002	-0.009***	-0.006**	-0.014**	-0.014***
	(0.0029)	(0.003)	(0.002)	(0.006)	(0.005)
E(Scholarship)/100 × Grade: 76-85	-0.001	-0.011***	-0.006***	-0.023***	-0.005
	(0.003)	(0.002)	(0.002)	(0.005)	(0.004)
E(Scholarship)/100 × Grade: 86-95	-0.003	-0.029***	-0.006**	-0.042***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.005)
E(Scholarship)/100 × Grade: 96-102	-0.003	-0.026***	-0.013***	-0.048***	-0.020***
	(0.004)	(0.003)	(0.004)	(0.007)	(0.005)
E(Dormitory)/100	0.608***	0.376***	0.444***	-0.165	0.037
	(0.154)	(0.120)	(0.143)	(0.274)	(0.186)
E(Dormitory)/100 × CentreNorth	-0.980***	0.211	-1.097***	0.347	-0.796***
	(0.172)	(0.146)	(0.173)	(0.349)	(0.298)
E(Dormitory)/100 × Female	-0.033	0.018	0.028	0.032	0.180***
	(0.030)	(0.036)	(0.026)	(0.074)	(0.046)
E(Dormitory)/100 × Higher Unemp. in res.	-0.365**	-0.633***	-0.152	0.234	-0.185
	(0.151)	(0.116)	(0.140)	(0.224)	(0.179)
E(Dormitory)/100 × Higher GDP in res.	0.089	-0.458***	0.777***	0.205	0.458*
	(0.109)	(0.112)	(0.117)	(0.244)	(0.252)
E(Dormitory)/100 × Higher Housing Price in res.	0.143***	-0.145***	-0.166***	-0.109	0.008
	(0.036)	(0.035)	(0.031)	(0.096)	(0.068)
E(Dormitory)/100 × HEU in residence	0.045	0.181***	0.110***	0.304***	-0.108
	(0.039)	(0.042)	(0.031)	(0.087)	(0.076)
E(Dormitory)/100 × Grade: 76-85	0.023	-0.015	0.002	-0.224***	0.193***
	(0.034)	(0.031)	(0.028)	(0.069)	(0.059)
E(Dormitory)/100 × Grade: 86-95	0.080**	0.029	0.019	-0.313***	0.233***
	(0.040)	(0.037)	(0.038)	(0.088)	(0.063)
E(Dormitory)/100 × Grade: 96-102	0.143***	0.051	0.018	-0.353***	0.500***
	(0.043)	(0.044)	(0.054)	(0.114)	(0.064)
E(Student Pkg)/100	-0.113	-0.163**	-0.099	-0.514**	0.142
	(0.074)	(0.064)	(0.066)	(0.215)	(0.122)
E(Student Pkg)/100 × CentreNorth	0.366***	-0.294***	0.137*	0.530*	-0.075
	(0.090)	(0.089)	(0.082)	(0.292)	(0.155)
E(Student Pkg)/100 × Female	-0.023	0.012	-0.013	-0.023	-0.179***
	(0.020)	(0.022)	(0.017)	(0.042)	(0.028)
E(Student Pkg)/100 × Higher Unemp. in res.	0.199***	0.029	0.021	0.128	0.172
	(0.072)	(0.061)	(0.065)	(0.209)	(0.119)
E(Student Pkg)/100 × Higher GDP in res.	-0.081	0.245***	0.031	-0.436**	0.048
	(0.067)	(0.083)	(0.058)	(0.212)	(0.123)
E(Student Pkg)/100 × Higher Housing Price in res.	-0.078**	-0.116***	0.074***	-0.022	0.118**
	(0.035)	(0.029)	(0.025)	(0.051)	(0.050)
E(Student Pkg)/100 × HEU in residence	-0.020	0.037	-0.004	0.048	0.104***
	(0.024)	(0.026)	(0.021)	(0.053)	(0.039)
E(Student Pkg)/100 × Grade: 76-85	-0.023	0.036*	-0.022	0.084**	-0.075**
	(0.023)	(0.020)	(0.018)	(0.040)	(0.032)
E(Student Pkg)/100 × Grade: 86-95	-0.034	0.042*	-0.042*	0.101**	-0.070*
	(0.026)	(0.023)	(0.023)	(0.047)	(0.036)
E(Student Pkg)/100 × Grade: 96-102	-0.017	-0.046*	-0.053*	0.147**	-0.117***
	(0.028)	(0.026)	(0.031)	(0.060)	(0.038)
Pl. in Canteen/100	-0.005	0.024***	0.008	0.002	-0.006
	(0.010)	(0.007)	(0.007)	(0.030)	(0.015)
Pl. in Canteen/100 × CentreNorth	-0.029**	-0.032***	-0.012	0.014	-0.065***
	(0.012)	(0.009)	(0.010)	(0.056)	(0.019)
Pl. in Canteen/100 × Female	0.006**	0.005	-0.005*	-0.009	-0.004
	(0.003)	(0.003)	(0.002)	(0.007)	(0.004)
Pl. in Canteen/100 × Higher Unemp. in res.	0.013	-0.004	0.010	-0.015	0.008
	(0.009)	(0.006)	(0.007)	(0.029)	(0.014)
Pl. in Canteen/100 × Higher GDP in res.	0.016*	-0.015**	0.005	-0.006	0.050***
	(0.008)	(0.007)	(0.008)	(0.049)	(0.015)
Pl. in Canteen/100 × Higher Housing Price in res.	0.006	0.011***	0.011***	-0.001	-0.0006
	(0.004)	(0.003)	(0.003)	(0.010)	(0.0055)
Pl. in Canteen/100 × HEU in residence	-0.013***	-0.004	-0.001	0.006	-0.003
	(0.004)	(0.004)	(0.003)	(0.009)	(0.006)
Pl. in Canteen/100 × Grade: 76-85	0.002	-0.002	0.003	-0.011*	0.007
	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)
Pl. in Canteen/100 × Grade: 86-95	0.008**	-0.002	0.008**	-0.004	0.017***
	(0.004)	(0.003)	(0.003)	(0.008)	(0.005)
Pl. in Canteen/100 × Grade: 96-102	0.011***	0.0009	0.018***	-0.004	0.034***
	(0.004)	(0.0037)	(0.005)	(0.011)	(0.006)
College	-0.072	0.823***	0.339	-1.073	-0.623
	(0.276)	(0.191)	(0.243)	(0.879)	(0.522)
College × CentreNorth	1.683***	-1.729***	-0.333	0.419	1.956**
	(0.359)	(0.290)	(0.358)	(1.447)	(0.834)
College × Female	-0.408***	0.184***	0.075	-0.034	-0.366***
	(0.075)	(0.070)	(0.058)	(0.149)	(0.104)
College × Higher Unemp. in res.	-0.031	-0.669***	-0.523**	0.377	0.660
	(0.264)	(0.175)	(0.235)	(0.857)	(0.513)
College × Higher GDP in res.	-1.349***	0.894***	0.135	-0.001	-0.744
	(0.272)	(0.269)	(0.286)	(1.207)	(0.703)
College × Higher Housing Price in res.	0.873***	0.351***	0.372***	-0.344	0.173
	(0.113)	(0.082)	(0.076)	(0.331)	(0.150)
College × HEU in residence	0.148	-0.042	0.099	0.198	0.115
	(0.095)	(0.088)	(0.070)	(0.188)	(0.147)
College × Grade: 76-85	0.172**	0.047	0.177***	0.342**	-0.058
	(0.083)	(0.063)	(0.061)	(0.143)	(0.119)
College × Grade: 86-95	0.165*	0.129*	0.149*	0.523***	0.189
	(0.097)	(0.073)	(0.081)	(0.168)	(0.134)

	Humanities	Languages	Social & Political sciences	Psychology	Math. & Physical sciences
College × Grade: 96-102	0.465***	0.083	0.337***	0.898***	0.504***
	(0.105)	(0.085)	(0.110)	(0.211)	(0.144)
non-DSU Scholar./100	-0.062	-0.219***	-0.200***	-0.283*	-0.258***
	(0.071)	(0.060)	(0.050)	(0.172)	(0.097)
non-DSU Scholar./100 × CentreNorth	0.169**	0.261***	0.249***	0.561**	0.707***
	(0.081)	(0.097)	(0.062)	(0.250)	(0.134)
non-DSU Scholar./100 × Female	-0.033**	-0.009	-0.064***	-0.073*	0.032
	(0.015)	(0.017)	(0.012)	(0.037)	(0.021)
non-DSU Scholar./100 × Higher Unemp. in res.	0.162**	0.174***	0.136***	0.162	0.282***
	(0.069)	(0.057)	(0.048)	(0.167)	(0.095)
non-DSU Scholar./100 × Higher GDP in res.	0.007	-0.174**	-0.199***	-0.205	-0.629***
	(0.048)	(0.086)	(0.044)	(0.195)	(0.107)
non-DSU Scholar./100 × Higher Housing Price in res.	0.032*	0.087***	0.130***	0.150***	-0.041
	(0.019)	(0.018)	(0.017)	(0.053)	(0.030)
non-DSU Scholar./100 × HEU in residence	0.015	0.047**	0.035**	-0.030	0.072***
	(0.018)	(0.019)	(0.014)	(0.048)	(0.027)
non-DSU Scholar./100 × Grade: 76-85	-0.005	0.040***	0.042***	0.102***	0.063**
	(0.017)	(0.015)	(0.013)	(0.036)	(0.025)
non-DSU Scholar./100 × Grade: 86-95	-0.004	0.082***	0.051***	0.122***	0.118***
	(0.020)	(0.017)	(0.017)	(0.042)	(0.028)
non-DSU Scholar./100 × Grade: 96-102	-0.062***	0.070***	0.051**	0.217***	0.099***
	(0.022)	(0.021)	(0.023)	(0.054)	(0.030)
E(non-DSU Dorm.)/100	0.654	-0.635*	-0.190	-0.668	1.415**
	(0.431)	(0.365)	(0.202)	(2.020)	(0.709)
E(non-DSU Dorm.)/100 × CentreNorth	0.054	-0.020	-0.227	-4.661	-2.390***
	(0.461)	(0.467)	(0.244)	(3.802)	(0.918)
E(non-DSU Dorm.)/100 × Female	-0.105	0.245**	-0.131**	-0.060	0.599***
	(0.126)	(0.122)	(0.063)	(0.240)	(0.173)
E(non-DSU Dorm.)/100 × Higher Unemp. in res.	-0.042	-0.717**	-0.209	-1.089	-1.824***
	(0.416)	(0.342)	(0.191)	(2.007)	(0.694)
E(non-DSU Dorm.)/100 × Higher GDP in res.	-2.402***	-0.439	-0.823***	5.044	0.524
	(0.307)	(0.398)	(0.189)	(3.293)	(0.704)
E(non-DSU Dorm.)/100 × Higher Housing Price in res.	1.531***	0.372**	0.346***	-2.119***	0.129
	(0.250)	(0.186)	(0.099)	(0.625)	(0.332)
E(non-DSU Dorm.)/100 × HEU in residence	0.086	0.238	0.313***	0.325	-0.653***
	(0.162)	(0.151)	(0.075)	(0.316)	(0.251)
E(non-DSU Dorm.)/100 × Grade: 76-85	-0.003	0.325***	0.223***	0.029	0.413**
	(0.140)	(0.117)	(0.068)	(0.223)	(0.194)
E(non-DSU Dorm.)/100 × Grade: 86-95	0.119	0.915***	0.249***	0.472*	0.124
	(0.158)	(0.127)	(0.090)	(0.252)	(0.226)
E(non-DSU Dorm.)/100 × Grade: 96-102	-0.089	1.164***	0.468***	-0.108	0.476**
	(0.177)	(0.141)	(0.109)	(0.346)	(0.240)
Excellence Dept.	0.243	-0.085	1.716***	-2.309***	0.694**
	(0.180)	(0.284)	(0.252)	(0.831)	(0.278)
Excellence Dept. × CentreNorth	-0.495**	-0.671*	-1.874***	0.870	-0.392
	(0.199)	(0.401)	(0.297)	(1.438)	(0.490)
Excellence Dept. × Female	-0.016	0.096	0.266***	0.065	0.032
	(0.041)	(0.101)	(0.072)	(0.202)	(0.074)
Excellence Dept. × Higher Unemp. in res.	-0.403**	-0.608**	-0.524**	1.528*	-0.715***
	(0.173)	(0.259)	(0.237)	(0.793)	(0.268)
Excellence Dept. × Higher GDP in res.	0.139	0.633*	0.848***	0.971	-0.318
	(0.116)	(0.351)	(0.206)	(1.221)	(0.441)
Excellence Dept. × Higher Housing Price in res.	-0.155***	-0.179*	-0.638***	-0.474*	0.186
	(0.056)	(0.097)	(0.099)	(0.268)	(0.122)
Excellence Dept. × HEU in residence	0.067	0.212*	-0.004	0.257	-0.276**
	(0.052)	(0.119)	(0.087)	(0.247)	(0.109)
Excellence Dept. × Grade: 76-85	0.079*	0.002	-0.134*	-0.415**	0.112
	(0.046)	(0.090)	(0.077)	(0.203)	(0.086)
Excellence Dept. × Grade: 86-95	0.060	0.381***	0.034	-0.563**	0.131
	(0.054)	(0.105)	(0.102)	(0.246)	(0.095)
Excellence Dept. × Grade: 96-102	0.025	0.119	-0.338**	-0.084	-0.194**
	(0.061)	(0.123)	(0.140)	(0.340)	(0.099)
Academics/100	-0.159*	0.033	0.172**	-0.336	-0.145
	(0.092)	(0.071)	(0.086)	(0.333)	(0.189)
Academics/100 × CentreNorth	0.464***	-0.229**	0.029	-0.095	0.320
	(0.107)	(0.115)	(0.117)	(0.519)	(0.258)
Academics/100 × Female	-0.003	0.016	-0.0010	0.074	0.012
	(0.028)	(0.032)	(0.0248)	(0.091)	(0.050)
Academics/100 × Higher Unemp. in res.	0.008	-0.028	-0.171**	0.454	0.265
	(0.083)	(0.061)	(0.080)	(0.313)	(0.182)
Academics/100 × Higher GDP in res.	-0.189**	0.481***	-0.031	0.405	0.260
	(0.076)	(0.107)	(0.093)	(0.430)	(0.211)
Academics/100 × Higher Housing Price in res.	-0.182***	-0.408***	-0.170***	-0.169	-0.365***
	(0.038)	(0.038)	(0.033)	(0.131)	(0.068)
Academics/100 × HEU in residence	-0.027	-0.136***	-0.034	-0.260**	-0.088
	(0.033)	(0.035)	(0.028)	(0.112)	(0.062)
Academics/100 × Grade: 76-85	-0.019	-0.075***	-0.023	0.065	0.026
	(0.032)	(0.028)	(0.027)	(0.085)	(0.057)
Academics/100 × Grade: 86-95	-0.066*	-0.046	-0.0008	-0.102	0.002
	(0.038)	(0.033)	(0.0358)	(0.106)	(0.065)
Academics/100 × Grade: 96-102	-0.033	-0.069*	-0.090*	-0.048	-0.262***
	(0.042)	(0.039)	(0.051)	(0.144)	(0.068)
Share of Intern. Acad.	0.263	0.122	-0.242***	0.110	-0.522**
	(0.168)	(0.096)	(0.089)	(0.355)	(0.261)
Share of Intern. Acad. × CentreNorth	0.079	-0.678***	0.348***	0.381	0.172
	(0.190)	(0.137)	(0.102)	(0.468)	(0.318)
Share of Intern. Acad. × Female	0.030	0.008	-0.033	-0.261***	-0.196***
	(0.036)	(0.037)	(0.021)	(0.094)	(0.053)
Share of Intern. Acad. × Higher Unemp. in res.	-0.233	-0.030	0.255***	0.147	0.169
	(0.162)	(0.087)	(0.085)	(0.335)	(0.248)
Share of Intern. Acad. × Higher GDP in res.	-0.301***	0.413***	-0.275***	0.192	0.349
	(0.110)	(0.119)	(0.073)	(0.336)	(0.251)
Share of Intern. Acad. × Higher Housing Price in res.	-0.039	-0.083**	0.103***	0.172*	0.083
	(0.039)	(0.032)	(0.023)	(0.094)	(0.063)
Share of Intern. Acad. × HEU in residence	0.015	0.010	0.059***	0.080	0.086
	(0.042)	(0.041)	(0.023)	(0.112)	(0.066)
Share of Intern. Acad. × Grade: 76-85	0.013	0.014	0.070***	0.136	-0.130**
	(0.040)	(0.032)	(0.023)	(0.091)	(0.057)
Share of Intern. Acad. × Grade: 86-95	0.048	0.087**	0.122***	0.305***	-0.097
	(0.048)	(0.038)	(0.030)	(0.109)	(0.065)

	Humanities	Languages	Social & Political sciences	Psychology	Math. & Physical sciences
Share of Intern. Acad. × Grade: 96-102	0.084	0.011	0.158***	-0.034	-0.196***
	(0.053)	(0.047)	(0.037)	(0.149)	(0.076)
Admin. staff	-0.124*	-0.212***	-0.214***	-0.051	-0.242**
	(0.067)	(0.055)	(0.057)	(0.148)	(0.106)
Admin. staff × CentreNorth	0.081	0.219***	0.205***	0.058	0.520***
	(0.077)	(0.074)	(0.072)	(0.257)	(0.148)
Admin. staff × Female	0.042**	0.013	-0.004	-0.081*	0.035
	(0.019)	(0.024)	(0.016)	(0.042)	(0.027)
Admin. staff × Higher Unemp. in res.	0.110*	0.214***	0.111**	-0.222	0.041
	(0.063)	(0.048)	(0.054)	(0.140)	(0.103)
Admin. staff × Higher GDP in res.	-0.072	-0.286***	-0.312***	-0.178	-0.611***
	(0.054)	(0.070)	(0.055)	(0.224)	(0.123)
Admin. staff × Higher Housing Price in res.	0.132***	0.400***	0.195***	0.113**	0.010
	(0.025)	(0.031)	(0.021)	(0.048)	(0.033)
Admin. staff × HEU in residence	-0.017	0.043	0.018	0.080	0.100***
	(0.025)	(0.029)	(0.019)	(0.052)	(0.036)
Admin. staff × Grade: 76-85	0.048**	0.052**	0.025	0.056	0.097***
	(0.021)	(0.022)	(0.018)	(0.038)	(0.031)
Admin. staff × Grade: 86-95	0.080***	0.071***	0.049**	0.190***	0.227***
	(0.024)	(0.025)	(0.023)	(0.047)	(0.034)
Admin. staff × Grade: 96-102	0.056**	0.082***	0.092***	0.238***	0.431***
	(0.027)	(0.028)	(0.031)	(0.065)	(0.037)
Field Academics/100	-0.064	0.592**	1.250**	4.169***	1.014**
	(0.299)	(0.231)	(0.540)	(1.006)	(0.512)
Field Academics/100 × CentreNorth	1.431***	1.632***	1.559**	-1.596	-1.033*
	(0.346)	(0.361)	(0.620)	(1.657)	(0.620)
Field Academics/100 × Female	0.170**	-0.162*	-0.136	-0.102	-0.158
	(0.078)	(0.088)	(0.141)	(0.260)	(0.118)
Field Academics/100 × Higher Unemp. in res.	0.592**	0.805***	-1.013**	-2.335**	-0.203
	(0.281)	(0.209)	(0.513)	(0.947)	(0.494)
Field Academics/100 × Higher GDP in res.	-0.451*	-1.622***	-2.356***	-1.421	0.577
	(0.238)	(0.327)	(0.400)	(1.384)	(0.486)
Field Academics/100 × Higher Housing Price in res.	0.263***	0.467***	0.860***	0.042	0.248
	(0.100)	(0.084)	(0.183)	(0.375)	(0.175)
Field Academics/100 × HEU in residence	-0.058	0.029	0.236	0.063	0.292*
	(0.090)	(0.091)	(0.162)	(0.322)	(0.166)
Field Academics/100 × Grade: 76-85	0.013	0.118	0.372**	0.411	-0.026
	(0.088)	(0.076)	(0.151)	(0.252)	(0.137)
Field Academics/100 × Grade: 86-95	-0.036	0.042	0.250	0.957***	-0.065
	(0.106)	(0.087)	(0.204)	(0.314)	(0.156)
Field Academics/100 × Grade: 96-102	-0.189	0.167	1.031***	0.341	0.914***
	(0.116)	(0.107)	(0.287)	(0.443)	(0.165)
Pub. funding (Mill.)	0.029***	0.012***	0.004	0.007	0.021*
	(0.007)	(0.005)	(0.006)	(0.013)	(0.011)
Pub. funding (Mill.) × CentreNorth	-0.044***	-0.009	-0.020***	0.011	-0.053***
	(0.008)	(0.006)	(0.007)	(0.019)	(0.018)
Pub. funding (Mill.) × Female	-0.004**	-0.001	-0.0008	-0.002	-0.0010
	(0.001)	(0.002)	(0.0011)	(0.003)	(0.0028)
Pub. funding (Mill.) × Higher Unemp. in res.	-0.013*	-0.018***	0.010*	-0.002	-0.019**
	(0.007)	(0.004)	(0.006)	(0.012)	(0.010)
Pub. funding (Mill.) × Higher GDP in res.	0.015***	-0.007	0.029***	-0.005	0.020
	(0.005)	(0.005)	(0.004)	(0.014)	(0.016)
Pub. funding (Mill.) × Higher Housing Price in res.	0.002	-0.002*	-0.003**	0.005	0.024***
	(0.002)	(0.001)	(0.001)	(0.005)	(0.004)
Pub. funding (Mill.) × HEU in residence	0.003*	0.007***	0.0007	0.013***	-0.002
	(0.002)	(0.002)	(0.0013)	(0.004)	(0.004)
Pub. funding (Mill.) × Grade: 76-85	-0.002	0.001	-0.0003	-0.008**	-0.008***
	(0.002)	(0.001)	(0.0012)	(0.003)	(0.003)
Pub. funding (Mill.) × Grade: 86-95	0.00004	0.0009	-0.003*	-0.006	-0.015***
	(0.00189)	(0.0016)	(0.002)	(0.004)	(0.004)
Pub. funding (Mill.) × Grade: 96-102	0.0006	0.0007	-0.002	-0.012**	-0.019***
	(0.0020)	(0.0020)	(0.002)	(0.005)	(0.004)
Avg contribution	-0.0010	0.006	0.017	0.007	0.013
	(0.0326)	(0.010)	(0.011)	(0.034)	(0.056)
Avg contribution × CentreNorth	0.010	-0.004	0.011	0.0002	-0.234***
	(0.033)	(0.015)	(0.014)	(0.0456)	(0.070)
Avg contribution × Female	-0.005	-0.003	0.0009	0.005	-0.008
	(0.004)	(0.004)	(0.0027)	(0.005)	(0.018)
Avg contribution × Higher Unemp. in res.	-0.027	-0.012	0.020*	0.036	-0.060
	(0.032)	(0.009)	(0.011)	(0.033)	(0.051)
Avg contribution × Higher GDP in res.	-0.013	-0.025*	0.011	-0.0003	0.141**
	(0.011)	(0.014)	(0.010)	(0.0324)	(0.055)
Avg contribution × Higher Housing Price in res.	-0.033***	-0.025***	-0.020***	0.020*	0.162***
	(0.006)	(0.005)	(0.003)	(0.010)	(0.029)
Avg contribution × HEU in residence	0.004	0.006	-0.001	0.011*	-0.014
	(0.005)	(0.005)	(0.003)	(0.006)	(0.026)
Avg contribution × Grade: 76-85	-0.005	0.001	-0.003	-0.019***	-0.036*
	(0.005)	(0.004)	(0.003)	(0.005)	(0.021)
Avg contribution × Grade: 86-95	0.003	0.004	-0.003	-0.038***	-0.076***
	(0.006)	(0.005)	(0.004)	(0.007)	(0.023)
Avg contribution × Grade: 96-102	0.015**	-0.004	-0.010*	-0.059***	-0.123***
	(0.006)	(0.006)	(0.005)	(0.013)	(0.024)
Distance	-0.016***	-0.021***	-0.019***	-0.027***	-0.028***
	(0.003)	(0.002)	(0.002)	(0.005)	(0.004)
Distance × CentreNorth	-0.012***	-0.013***	-0.006**	-0.003	-0.006
	(0.003)	(0.002)	(0.003)	(0.006)	(0.005)
Distance × Female	0.0001	0.00009	-0.0005	0.0004	-0.0005
	(0.0007)	(0.00071)	(0.0006)	(0.0012)	(0.0010)
Distance × Higher Unemp. in res.	-0.008***	0.002	-0.004*	0.011**	0.008**
	(0.003)	(0.002)	(0.002)	(0.005)	(0.004)
Distance × Higher GDP in res.	0.0008	0.005***	-0.006***	0.002	0.0006
	(0.0020)	(0.002)	(0.002)	(0.004)	(0.0031)
Distance × Higher Housing Price in res.	-0.0007	-0.002**	0.003***	-0.002	-0.003**
	(0.0010)	(0.001)	(0.001)	(0.002)	(0.001)
Distance × HEU in residence	0.007***	0.008***	0.006***	0.005***	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Distance × Grade: 76-85	0.002**	0.0010	0.0009	-0.001	0.00009
	(0.001)	(0.0007)	(0.0006)	(0.001)	(0.00117)
Distance × Grade: 86-95	0.003***	0.002**	0.003***	-0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

	Humanities	Languages	Social & Political sciences	Psychology	Math. & Physical sciences
Distance × Grade: 96-102	0.006***	0.002***	0.005***	0.00004	0.005***
	(0.001)	(0.001)	(0.001)	(0.00170)	(0.001)
Distance^2/100	0.0008	0.002***	0.001***	0.003***	0.003***
	(0.0005)	(0.000)	(0.000)	(0.001)	(0.001)
Distance^2/100 × CentreNorth	0.002***	0.002***	0.002***	0.0004	0.002***
	(0.001)	(0.000)	(0.000)	(0.0010)	(0.001)
Distance^2/100 × Female	-0.00002	0.000007	-0.00002	-0.00010	-0.00000001
	(0.00007)	(0.000064)	(0.00005)	(0.00011)	(0.00009433)
Distance^2/100 × Higher Unemp. in res.	0.001**	-0.0004*	0.0005	-0.001**	-0.0010*
	(0.000)	(0.0002)	(0.0003)	(0.001)	(0.0005)
Distance^2/100 × Higher GDP in res.	-0.0008**	-0.001***	-0.0003	-0.0005	-0.002***
	(0.0003)	(0.000)	(0.0003)	(0.0007)	(0.000)
Distance^2/100 × Higher Housing Price in res.	0.00003	0.0002**	-0.0003**	0.0003	0.0003*
	(0.00012)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Distance^2/100 × HEU in residence	-0.0006***	-0.0007***	-0.0005***	-0.0004**	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Distance^2/100 × Grade: 76-85	-0.0002***	-0.0001**	-0.00005	0.00008	-0.00002
	(0.0001)	(0.0001)	(0.00006)	(0.00012)	(0.00011)
Distance^2/100 × Grade: 86-95	-0.0003***	-0.0002***	-0.0002***	0.0002*	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Distance^2/100 × Grade: 96-102	-0.0005***	-0.0003***	-0.0004***	-0.000005	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.000159)	(0.0001)
HEU in province	1.009**	0.056	0.245	1.521***	0.663
	(0.423)	(0.258)	(0.299)	(0.199)	(1.043)
HEU in province × CentreNorth	0.199	1.046***	0.527*	-0.142	0.411
	(0.429)	(0.256)	(0.314)	(0.308)	(1.050)
HEU in province × Female	-0.259***	-0.146*	-0.098*	-0.044	-0.276***
	(0.075)	(0.081)	(0.059)	(0.159)	(0.105)
HEU in province × Higher Unemp. in res.	0.211	1.047***	1.302***		0.739
	(0.413)	(0.236)	(0.292)		(1.042)
HEU in province × Higher GDP in res.	0.247	-0.298*	0.146	0.103	0.435*
	(0.164)	(0.156)	(0.126)	(0.334)	(0.224)
HEU in province × Higher Housing Price in res.	-0.828***	-0.242***	-0.444***	-1.305***	-0.475***
	(0.099)	(0.079)	(0.073)	(0.196)	(0.136)
HEU in province × HEU in residence	0.240**	0.737***	0.423***	0.342*	0.856***
	(0.096)	(0.100)	(0.074)	(0.198)	(0.170)
HEU in province × Grade: 76-85	0.021	-0.119*	-0.068	-0.011	0.039
	(0.082)	(0.070)	(0.063)	(0.147)	(0.120)
HEU in province × Grade: 86-95	0.117	-0.032	0.025	-0.145	0.030
	(0.096)	(0.083)	(0.084)	(0.170)	(0.136)
HEU in province × Grade: 96-102	0.250**	-0.014	0.013	0.235	0.090
	(0.110)	(0.102)	(0.118)	(0.219)	(0.143)
HEU in region	2.260***	1.566***	2.507***	1.754***	2.231***
	(0.277)	(0.212)	(0.233)	(0.591)	(0.392)
HEU in region × CentreNorth	-0.185	-0.847***	-0.021	-0.947	0.226
	(0.333)	(0.219)	(0.274)	(0.626)	(0.472)
HEU in region × Female	0.012	0.079	-0.047	-0.084	-0.086
	(0.082)	(0.089)	(0.072)	(0.155)	(0.116)
HEU in region × Higher Unemp. in res.	-0.963***	-0.273	-1.260***	0.391	-0.029
	(0.255)	(0.178)	(0.214)	(0.553)	(0.361)
HEU in region × Higher GDP in res.	-1.188***	0.085	-1.698***	-0.538*	-1.733***
	(0.216)	(0.163)	(0.195)	(0.287)	(0.328)
HEU in region × Higher Housing Price in res.	0.032	-0.140	0.073	0.633***	-0.173
	(0.106)	(0.091)	(0.087)	(0.172)	(0.156)
HEU in region × HEU in residence	0.204*	-0.118	0.027	-0.095	-0.346*
	(0.114)	(0.124)	(0.091)	(0.251)	(0.200)
HEU in region × Grade: 76-85	-0.029	0.024	-0.019	-0.266*	0.269**
	(0.091)	(0.079)	(0.076)	(0.148)	(0.132)
HEU in region × Grade: 86-95	-0.045	-0.089	0.053	-0.030	0.170
	(0.107)	(0.093)	(0.102)	(0.177)	(0.149)
HEU in region × Grade: 96-102	-0.028	-0.084	-0.120	-0.315	0.363**
	(0.123)	(0.110)	(0.138)	(0.235)	(0.163)
Unemployment	0.009	-0.041	-0.003	-0.334	0.113
	(0.056)	(0.044)	(0.037)	(0.218)	(0.105)
Unemployment × CentreNorth	-0.709***	-0.283***	-0.106**	0.482	-0.902***
	(0.073)	(0.056)	(0.052)	(0.380)	(0.156)
Unemployment × Female	0.065***	0.028	-0.016	-0.029	-0.020
	(0.017)	(0.021)	(0.014)	(0.034)	(0.026)
Unemployment × Higher Unemp. in res.	-0.097*	-0.150***	-0.132***	0.009	-0.151
	(0.053)	(0.038)	(0.034)	(0.215)	(0.103)
Unemployment × Higher GDP in res.	0.623***	0.285***	0.133***	-0.540*	0.774***
	(0.056)	(0.050)	(0.044)	(0.323)	(0.131)
Unemployment × Higher Housing Price in res.	-0.105***	-0.102***	-0.009	0.081	0.013
	(0.023)	(0.022)	(0.018)	(0.068)	(0.037)
Unemployment × HEU in residence	0.049**	0.062**	0.053***	-0.008	0.112***
	(0.020)	(0.025)	(0.018)	(0.040)	(0.036)
Unemployment × Grade: 76-85	-0.010	-0.025	-0.002	0.004	-0.088***
	(0.019)	(0.019)	(0.015)	(0.031)	(0.029)
Unemployment × Grade: 86-95	-0.027	-0.037*	0.015	0.010	-0.078**
	(0.021)	(0.022)	(0.020)	(0.038)	(0.034)
Unemployment × Grade: 96-102	0.003	-0.069***	0.033	0.021	-0.043
	(0.024)	(0.025)	(0.026)	(0.052)	(0.036)
Housing price	0.097**	-0.054*	0.118***	0.057	0.126**
	(0.045)	(0.030)	(0.031)	(0.134)	(0.061)
Housing price × CentreNorth	0.170***	0.223***	-0.008	-0.019	0.270***
	(0.051)	(0.035)	(0.040)	(0.221)	(0.078)
Housing price × Female	-0.053***	-0.015	-0.009	0.0005	0.055***
	(0.011)	(0.012)	(0.009)	(0.0254)	(0.016)
Housing price × Higher Unemp. in res.	0.111***	0.052**	-0.051*	0.041	-0.069
	(0.042)	(0.027)	(0.029)	(0.131)	(0.059)
Housing price × Higher GDP in res.	-0.177***	0.0010	-0.029	0.026	-0.314***
	(0.033)	(0.0304)	(0.030)	(0.180)	(0.059)
Housing price × Higher Housing Price in res.	0.128***	-0.005	-0.035***	0.024	0.036*
	(0.015)	(0.013)	(0.011)	(0.034)	(0.019)
Housing price × HEU in residence	0.033**	0.021	0.037***	-0.014	-0.074***
	(0.014)	(0.014)	(0.010)	(0.030)	(0.022)
Housing price × Grade: 76-85	0.007	0.018*	0.011	0.037	0.061***
	(0.013)	(0.011)	(0.009)	(0.023)	(0.017)
Housing price × Grade: 86-95	-0.012	0.024*	0.003	0.001	0.022

	Humanities	Languages	Social & Political sciences	Psychology	Math. & Physical sciences
	(0.015)	(0.013)	(0.012)	(0.029)	(0.020)
Housing price × Grade: 96-102	-0.028*	0.064***	-0.002	0.010	0.007
	(0.017)	(0.015)	(0.017)	(0.037)	(0.021)
Regional GDP	0.088**	0.003	0.116***	-0.106	0.150
	(0.042)	(0.032)	(0.027)	(0.158)	(0.098)
Regional GDP × CentreNorth	-0.431***	-0.206***	-0.136***	0.164	-0.517***
	(0.058)	(0.044)	(0.041)	(0.285)	(0.124)
Regional GDP × Female	0.029**	0.022	-0.006	-0.040	0.018
	(0.014)	(0.015)	(0.012)	(0.029)	(0.022)
Regional GDP × Higher Unemp. in res.	-0.021	-0.058**	-0.057**	-0.079	-0.120
	(0.039)	(0.027)	(0.024)	(0.156)	(0.096)
Regional GDP × Higher GDP in res.	0.346***	0.190***	0.188***	-0.291	0.334***
	(0.047)	(0.041)	(0.036)	(0.242)	(0.097)
Regional GDP × Higher Housing Price in res.	-0.099***	-0.067***	-0.091***	0.019	-0.118***
	(0.019)	(0.016)	(0.014)	(0.042)	(0.030)
Regional GDP × HEU in residence	0.008	-0.014	-0.026*	-0.068**	0.051*
	(0.017)	(0.019)	(0.014)	(0.035)	(0.029)
Regional GDP × Grade: 76-85	-0.016	0.001	-0.020	0.056**	-0.019
	(0.015)	(0.014)	(0.012)	(0.026)	(0.025)
Regional GDP × Grade: 86-95	-0.043**	0.002	-0.004	0.106***	-0.008
	(0.017)	(0.016)	(0.017)	(0.033)	(0.028)
Regional GDP × Grade: 96-102	-0.032*	-0.026	-0.013	0.122***	0.089***
	(0.020)	(0.019)	(0.022)	(0.044)	(0.031)
Observations	880840	845104	1440947	172391	422577
Pseudo R^2	0.63	0.57	0.60	0.63	0.69
Log Likelihood	-21946.1	-27870.1	-33683.4	-7137.9	-10891.5

Notes: Conditional Logit regression by field of study estimated on the sample of Italian students enrolled for the first time in the academic year 2014-2015. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All the variables referring to HEUs' and areas' characteristics are interacted for individual variables. Variable definitions are reported in Table 3.6. In particular, Higher unemp. in res. indicates students that reside in provinces with an unemployment rate higher than the average; Higher GDP in res. takes value 1 if the student lives in a region with a GDP higher than the average GDP; Higher Housing Price indicates students that reside in provinces with a housing price higher than the national average; Grade: 76-85, Grade: 86-95, and Grade: 96-102 indicate students that have obtained a high school diploma with a final grade in the specified bracket.

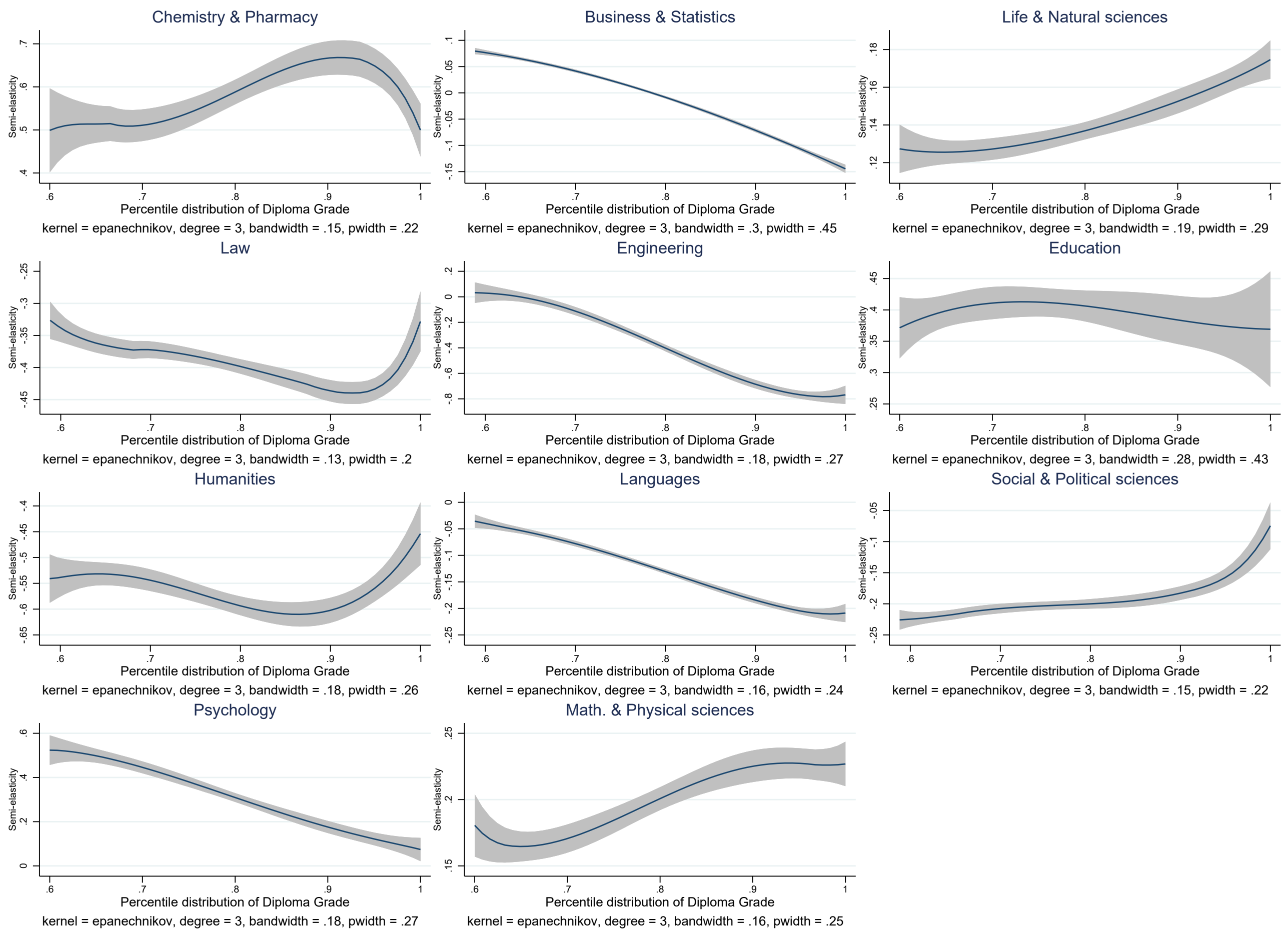


Figure 3A.1: Individual semi-elasticities to expected Scholarships with respect to High School Diploma Grade

Notes: The figure reports the results of non parametric regressions between semi-elasticities with respect to $E(Scholarships)$ and percentile distribution of high school diploma grade by field of study. Semi-elasticities measure the percentage change in students' choices probabilities caused by a 1% increase in the DSU indicator. Each semi-elasticity is computed on the basis of the individual distribution of parameters estimated with the LCM. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

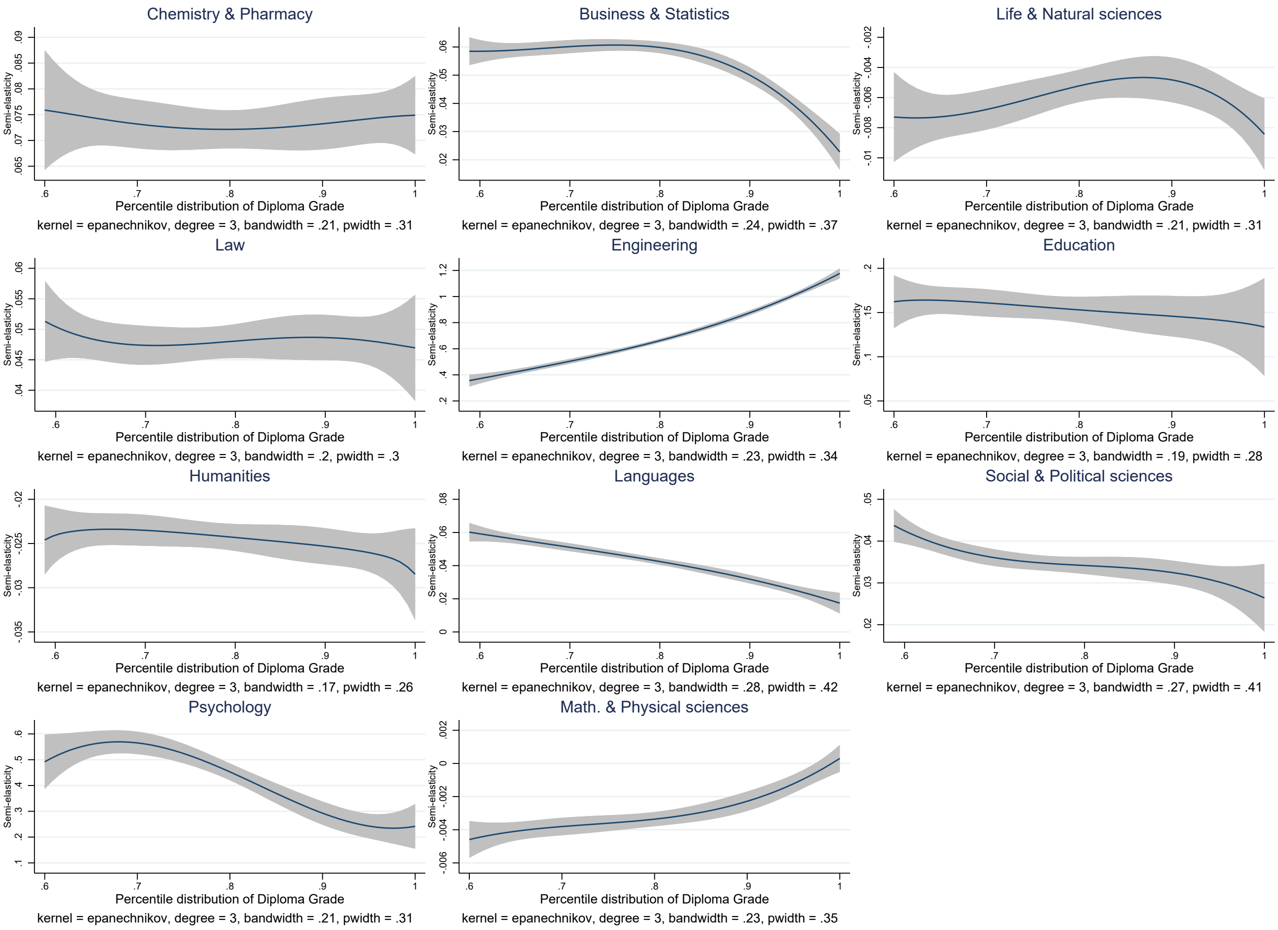


Figure 3A.2: Individual semi-elasticities to expected places in Dormitories with respect to High School Diploma Grade

Notes: Notes: The figure reports the results of non parametric regressions between semi-elasticities with respect to $E(Dormitory)$ and percentile distribution of high school diploma grade by field of study. Semi-elasticities measure the percentage change in students' choices probabilities caused by a 1% increase in the DSU indicator. Each semi-elasticity is computed on the basis of the individual distribution of parameters estimated with the LCM. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

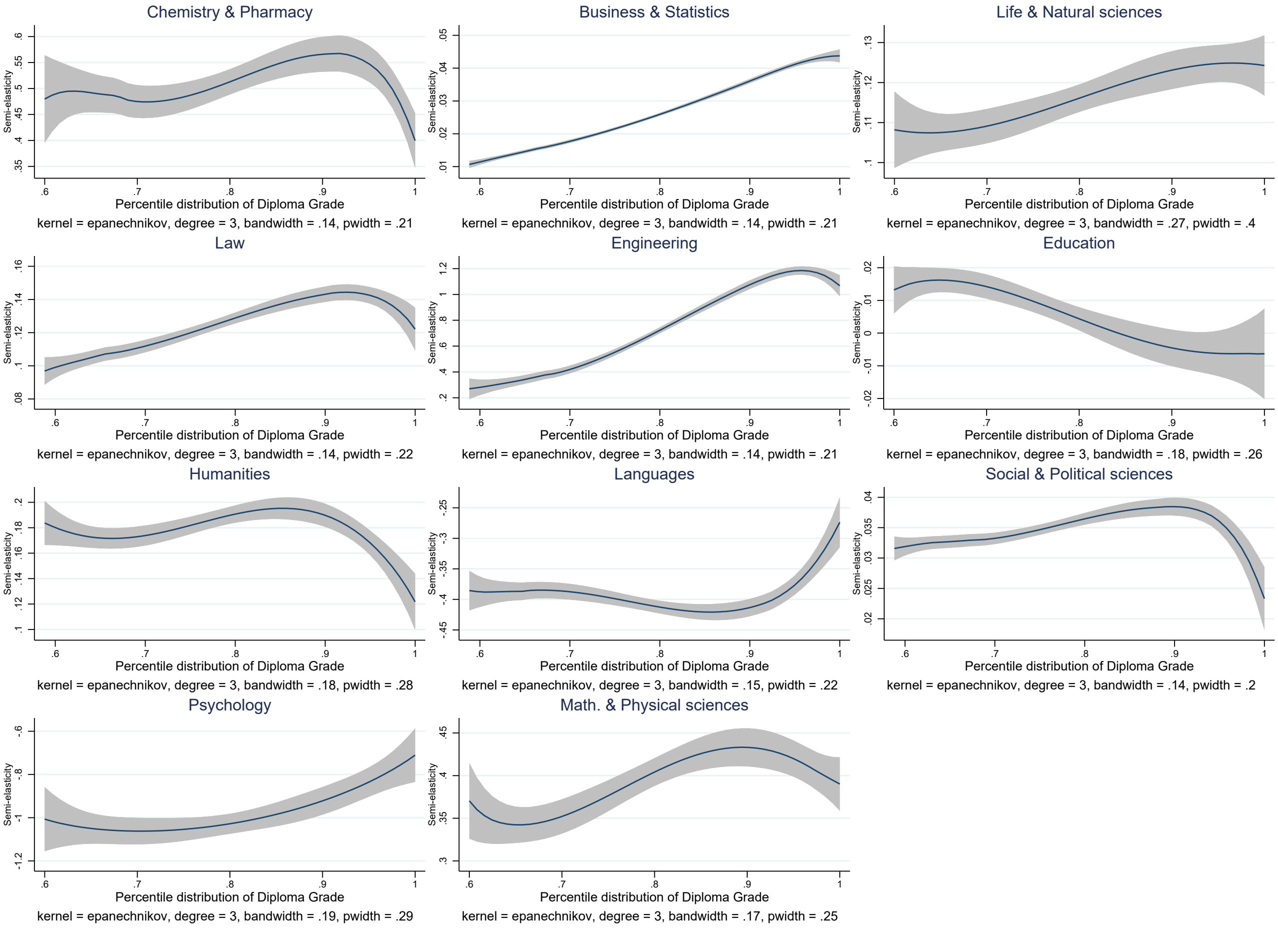


Figure 3A.3: Individual semi-elasticities to expected Student Packages with respect to High School Diploma Grade

Notes: The figure reports the results of non parametric regressions between semi-elasticities with respect to $E(StudentPackage)$ and percentile distribution of high school diploma grade by field of study. Semi-elasticities measure the percentage change in students' choices probabilities caused by a 1% increase in the DSU indicator. Each semi-elasticity is computed on the basis of the individual distribution of parameters estimated with the LCM. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

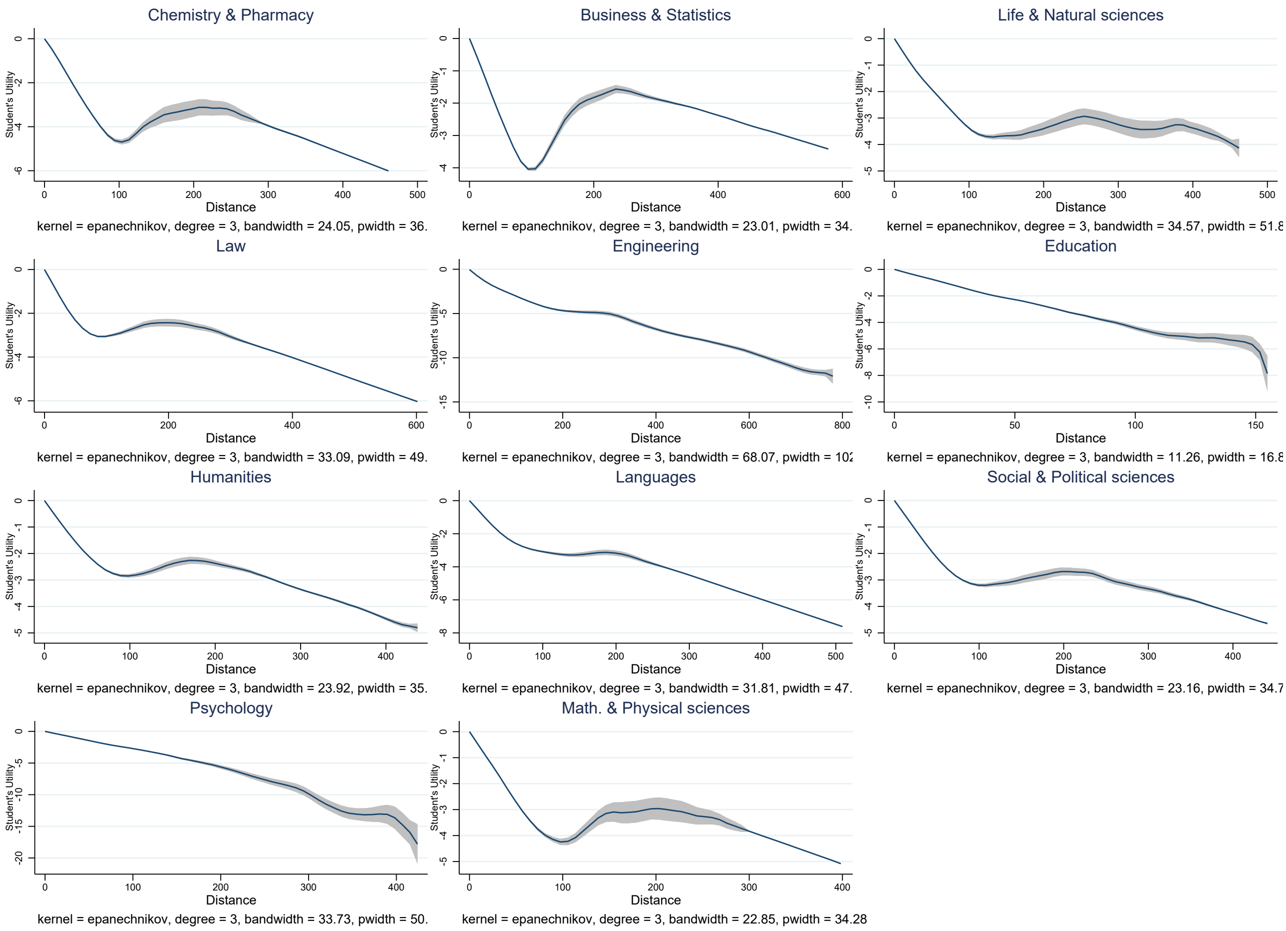


Figure 3A.4: Utility of distance

Notes: The figure reports the results of a non parametric regression between individual utility functions and the distance between students' city of residence and HEU's hosting city by field of study. Each regression is estimated using the individual distribution of parameters estimated through the LCM. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

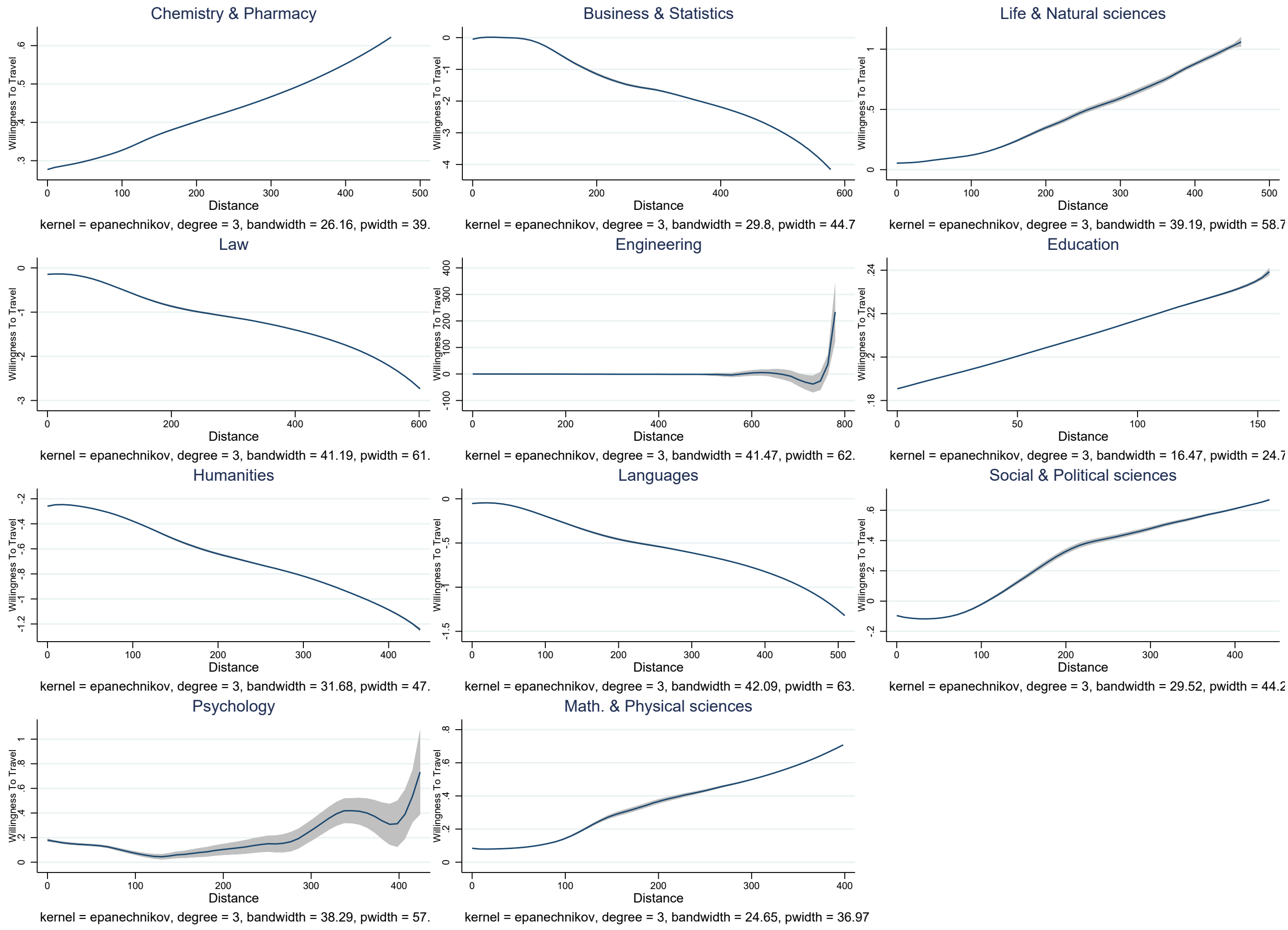


Figure 3A.5: Individual willingness to travel to a 1% increase in expected Scholarships

Notes: The figure reports the results of a non parametric regression between individual WTT with respect to $E(Scholarships)$ and the distance between students' city of residence and HEU's hosting city. Each regression is estimated using the individual distribution of parameters estimated through the LCM. Each WTT measures the number of additional kilometers that the student is willing to travel with respect to the chosen HEU for a 1% increase in DSU policy indicators. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

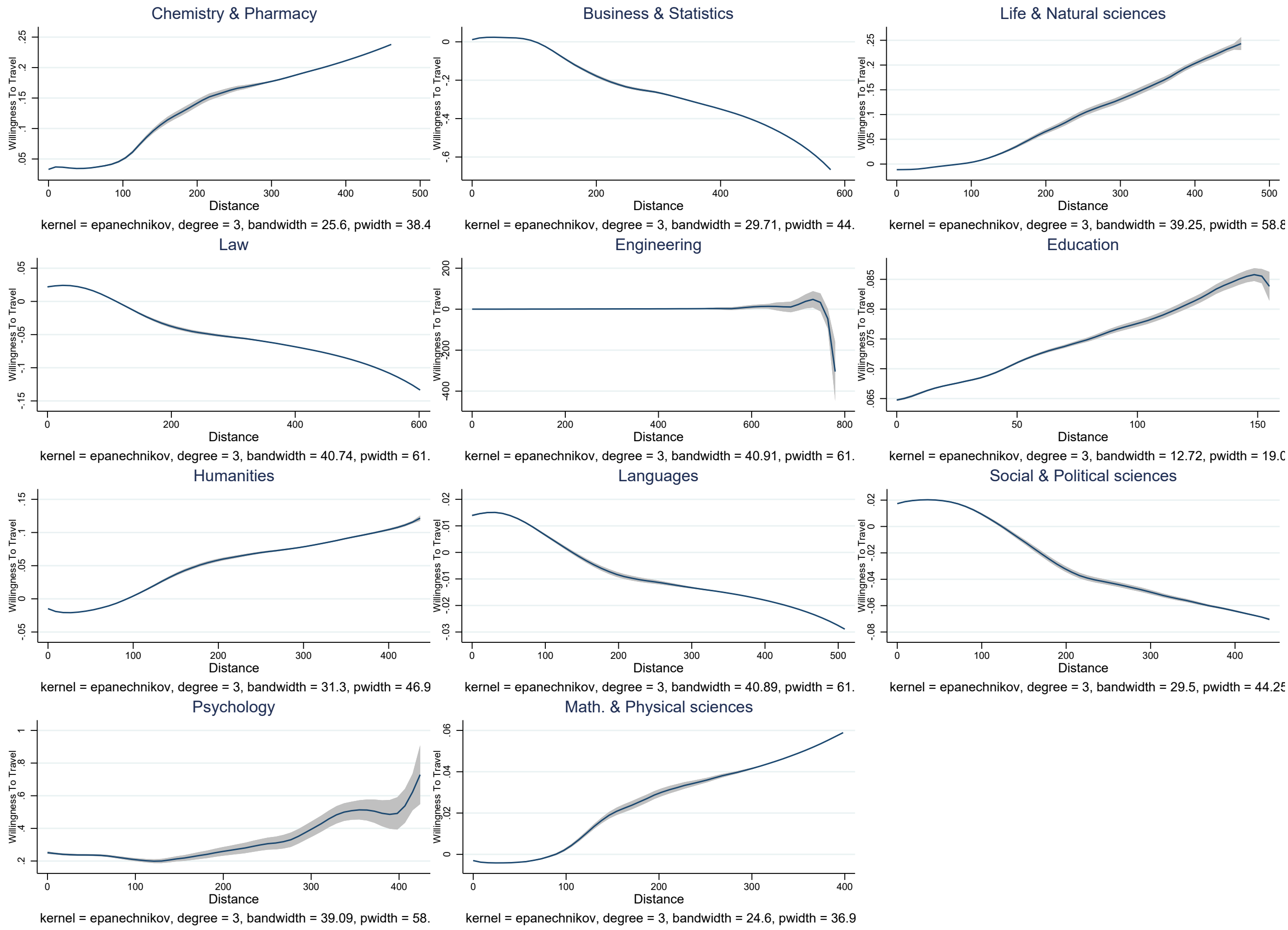


Figure 3A.6: Individual willingness to travel to a 1% increase in expected Places in Dormitories

Notes: The figure reports the results of a non parametric regression between individual WTT with respect to $E(Dormitory)$ and the distance between students' city of residence and HEU's hosting city. Each regression is estimated using the individual distribution of parameters estimated through the LCM. Each WTT measures the number of additional kilometers that the student is willing to travel with respect to the chosen HEU for a 1% increase in DSU policy indicators. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

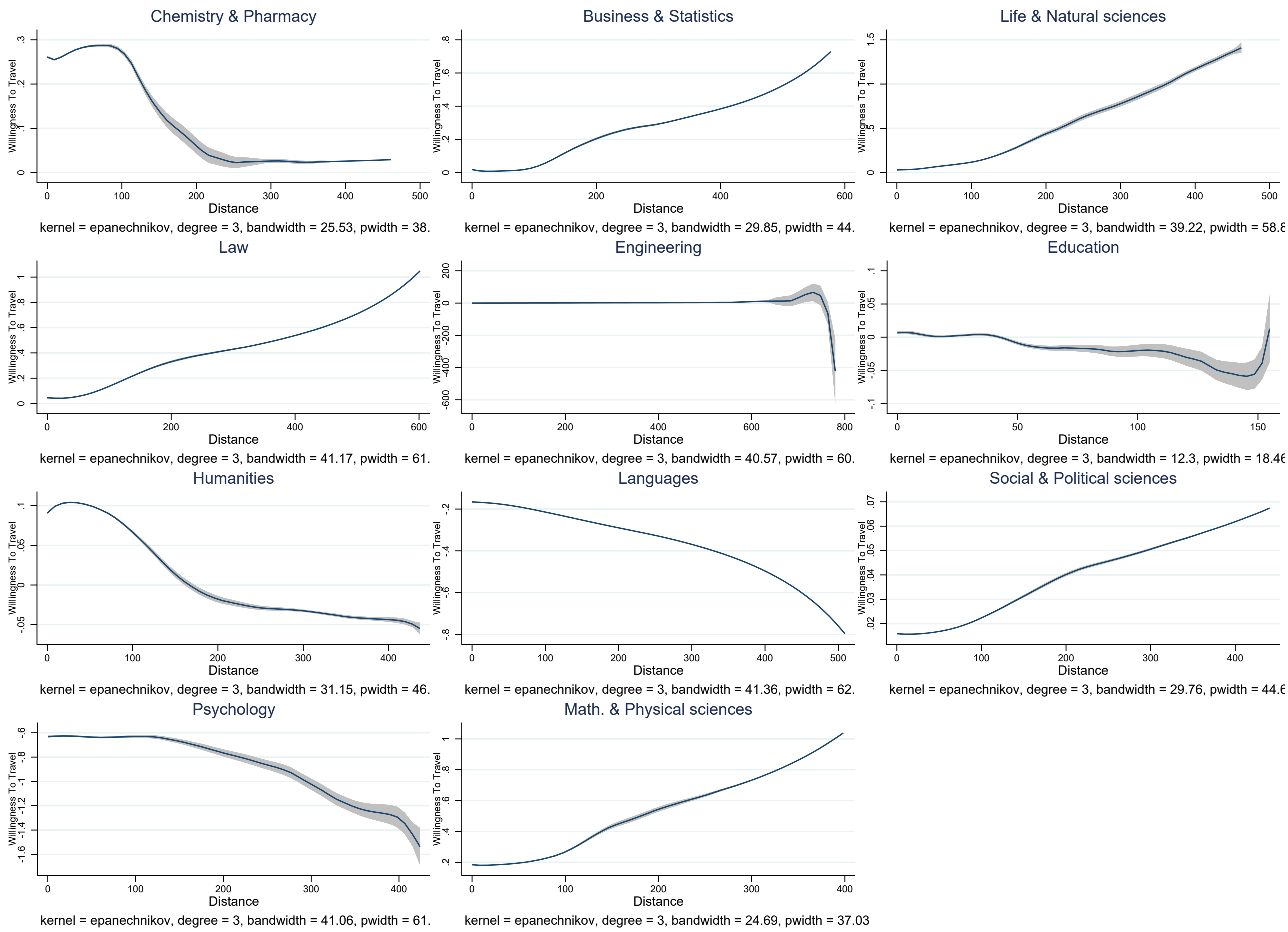


Figure 3A.7: Individual willingness to travel to a 1% increase in expected Student Packages

Notes: The figure reports the results of a non parametric regression between individual WTT with respect to $E(StudentPackage)$ and the distance between students' city of residence and HEU's hosting city. Each regression is estimated using the individual distribution of parameters estimated through the LCM. Each WTT measures the number of additional kilometers that the student is willing to travel with respect to the chosen HEU for a 1% increase in DSU policy indicators. In each plot we report the information regarding the kernel function used, the degree of the polynomial and the bandwidth chosen.

Bibliography

Agasisti, T. and Dal Bianco, A. (2007). 'Determinants of College Student Migration in Italy: Empirical Evidence from a Gravity Approach'. *SSRN Electronic Journal*.

Agrawal, D. R. and Foremny, D. (2018). 'Relocation of the Rich: Migration in Response to Top Tax Rate Changes from Spanish Reforms'. *The Review of Economics and Statistics*.

Akcigit, U., Grigsby, J., Nicholas, T., and Stantcheva, S. (2018). 'Taxation and Innovation in the 20th Century'. *Nber Working Paper Series* 24982.

Arcidiacono, P and Ellickson, P. B. (2011). 'Practical Methods for Estimation of Dynamic Discrete Choice Models'. *Annual Review of Economics, Vol 3* 3, 363–394.

Baccara, M., İmrohoroğlu, A., Wilson, A. J., and Yariv, L. (2012). 'A Field Study on Matching with Network Externalities'. *American Economic Review* 102.5, 1773–1804.

Bakija, J. and Slemrod, J. (2004). *Do the Rich Flee from High State Taxes? Evidence from Federal Estate Tax Returns*. Tech. rep.

Balia, S., Brau, R., and Moro, D. (2020). 'Choice of hospital and long-distances: Evidence from Italy'. *Regional Science and Urban Economics* 81.November 2019, 103502.

Balsmeier, B., Frick, B., and Hickfang, M. (2018). 'The impact of skilled immigrants on their local teammates' performance'. *Applied Economics Letters*, 1–7.

Bell, A., Chetty, R., Jaravel, X., Petkova, N., and Van Reenen, J. (2019a). 'Joseph Schumpeter Lecture, EEA Annual Congress 2017: Do Tax Cuts Produce more Einsteins? The Impacts of Financial Incentives VerSus Exposure to Innovation on the Supply of Inventors'. *Journal of the European Economic Association* 17.3, 651–677.

— (2019b). 'Who Becomes an Inventor in America? The Importance of Exposure to Innovation*'. *The Quarterly Journal of Economics* 134.2, 647–713.

Berlinschi, R., Schokkaert, J., and Swinnen, J. (2013). 'When drains and gains coincide: Migration and international football performance'. *Labour Economics* 21, 1–14.

Biancardi, D. and Bratti, M. (2019). 'The effect of introducing a Research Evaluation Exercise on student enrolment: Evidence from Italy'. *Economics of Education Review* 69, 73–93.

Bratti, M. and Verzillo, S. (2019). 'The 'gravity' of quality: research quality and the attractiveness of universities in Italy'. *Regional Studies* 53.10, 1385–1396.

Brueckner, J. K. (2000). 'Welfare Reform and the Race to the Bottom: Theory and Evidence'. *Southern Economic Journal* 66.3, 505–525.

Bryson, A., Frick, B., and Simmons, R. (2013). 'The Returns to Scarce Talent: Footedness and Player Remuneration In European Soccer'. *Journal of Sports Economics* 14.6, 606–628.

Buettner, T. and Janeba, E. (2016). 'City competition for the creative class'. *Journal of Cultural Economics* 40.4, 413–451.

Cameron, A. C. and Trivedi, K. P. (2005). *Microeconometrics: Methods and Applications.* Cambridge University Press.

Cammelli, A. and Gasperoni, G. (2015). '16th Almalaurea report on Italian university graduates' profile: Opportunities and Challenges for Higher Education in Italy'. *AlmaLaurea Working Papers* No. 74.

Castleman, B. L. and Long, B. T. (2016). 'Looking beyond Enrollment: The Causal Effect of Need-Based Grants on College Access, Persistence, and Graduation'. *Journal of Labor Economics* 34.4, 1023–1073.

Cattaneo, M., Malighetti, P., Paleari, S., and Redondi, R. (2016). 'The role of the air transport service in interregional long-distance students' mobility in Italy'. *Transportation Research Part A: Policy and Practice* 93, 66–82.

Cattaneo, M., Malighetti, P., Meoli, M., and Paleari, S. (2017). 'University spatial competition for students: the Italian case'. *Regional Studies* 51.5, 750–764.

Chiappori, P.-A. and Salanié, B. (2016). 'The Econometrics of Matching Models'. *Journal of Economic Literature* 54.3, 832–861.

Ciriaci, D. (2014). 'Does University Quality Influence the Interregional Mobility of Students and Graduates? The Case of Italy'. *Regional Studies* 48.10, 1592–1608.

Clemens, M. A. (2011). 'Economics and Emigration: Trillion-Dollar Bills on the Sidewalk?' *Journal of Economic Perspectives* 25.3, 83–106.

D'Agostino, A., Ghellini, G., and Longobardi, S. (2019). 'Out-migration of university enrolment: the mobility behaviour of Italian students'. *International Journal of Manpower* 40.1, 56–72.

Dardanoni, V., Laudicella, M., and Li Donni, P. (Feb. 2018). 'Hospital Choice in the NHS'. 18/04.

Declercq, K. and Verboven, F. (2018). 'Enrollment and degree completion in higher education without admission standards'. *Economics of Education Review* 66, 223–244.

Deming, D. and Dynarski, S. (2009). 'Into College, Out of Poverty? Policies to Increase the Postsecondary Attainment of the Poor'. *National Bureau of Economic Research Working Paper* 15387.

Dotti, N. F., Fratesi, U., Lenzi, C., and Percoco, M. (2013). 'Local Labour Markets and the Interregional Mobility of Italian University Students'. *Spatial Economic Analysis* 8.4, 443–468.

Dwenger, N., Storck, J., and Wrohlich, K. (2012). 'Do tuition fees affect the mobility of university applicants? Evidence from a natural experiment'. *Economics of Education Review* 31.1, 155–167.

Ernst & Young (2013). *Tax and career facilities for professional football players in 2013*. Tech. rep.

Esteller, A., Piolatto, A., and Rablen, M. D. (2016). 'Taxing high-income earners: Tax avoidance and mobility'. *IFS Working Paper* W16/07.

EUA, E. U. A. (2019). *EUA's public funding observatory*. Brussels: EUA.

European Commission (2018). *TEDB - Taxes in Europe database*.

Fan, J. and Gijbels, I. (1996). *Local Polynomial Modelling and its Applications*.

Feldstein, M. and Wrobel, M. V. (1998). 'Can state taxes redistribute income?' *Journal of Public Economics* 68.3, 369–396.

Ferreira, S. G., Varsano, R., and Afonso, J. R. (2005). 'Inter-jurisdictional fiscal competition: a review of the literature and policy recommendations'. *Revista de Economia Política* 25.3, 295–313.

Florida, R. (2002). 'The economic geography of talent'. *Annals of the Association of American Geographers* 92.4, 743–755.

Fox, J. T. (2007). ‘Semiparametric estimation of multinomial discrete-choice models using a subset of choices’. *The RAND Journal of Economics* 38.4, 1002–1019.

— (2018). ‘Estimating Matching Games with Transfers’. *Quantitative Economics* 9, 1–38.

Fratesi, U. and Percoco, M. (2014). ‘Selective Migration, Regional Growth and Convergence: Evidence from Italy’. *Regional Studies* 48.10, 1650–1668.

Freeman, R. B. (2006). ‘People Flows in Globalization’. *Journal of Economic Perspectives* 20.2, 145–170.

Giambona, F., Porcu, M., and Sulis, I. (2017). ‘Students Mobility: Assessing the Determinants of Attractiveness Across Competing Territorial Areas’. *Social Indicators Research* 133.3, 1105–1132.

Gibbons, S. and Vignoles, A. (2012). ‘Geography, choice and participation in higher education in England’. *Regional Science and Urban Economics* 42.1-2, 98–113.

Greene, W. H. and Hensher, D. A. (2003). ‘A latent class model for discrete choice analysis: contrasts with mixed logit’. *Transportation Research Part B: Methodological* 37.8, 681–698.

Gutacker, N., Siciliani, L., Moscelli, G., and Gravelle, H. (2016). ‘Choice of hospital: Which type of quality matters?’ *Journal of Health Economics* 50, 230–246.

Herm, S., Callsen-Bracker, H.-M., and Kreis, H. (2014). ‘When the crowd evaluates soccer players’ market values: Accuracy and evaluation attributes of an online community’. *Sport Management Review* 17.4, 484–492.

Hess, S. and Train, K. (2017). ‘Correlation and scale in mixed logit models’. *Journal of Choice Modelling* 23.

Hole, A. R. (2008). ‘Modelling heterogeneity in patients’ preferences for the attributes of a general practitioner appointment’. *Journal of Health Economics* 27.4, 1078–1094.

Hübner, M. (2012). ‘Do tuition fees affect enrollment behavior? Evidence from a ’natural experiment’ in Germany’. *Economics of Education Review* 31.6, 949–960.

International Bureau of Fiscal Documentation (IBFD) (2018). *Country surveys.*

ISTAT, I. N.d. S. (2019). *University Indicators.*

Jacquet, L. and Lehmann, E. (2019). ‘Optimal Income Taxation with Composition Effects’. *CRED working paper* 1.

Kelchtermans, S. and Verboven, F. (2010). 'Partecipation and study decisions in a public system of higher education'. *Journal of Applied Econometrics* 25, 255–391.

Kenyon, D. A. (1997). 'Theories of interjurisdictional competition'. *New England Economic Review* Mar, 13–36.

Kerr, W. R. (2013). 'US high-skilled immigration, innovation, and entrepreneurship: Empirical approaches and evidence'. *National Bureau of Economic Research Working Paper Series 19377*, 193–221.

Kim, J. S. (2018). 'Structural Estimation of Pairwise Stable Networks: An Application to Social Networks in Rural India'. *SSRN* March, 2018, 1–35.

Kleven, H., Landais, C., Muñoz, M., and Stantcheva, S. (2019). 'Taxation and Migration: Evidence and Policy Implications'. *NBER Working Papers* 25740.

Kleven, H. J., Landais, C., Saez, E., and Schultz, E. A. (2013). 'Taxation and International Migration of Top Earners: Evidence from European Football Market'. *American Economic Review* 103.5, 1892–1924.

Kleven, H. J., Landais, C., Saez, E., and Schultz, E. (2014). 'Migration and Wage Effects of Taxing Top Earners: Evidence from the Foreigners' Tax Scheme in Denmark'. *The Quarterly Journal of Economics* 129.1, 333–378.

KPMG - International (2018). *Tax Insights*.

Krenn, P. (2017). 'The Impact of Taxes on Competition for CEOs'. *European Accounting Review* 26.3, 503–530.

Krieger, T. and Lange, T. (2010). 'Education policy and tax competition with imperfect student and labor mobility'. *International Tax and Public Finance* 17.6, 587–606.

Krugman, P. (1991). 'Increasing returns and economic geography'. *Journal of Political Economy* 99.3, 483.

Kuehn, J. (2017). 'The Effect of Competition on the Demand for Skilled Labor: Matching with Externalities in the NBA'. *SSRN Electronic Journal*.

Lehmann, E., Simula, L., and Trannoy, A. (2014). 'Taxmeif You Can! Optimal Nonlinear Income Tax Between Competing Governments'. *Quarterly Journal of Economics* 129.4, 1995–2030.

Long, T. B. (2004). 'How have college decisions changed over time? An application of the conditional logistic choice model'. *Journal of Econometrics* 121.1-2, 271–296.

Lupi, C. and Ordine, P. (2009). ‘Family Income and Students’ Mobility’. *Giornale degli Economisti e Annali di Economia* 68.1, 1–23.

Manski, C. F. (1975). ‘Maximum score estimation of the stochastic utility model of choice’. *Journal of Econometrics* 3.3, 205–228.

Mathur, V. K. and Stein, S. H. (2004). ‘Do amenities matter in attracting knowledge workers for regional economic development?*’. *Papers in Regional Science* 84.2, 251–269.

Mcfadden, D. (1974). ‘Conditional logit analysis of qualitative choice behavior’. *in P. Zarembka, ed., Forntiers in Econometrics*, 105–142.

— (1978). ‘Modeling the choice of residential location’. *in A. Karlqvist, L Lundqvist, F. Snickars, and J. Weibull, eds., Spatial Interaction Theory and Planning Models*, 75–96.

McFadden, D. and Train, K. (2000). ‘Mixed MNL models for discrete response’. *Journal of Applied Econometrics* 15.5, 447–470.

McGuire, T. J. (1991). ‘Federal Aid to States and Localities and the Appropriate Competitive Framework’. *Competition among States and Local Governments: Efficiency and Equity in American Federalism.* Ed. by D. A. Kenyon and J. Kincaid. Urban Institute Press.

Mertens, K. and Montiel Olea, J. L. (2018). ‘Marginal Tax Rates and Income: New Time Series Evidence’. *The Quarterly Journal of Economics* 133.4, 1803–1884.

Milligan, K. and Smart, M. (2019). ‘An Estimable Model of Income Redistribution in a Federation: Musgrave Meets Oates’. *American Economic Journal: Economic Policy* 11.1, 406–434.

Mindruta, D., Moeen, M., and Agarwal, R. (2016). ‘A two-sided matching approach for partner selection and assessing complementarities in partners’ attributes in inter-firm alliances’. *Strategic Management Journal* 51.37, 206–231.

Mirrlees, J. A. (1982). ‘Migration and optimal income taxes’. *Journal of Public Economics* 18.3, 319–341.

Modena, F., Rettore, E., and Tanzi, G. M. (2018). ‘The Effect of Grants on University Drop-Out Rates: Evidence on the Italian Case’. *Temi di discussione (Economic Working Papers), Bank of Italy.*

Moretti, E. (2004). ‘Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data’. *Journal of Econometrics* 121.1-2, 175–212.

Moretti, E. and Wilson, D. J. (2014). ‘State incentives for innovation, star scientists and jobs: Evidence from biotech’. *Journal of Urban Economics* 79, 20–38.

— (2017). ‘The effect of state taxes on the geographical location of top earners: Evidence from star scientists’. *American Economic Review* 107.7, 1858–1903.

Murphy, R., Scott-Clayton, J., and Wyness, G. (2019). ‘The end of free college in England: Implications for enrolments, equity, and quality’. *Economics of Education Review* 71, 7–22.

Musgrave, R. (1959). *The theory of public finance : a study in public economy*. New York: McGraw-Hill.

Oates, W. E. (1972). *Fiscal federalism*. Harcourt Brace Jovanovich, p. 256.

Oggenfuss, C. and Wolter, S. C. (2019). ‘Are they coming back? The mobility of university graduates in switzerland’. *Review of Regional Research*, 1–20.

Organization for Economic Cooperation and Development (OECD) (2018). *Taxing wages*. Paris.

Peeters, T. (2018). ‘Testing the Wisdom of Crowds in the field: Transfermarkt valuations and international soccer results’. *International Journal of Forecasting* 34.1, 17–29.

Pigini, C. and Staffolani, S. (2013). ‘Enrollment costs, university quality and higher education choices in Italy’. *MPRA Paper*.

— (2015). ‘The effect of university costs and institutional incentives on enrolments: Empirical evidence for italian regions’. *AIEL Series in Labour Economics* 8, 261–282.

Piketty, T. and Saez, E. (2013). ‘Optimal Labor Income Taxation’. *Handbook of Public Economics*. Vol. 5. Elsevier, pp. 391–474.

Piketty, T., Saez, E., and Stantcheva, S. (2014). ‘Optimal Taxation of Top Labour Incomes: A Tale of Three Elasticities’. *American Economic Journal: Economic Policy* 6.1, 230–271.

Politis, D. N., Romano, J. P., and Wolf, M. (1999). *Subsampling*. Springer Series in Statistics. New York, NY: Springer New York.

PriceWaterhouseCoopers (PwC) (2018). *Worldwide Tax Summaries*.

Romano, J. and Shaikh, A. M. (2008). ‘Inference for identifiable parameters in partially identified econometric models’. *Journal of Statistical Planning and Inference* 138.9, 2786–2807.

Rosen, S. (1981). ‘The Economics of Superstars’. *The American Economic Review* 71.5, 845–858.

Ruiz del Portal, X. (2017). 'Optimal mixed taxation, public goods and the problem of high-skilled emigration'. *Journal of Economics* 122.2, 97–119.

Rust, J. (1987). 'Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher'. *Econometrica* 55.5, 999.

Saez, E., Slemrod, J., and Giertz, S. H. (2012). 'The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review'. *Journal of Economic Literature* 50.1, 3–50.

Salter, A. J. and Martin, B. R. (2001). 'The economic benefits of publicly funded basic research: A critical review'. *Research Policy* 30.3, 509–532.

Sanandaji, T. (2014). 'The international mobility of billionaires'. *Small Business Economics* 42.2, 329–338.

Santiago, D. and Fox, J. T. (2008). 'A Toolkit for Matching Maximum Score Estimation and Point and Set Identified Subsampling Inference'. *Working paper, Rice University.*

Schmidheiny, K. and Brülhart, M. (2011). 'On the equivalence of location choice models: Conditional logit, nested logit and Poisson'. *Journal of Urban Economics* 69.2, 214–222.

Schmidheiny, K. and Slotwinski, M. (2018). 'Tax-induced mobility: Evidence from a foreigners' tax scheme in Switzerland'. *Journal of Public Economics* 167, 293–324.

Schwert, M. (2018). 'Bank Capital and Lending Relationships'. *Journal of Finance* 73.2, 787–830.

Simula, L. and Trannoy, A. (2010). 'Optimal income tax under the threat of migration by top-income earners'. *Journal of Public Economics* 94.1-2, 163–173.

— (2017). 'The Dark Side of Tax Breaks for Foreigners'. *Working Paper.*

Sivey, P. (2012). 'The effect of waiting time and distance on hospital choice for English cataract patients'. *Health economics* 21, 444–456.

Spiess, C. K. and Wrohlich, K. (2010). 'Does distance determine who attends a university in Germany?' *Economics of Education Review* 29.3, 470–479.

Stantcheva, S., Akcigit, U., and Baslandze, S. (2016). 'Taxation and the International Mobility of Inventors'. *American Economic Review* 106.10, 2930–2981.

Storn, R. and Price, K. (1997). 'Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces'. *Journal of Global Optimization* 11.4, 341–359.

Suhonen, T. (2014). 'Field-of-Study Choice in Higher Education: Does Distance Matter?' *Spatial Economic Analysis* 9.4, 355–375.

Tiebout, C. (1956). 'A Pure Theory of Local expenditures'. *Journal of Political Economy* 64.5, 416–424.

Train, K. E. (2003). *Discrete choice methods with simulation.* Vol. 9780521816, pp. 1–334.

Türk, U. (2019). 'Socio-Economic Determinants of Student Mobility and Inequality of Access to Higher Education in Italy'. *Networks and Spatial Economics* 19.1, 125–148.

Valero, A. and Van Reenen, J. (2019). 'The economic impact of universities: Evidence from across the globe'. *Economics of Education Review* 68, 53–67.

Varkevisser, M., Geest, S. A. van der, and Schut, F. T. (2012). 'Do patients choose hospitals with high quality ratings? Empirical evidence from the market for angioplasty in the Netherlands'. *Journal of Health Economics* 31.2, 371–378.

Varner, C. and Young, C. (2012). 'Millionaire Migration in California: The Impact of Top Tax Rates'. *Working paper, Stanford University Center on Poverty and Inequality.*

Vasilakis, C. (2017). 'Does talent migration increase inequality? A quantitative assessment in football labour market'. *Journal of Economic Dynamics and Control* 85, 150–166.

Vergolini, L. and Zanini, N. (2015). 'Away, but not too far from home. The effects of financial aid on university enrolment decisions'. *Economics of Education Review* 49, 91–109.

Viesti, G. (2016). 'Università in declino: un'indagine sugli atenei da Nord a Sud'. *Scuola democratica, Learning for Democracy* 3, 406.

Wildasin, D. (1991). 'Income Redistribution in a Common Labor Market'. *American Economic Review* 81.4, 757–74.

Wildasin, D. E. (1988). 'Nash Equilibria in Models of Fiscal Competition'. *Journal of Public Economics* 35, 229–240.

Yang, Y., Shi, M., and Goldfarb, A. (2009). 'Estimating the Value of Brand Alliances in Professional Team Sports'. *Marketing Science* 28.6, 1095–1111.

Young, C. and Varner, C. (2011). 'Millionaire Migration and State Taxation of Top Incomes: Evidence From a Natural Experiment'. *National Tax Journal* 64.2, 255–83.

Young, C., Varner, C., Lurie, I. Z., and Prisinzano, R. (2016). 'Millionaire Migration and Taxation of the Elite: Evidence from Administrative Data'. *American Sociological Review* 81.3, 421–446.