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Medical Brain Drain – Assessing the Role of Job Attributes and Individual Traits

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ABSTRACT

Medical Brain Drain – Assessing the Role of Job Attributes and Individual Traits*

We study physicians' migration intentions by undertaking a Discrete Choice Experiment with senior Italian medical students. Using the mixed logit models, we estimate how much income students are willing to forego for various job characteristics, including the job location. We find that future doctors are willing to sacrifice €13,500/year on average to remain in their home country. Those with higher willingness to take risks, competitiveness, cognitive skills and altruism levels are more likely to migrate abroad, with implications for the quality of future doctors remaining in their home country. Furthermore, the valuations of several job characteristics differ substantially for jobs located in the home country or abroad, informing the design of job contracts that shall help retain young doctors.

JEL Classification: F66, I18, J08

Keywords: brain drain, medical workforce, job design, personality traits, discrete choice experiments

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1 Introduction

Economic research has long focused on the determinants and consequences of the "brain drain" from low- to high-income countries (see Docquier and Rapoport, 2012, for a review). Instead, the analysis of the flows of high-skilled workers across high-income countries has received less attention.[1] Our paper contributes to this growing body of literature by studying the migration intentions of Italian medical students.

Why the medical brain drain, and why Italy? While the brain drain interests most high-skilled occupations, the emigration of physicians may have negative side effects on healthcare quality and thus population health for countries that are not able to attract doctors from abroad. Moreover, the medical brain drain imposes fiscal costs on sending countries that finance doctors' training with public money.

Italy is a European country that has long been affected by the brain drain (see Hellemans, 2001; Becker et al., 2004). According to Riccò et al. (2020), around 1000 medical doctors are leaving Italy every year to work abroad (a seventh of all new medical specialists), making it rank fourth in Europe for the number of emigrating medical doctors (MDs) between 1990 and 2014 (Adovor et al., 2021). In addition, the number of foreign MDs working in Italy is far lower than the OECD average (OECD, 2021). As stressed by La Colla (2019), these two factors have contributed to generate a shortage of doctors. Paterlini (2019) estimated that Italy will be short of 16,700 medical specialists by 2025 if the current trends continue. The Covid-19 crisis has revamped the political attention on this shortage: during the first outbreak of the pandemic, regional healthcare authorities urged the central government to allow them to recruit retired doctors and retain those who are working until they reach 70, generating increasing burnout (Paterlini, 2022).

The literature on physician migration has largely focused on documenting global migration trends, their macro-level determinants, and their consequences for low-income sending countries (Clemens and Pettersson Gelander, 2006; Clemens, 2007; Bhargava and Docquier, 2008; Bhargava et al., 2011). For instance, Adovor et al. (2021) identify economic characteristics at source and destination countries, dyadic factors like linguistic and geographical proximity, and lax immigration policies to be significant determinants

[1] Important studies in this area include the analysis of the mass exodus of PhD holders and researchers in science and technology from Europe to the U.S. (Docquier and Rapoport, 2012); the brain drain from Southern European countries like Italy and Greece, hit hard by the financial crisis of 2008 (Theodoropoulos et al., 2014); (Anelli and Peri, 2017); and large scale migration from eastern to western Europe due to free labour mobility provisions since the accession of the European Union (Mayr and Peri, 2009).

of medical migration flows (see also Botezat and Ramos, 2020).

Our study, by contrast, contributes to the literature by focusing on the determinants of future doctors' emigration from a high-income country, and on investigating the role played by micro-level determinants of emigration, including individual traits and the job characteristics that physicians weigh in their home country versus abroad while making migration decisions. We seek to answer to three central research questions:

1. Do future doctors value jobs located in their home country more than comparable jobs located abroad?

2. Do job location preferences depend on personal characteristics?

3. Does future doctors' valuation of job attributes differ with the location of jobs?

Answering the first question is relevant to assess future doctors' willingness to stay in their home country; the second question aims at describing the patterns of selection into migration of future doctors, and helps understand the characteristics of the pool of doctors that are more willing to remain in their home country; and the third question seeks to uncover the features of jobs that future doctors weigh the most in their home country vs. abroad, contributing to understand how job design may curb the emigration of young doctors.

To the best of our knowledge, the only available evidence on these matters is reported by Riccò et al. (2020), who carried out a web-based survey on a sample of 782 Italian medical doctors working in Italy and abroad and enrolled in a Facebook group discussing medical migration. According to the subjective views of the selected sample of doctors who took part in the survey, the inadequacy of training and medical infrastructures, low wages, and uncertain career progression in Italy are the most relevant motivators towards migration, while language difficulties, cultural integration and the fear of being under-skilled are the most relevant barriers.

In the absence of high quality secondary data on migration intentions and outcomes, and of quasi-experimental variation of physician job characteristics, we study the relationship between physician job attributes and emigration preferences by performing a Discrete Choice Experiment (DCE) with medical students at 12 universities in Italy. A DCE is a survey experiment where respondents are presented with a series of hypothetical but realistic choice sets, with each alternative described by a bundle of attributes. Respondents

are then asked to choose their most preferred option, which allows for the inference of trade-offs between job attributes. In our DCE, each student chooses sixteen times their most preferred between two hypothetical jobs that vary in terms of six attributes: professional development opportunity, income, job security, working conditions, match of skills with job requirements, and - crucially - country of the job. In each hypothetical scenario, respondents trade off these job attributes by choosing one of the two jobs or opting out from either.

There are papers in the medical migration literature that use DCEs to study the retention of medical workforce in rural areas (Ryan et al., 2012; Gallego et al., 2015) and papers that investigate what job characteristics that are most important to attract medical students to certain specialities (Sivey et al., 2012; Mandeville et al., 2016; Cleland et al., 2017). Although these DCEs are informative about the relative importance of job characteristics for doctors, to our knowledge the existing DCE literature does not use country as one of the attributes that define a job and thus does not explicitly investigate how valuations of different job characteristics change by home and foreign countries.

From this perspective, our paper contributes to the literature that uses experimental methods to learn about the determinants of migration (see McKenzie, 2015, for a review). For instance, our work is close to the analysis of Batista and McKenzie (2021), who use laboratory experiments on samples in Lisbon and Nairobi to test how potential migrants trade-off different attributes of potential migration destinations and that include migration costs, returns to skills, unemployment risk and social benefits. Unlike their analysis, however, we focus on attributes of jobs rather than of the country of destination.

Following Train and Weeks (2005), we analyse the data using mixed logit models estimated in the willingness-to-pay space. We summarise our findings as follows. First, we find that students are willing to give up €13,515 (Purchasing Power Parity adjusted) net annual income on average to stay in Italy. There is, however, large heterogeneity behind this mean value, and roughly one sixth of the students are willing to forgo an average of €7,841 to go to their favorite foreign European country. Other job attributes also matter: on average, future doctors are attracted by high-paying jobs that offer good working conditions, good professional development opportunities, and are not fixed-term. Skill mismatch, instead, is less important. We also illustrate the relevance of each job attribute in triggering migration decisions with a set of counterfactual simulations.

Second, several observed background characteristics of the students as well as their

personality traits contribute to explain the heterogeneity documented by the mixed logit model in the valuation for job location. We find that students who do not want to specialise at their own University, those without a partner, those who know the language of their favourite foreign country and those who have personal ties in their favorite European country are more predisposed to moving abroad. In terms of personality traits, we find that students with higher levels of cognitive skills, altruism, risk tolerance and competitiveness are more inclined to move abroad. Contrarily, we find limited evidence that the Big-5 personality traits and locus of control impact migration intentions. These findings help to describe the characteristics of the medical doctors that are less willing to remain in Italy, and contribute to an emerging literature documenting the role of cognitive and non-cognitive traits for emigration decisions (Jaeger et al., 2010; Ayhan et al., 2020; Caliendo et al., 2019; Fouarge et al., 2019; Bütikofer and Peri, 2021). In addition, to the best of our knowledge, this is the first study to investigate the role of competitiveness in determining migration intentions.

Third, we find that future doctors' willingnesses to pay (WTP) estimates [2] for several job features differ significantly between jobs located in Italy and abroad. Specifically, future doctors have a very high WTP for permanent contracts in Italy but prefer temporary contracts with renewal possibility abroad. Consistently, they also care for good professional development opportunities more in Italy than abroad. Moreover, they do not like lacking skills for the jobs abroad where they may already be facing other difficulties involved with settling in within a new institutional environment, and possibly also language barriers. But they do not mind it in Italy where their longer-term prospects may make them more inclined to accept an initial period of training. By contrast, their preferences for good working conditions (workload, overtime work, night shifts) are comparable across jobs located both in Italy and abroad.

Our findings have important implications for our understanding of the individual drivers of selection into migration of medical doctors and for the design of job contracts that help retain young doctors in countries facing a potential medical workforce shortage. Since we estimate that most young Italian doctors are willing to forgo a considerable amount of salary in order to remain in the country, the existence of a brain drain among young medical professionals seems to be mostly related with poor working conditions and

[2]Strictly speaking, here "WTP" means willingness to forgo income but the term is used for convenience thereafter.

lacking professional development opportunities in Italy - something future doctors are very keen on when searching for jobs in Italy. Moreover, the preference for fixed-term jobs with renewal possibilities and a lower WTP for professional development opportunities abroad suggest that future Italian doctors may be considering migration as temporary. However, preferences may change once they settle in a foreign country. Considering that salary is an important determinant of migration decisions, policies granting tax breaks to return migrants - like the "Controesodo" (mass return) policy established by the Italian Government in 2010 (see e.g. Bassetto and Ippedico, 2022; Creanza, 2023) - may facilitate the return of migrating doctors.

2 Survey design

2.1 The discrete choice experiment

A DCE is a stated preference method used to elicit individuals' preferences for alternatives. These alternatives are defined on the basis of attributes, and unique alternatives are formed by varying the attributes' levels. The respondents are posed with multiple scenarios where they have to choose between two or more alternatives each time. The resulting choice patterns can then be used to determine the relative importance of these attributes and the trade-offs between them. One of the attributes usually is a continuous monetary (or time) variable which allows researchers to express the preferences for certain attributes in terms of willingness to pay (or willingness to wait).

In our DCE, we ask future medical doctors to assume that they had just completed their specialisation of choice, and confront them with 16 choice tasks. In each task, they have to choose between two hypothetical jobs that differ with respect to several attributes. An opt-out option is also included, and the selection of this option signifies that neither of the job offers meets the student's reservation level of utility. Considering that in reality no job seeker is forced to choose among two alternative job offers, but can always continue to search, forcing the choice of a job among the proposed ones could have generated unrealistic choice patterns. This is especially true for medical doctors. According to Almalaurea data,[3] the unemployment rate of medicine graduates at 5 years from graduation is almost negligible, below 1%, compared to an average of 7% among all

[3]https://www.almalaurea.it/universita/occupazione/occupazione18

other graduates. This means they can shop for the "best" jobs without having to worry too much about unemployment risk.

We decided on the job attributes and their levels from previous literature in labour economics that uses DCEs to assess workers' willingness to pay for different job features (see e.g. Mas and Pallais, 2017; Non et al., 2022; Datta, 2019), and studies that develop DCEs on specialty choice as well on the retention of medical staff in developing countries and rural areas (Hanson and Jack, 2010; Mandeville et al., 2014, 2016). We also carried out a focus group with the student representatives from the fifth and sixth grades of the medical school at the University of Padova, that broadly confirmed our initial attribute choice. The eventual choice of attributes and their corresponding levels is reported in Table 1 and described in what follows. Appendix Figure A1 reports the introduction to the choice tasks provided to students and a choice task example.

1. *Location.* In the survey, students were initially asked to name their favourite foreign European country. We restricted the exercise to European countries to limit hypothetical bias.[4] When thinking about their favourite foreign European country, we prompted students not to think about aspects related with the labour market - such as wages, working conditions, training or research opportunities - but about other aspects that attract them - such as weather, food, culture, or the functioning of institutions. Appendix Table A1 reports the distribution of the favourite European country selected by individuals in our final sample, and shows that the UK, Spain, Switzerland and France are the most commonly chosen countries. We then proposed to students jobs located either in Italy or in their favourite foreign European country. Alternatively, we could have only mentioned that the job was located "abroad", but individual differences in the interpretation of what "abroad" means could have generated unobserved heterogeneity in WTP estimates for job location. The same would have happened if we had named some specific foreign country, because of individual differences in their feelings for a given country.[5] Furthermore, note that

[4]For instance, working as a doctor in the US requires to pass a formal exam, and we did not want that students had to make assumptions on this matter. Eventually, we discarded from the final sample 6 students who listed a non-European country as their favourite country. Despite Brexit, we retained students who chose the UK, but we will show that our results hold irrespective of their inclusion.

[5]To put it another way, by asking them to pick their favourite foreign country we ask respondents to put themselves in the situation where, conditional on intention to migrate, they have already maximized expected utility as the difference between non-work related expected benefits and costs across all foreign European countries.

- to ease identification of the preferences for other job attributes - the design asks respondents to make comparisons between jobs located in different countries *as well as* between jobs located in the same country (the countries considered being Italy or the respondent's favourite foreign European countries). This consideration holds for the other job attributes too.[6]

2. *Income.* Income is the numeraire variable, which allows for the calculation of the WTP for changes in the levels of all the other attributes. In other words, we can deduce how much income a student is willing to sacrifice as they go from one level of an attribute to a more preferred level. We presented Purchasing Power Parity (PPP) adjusted net income levels and instructed the students that, if the job offer refers to a foreign country where the cost of living is higher (lower) than in Italy, they should assume to earn proportionally more (less) in order to maintain their purchasing power equal to what they would have in Italy with that sum. We also asked them to assume that the salary is representative for the first two years after the starting of the job, and would increase by 5% every 2 years (see Anelli, 2019). The choice of income levels is based on OECD data on the salaries of doctors in European countries, and described in detail in Appendix B.

3. *Job security.* This attribute represents the duration of the contract, and can be expected to influence doctors' choices not only by itself but also through an interaction effect with the country of work. For example, if an individual wants to work abroad only for a few years to enjoy the experience of working and living abroad, but wants to settle in Italy in the long term, then obtaining a permanent job abroad would not be as important as it might be in the home country.

4. *Professional development opportunities.* This is an indicator of the research and training opportunities offered by the job. For instance, multiple studies have provided evidence that the intellectual content of the job is an important determinant of specialty choice (AMWAC, 2005; Horn et al., 2008). The impact of this attribute on choice may also differ by job location. If migration intentions are only tempo-

[6] A related concern is whether respondents were aware of the average level of the attributes in the countries involved in the comparisons and, as a result, could have deemed the alternative levels of the attributes provided in each scenario as implausible with respect to the average. We hasten to stress that, while they may differ from the average job available in each country, none of the combinations of attributes provided in our tasks is utterly unrealistic within the European context.

rary, professional development opportunities may be perceived to be more valuable for jobs located in the home country, where future doctors want to establish their careers in the long run.

5. *Working conditions.* Working conditions or workload is a highly relevant attribute considered by doctors making a job choice and has been used by many studies on specialty choice and medical staff preferences (Kolstad, 2011; Sivey et al., 2012). Again, their impact may differ by job location if doctors are willing to stand bad working conditions for a short period abroad in exchange for the "foreign" experience.

6. *Match of skills with job content.* Skill mismatch is a relevant determinant of job turnover and job satisfaction, as well as of individual productivity at work (see Brunello and Wruuck, 2021, for a review). While overskilling may generate frustration, underskilling requires training. The impact of this attribute on choice may also differ by job location. For example, individuals may be unwilling to invest in skills for a job abroad if they already face other non-monetary costs related with adaptation to a foreign environment - including language training.

A full factorial design using these six attributes and their defined levels would lead to $(2^2 \times 3^3 \times 6) = 648$ different job profiles and ${}^{648}C_2 = 209,628$ possible choices between any two jobs. Since this is clearly not feasible to be implemented, we used a D-efficient design to restrict the number of choice sets to 16. The efficiency of a design can be maximised before undertaking a survey by assuming prior parameter estimates and estimating an asymptotic variance-covariance (AVC) matrix of these parameter estimates (usually by simulation methods, but analytical methods can also be used). The D-error is given by $det(\Omega)^{1/K}$, where Ω is the AVC matrix and K is the number of model parameters to be estimated. A D-efficient design is the design that minimises the D-error and selects a list of choice sets in which dominant alternatives do not appear, choice sets are not repeated, and the number of choice sets for which the answer can be inferred from the previous one is minimised (assuming transitivity and monotonicity of preferences). We obtained the D-efficient design by specifying the most complex version of the model that we were interested in estimating, which included up to a cubic income term and interaction terms between country and other attributes.

In addition to the 16 tasks selected with the D-efficient procedure, we included an additional task in which one job option strictly dominated the other. This serves as a check for whether subjects were paying sufficient attention while participating in the experiment and/or whether they understood the instructions provided to complete the DCE tasks. We excluded from the final sample 13 subjects who did not select the strictly dominant job option (see Section 3.2).

Finally, to even out any possible effects from the order of appearance of the job attributes in the choice sets and limit the potential for attribute non-attendance (see Hole, 2011), we used three different versions of the questionnaire, each with a different order of the attributes in the DCE choice sets. Subjects were randomly assigned to one of the three versions.

2.2 Background characteristics and personality traits

After finishing the choice tasks, we asked respondents to complete a comprehensive questionnaire on their socio-demographic characteristics and their personality traits. Background information includes the students' age, gender, country and region of birth, their specialisation area of interest and if they'd like to undertake the specialisation in the same University where they are currently enrolled, their grade point average at university, whether they have a partner, whether they have done an Erasmus (foreign student exchange) program, family income and parents' occupations, whether they know the language of their favourite European country, and whether any of their personal ties (parents, friends, or acquaintances) lives there.

We have also collected a large battery of personality characteristics of the students, that include self-efficacy (individuals' belief in their capacity to undertake given tasks); locus of control (the degree to which people believe that the control over the outcome of events in their lives depends on themselves or on external forces) intrinsic and extrinsic motivation (whether people perform tasks for the plasure of doing them or because of outside causes, such as punishments or rewards); risk attitudes; competitiveness; altruism; the Big-5 personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism).

Details on the survey items used for the measurement of these traits and the construction of the corresponding indices are reported in Appendix C. In order to understand selection into migration, in the empirical analysis we will investigate the heterogeneity in

future doctors' WTP for remaining in Italy along these traits.

3 Data

3.1 Sampling

We conducted an online survey (in Italian) with medical students enrolled in Italian universities. We refer readers to Appendix D for a detailed presentation of the institutional setup governing medical education and access to the medical profession in Italy. To gain permission to contact the students and to reach them with appropriate communication strategies, we got in touch with all the Italian universities with a medical school via the national board of medical school deans, and by writing individual emails to all deans and course managers. In total, 12 out of 40 medical schools replied to our appeal and supported us in the data collection (11 are public, one is private). Appendix Table A2 reports the list of universities involved in our study and the distribution of respondents in our final sample by university.

The survey instrument was made available to students through a dedicated online link. We included the link in an invitation message and forwarded the text to the deans. Then, each university autonomously decided the most effective way to engage the students in the survey (some acted via the students' representatives, other posted messages in the students' electronic board, other used emails). The data was collected in November 2020 at the University of Padova, that served as a pilot, and between April and July 2021 at all other Universities. We allowed all interested students to respond to the survey, but since our experiment requires the students to imagine themselves after their specialisation, to minimise hypothetical bias we only use data for students enrolled in the fourth to final (sixth) year and who stated that they are planning to attend a specialisation course.

3.2 Sample selection

We collected data on 1,225 respondents who aim to pursue a specialisation - the others were automatically excluded from completing the DCE task by the survey instrument. From this sample, we dropped 18 non-Italian students, 6 students who listed a non-European favourite country, 13 students who ticked the strictly-dominated job offer, thereby failing the rationality test, 7 students with missing data on key covariates, and

654 students enrolled in grades 1-3 and excluded from our analysis. Our final sample includes 527 respondents, each completing 16 choice tasks, for a total of 8,432 choices.

3.3 Sample representativeness

A relevant issue in terms of the external validity of our findings concerns sample representativeness. While all students at each participating university were invited to take the survey, not all of them did so. This non-response problem may lead us to analyse a sample that potentially does not represent the reference population. To assess the representativeness of our sample, we obtained population-level statistics on the age, gender and number of students by University using data from the register of university students held by the Ministry of Education (Anagrafe Nazionale degli Studenti). We then used minimum entropy balancing (Hainmueller, 2012) to reweight our sample to closely match population level statistics on age, gender and macro-regions (North, Centre and South of Italy). Table 2 shows how the original and the reweighted sample compare to the population level statistics. We conclude that reweighting attributed relatively less weight to respondents from Northern Italy, that are over-represented in the sample. Descriptive statistics on the socio-demographic characteristics of our sample are presented in Table 3. The Table compares the mean values of many variables of interest before and after reweighting. Eventually, the sample looks very similar to the population along these demographic variables, and the impact of reweighting is marginal.

3.4 Choice task checks

After completing the choice task, we prompted students with some questions about the choice tasks. Following Xie et al. (2020), we asked respondents about their self-reported difficulty level of understanding and answering to the DCE task. On understandability, all subjects in our final sample reported that the task was either very clear (65%) or clear (35%), and no subject stated that it was unclear or very unclear. On difficulty, 52% of subjects rated the tasks as not difficult, 46% as difficult, and 2% as very difficult. Overall, the results support the acceptability of the task from respondents, and confirm the initial views of the medical student representatives in Padova, who deemed the choice tasks as feasible in a pre-test phase.

We also asked students to rank the listed job attributes according to their self-assessed

importance. We found that the average ranking of self-assessed attributes' importance mirrors the ranking of attributes by the average WTPs that we estimate from the mixed logit model. Overall, these findings reassure us about the internal consistency of the choices.

Finally, we also directly inquired those students who participated in 2021 about how much they think the Covid-19 pandemic affected their decision to move abroad. Close to 69% of respondents reported that Covid-19 had no impact on their migration intention, 20% have a stronger preference to stay, and 11% have a stronger preference to move. As a result, we believe that - if anything - our setup could be overestimating the willingness to pay to stay in the home country that students may manifest after the Covid-19 pandemic is over.

4 Empirical methodology

Our analysis is rooted in the random utility framework (McFadden et al., 1973), and we assume that decision makers maximise their expected utility - which depends on alternatives' attributes - subject to random errors. In our model, individual i in a sample of size N obtains utility from choosing a job alternative j in a choice set t. Thus, the utility function of the individual can be represented as:

$$U_{ijt} = \mathbf{ASC_j} + \alpha_i Income_{jt} + \mathbf{X_{jt}}\beta_\mathbf{i} + \varepsilon_{ijt} \tag{1}$$

where $i = 1, \ldots, N$; $t = 1, \ldots, 16$; $j = 1, 2, 3$ - where 3 is for opt-out. $\mathbf{ASC_j}$ is a vector of alternative specific constants, that capture the mean value of the error term ε_{ijt} for a given alternative and account for potential order biases in picking jobs located in the left or right column of the screen; $Income_{ijt}$ is the income level of alternative j in task t, $\mathbf{X_{jt}}$ is a vector of a non-monetary job attributes (that include professional development opportunities, job security, working conditions, match of skills with job content, and country of the job) of alternative j in task t, and α_i and $\beta_\mathbf{i}$ are individual level parameters attached to these job attributes. We also assume that the error term is extreme-value distributed, with variance $\mu_i^2(\pi^2/6)$.

Under standard assumptions on the preferences of students, and after choosing a distribution for the parameters α_i and $\beta_\mathbf{i}$, the probability of choosing one of the proposed alternatives can be estimated with a mixed logit model (McFadden and Train, 2000).

In this "preference space" representation of the model, coefficients α_i and $\beta_{\mathbf{i}}$ identify the preferences of individual i for income and the other job attributes. We can alternatively express such preferences in terms of individuals' willingness-to-pay (WTP) for the non-monetary job attributes, which are given by the marginal rate of substitution between income and any other non-monetary job attribute a:

$$WTP_i^a = MRS_i^{a,Income} = \frac{\beta_{i,a}}{\alpha_i} \tag{2}$$

As a result, the assumptions on the distribution of the preference coefficients determine the distribution of the WTPs. A standard choice is to assume a normal distribution for each of the non-monetary attributes and to keep the income parameter constant across individuals. While this choice is very convenient from a modelling perspective, as it implies that the WTPs follow normal distributions, in our application it may be rather untenable to assume that all future doctors have the same preference for income. An alternative practice, which allows for heterogeneity in preferences for income, is to assume that the income coefficient has a log-normal distribution. This choice would ensure that the income effect would be positive, but the resulting WTP distributions may be highly skewed, leading to unrealistic estimates of the mean and standard deviation of WTPs (Train and Weeks, 2005; Hole and Kolstad, 2012).

A workaround to these limitations of the preference space is to re-parametrise the model and estimate it in the "WTP-space". More specifically, Equation 1 can be re-written in terms of attributes' WTPs by factoring out the income parameter, and by making assumptions for the distributions of the WTPs attached to each job attributes instead of the parameters. As a result, the model can be represented as:

$$\begin{aligned} U_{ijt} &= \alpha_i[\mathbf{ASC_j} + Income_{jt} + \mathbf{X_{jt}}(\frac{\beta_{\mathbf{i}}}{\alpha_{\mathbf{i}}})] + \varepsilon_{ijt} \\ &= \alpha_i[\mathbf{ASC_j} + Income_{jt} + \mathbf{X_{jt}}\mathbf{WTP_i}] + \varepsilon_{ijt} \end{aligned} \tag{3}$$

Following Hole and Kolstad (2012), we assume normal distributions for the WTPs of the job characteristics and a log-normal distribution for the income parameter α_i. The model is estimated using simulated maximum likelihood and allowing for the clustering

of standard errors by individual.[7]

While the model described thus far allows to estimate a distribution of individual-level WTPs, the heterogenity in WTPs across individuals is allowed to depend on unobservables only. However, in order to understand selection into migration, we would like to describe how future doctors' WTP for job location depends on the observable socio-demographic, cognitive and non-cognitive characteristics presented in Section 2.1. We let individual i's trait T be defined in terms of a dummy variable T_i. For example, T_i could represent the gender variable "Female", which takes a value of 1 if individual i is female and 0 if male. We also express vector $\mathbf{X_{jt}}$ as $\mathbf{X_{jt}} = (Country_{jt}, \tilde{\mathbf{X}}_{\mathbf{jt}})$, where $Country_{jt}$ is a dummy variable representing job location, that takes a value of 0 if the location is Italy and 1 if the job is located abroad, and the vector $\tilde{\mathbf{X}}_{\mathbf{jt}}$ collects the other job attributes. We can then assess how the WTP for jobs located in Italy vs. abroad varies across levels of T_i by specifying our model as follows:

$$\begin{aligned} U_{ijt} = \alpha_i[&\mathbf{ASC_j} + Income_{jt} + \tilde{\mathbf{X}}_{\mathbf{jt}}\tilde{\mathbf{WTP}}_{\mathbf{i}} + \\ &+ WTP_i^{c0} Country \times (1 - T_i) + WTP_i^{c1} Country \times T_i] + \varepsilon_{ijt} \end{aligned} \tag{4}$$

Equation 4 allows for heterogeneous distributions WTP_i^{c0} and WTP_i^{c1} of the WTP for job location across the two groups defined by T_i.[8] The caveat of this specification is that the income parameter α_i remains homogeneous in its distribution across the two groups. Considering that income is expressed in purchase-power-parity terms across countries, and that we reminded respondents about this interpretation before carrying out the choice tasks, we deem this as an acceptable restriction. An alternative strategy could have been to estimate the model separately in each of the sub-samples defined by T_i. However, we prefer the specification with interaction terms to facilitate hypothesis testing of whether the distributions of the WTP for job location across the two groups defined by T_i are significantly different or not in terms of their mean and SD.

Finally, we are also interested in understanding how the distributions of WTPs for job characteristics change by job location. Whether doctors value job characteristics

[7]We set the number of draws to 5,000 after verifying the stability of the estimated WTPs to a different number of draws ranging from 1000 to 5,000.

[8]For traits measured using a continuous variable, we distinguish between subjects with a value of the trait above and below the median.

differently at home or abroad is important to design jobs that may incentivise young doctors to work in their home country. In order to do this, for each of the job attributes $\tilde{X}^a_{jt}$ in vector $\tilde{\mathbf{X}}_{\mathbf{jt}}$, we augment our baseline model in Equation 3 with an interaction term between $Country_{ijt}$ and $\tilde{X}^a_{jt}$,

$$U_{ijt} = \alpha_i[\mathbf{ASC_j} + Income_{jt} + \mathbf{X_{jt}}\mathbf{WTP_i} + Country \times \tilde{X}^a_{jt} WTP_i^{ca}] + \varepsilon_{ijt} \qquad (5)$$

where the term WTP_i^{ca} attached to $Country \times \tilde{X}^a_{ijt}$ represents the additional amount of money an individual is willing to sacrifice in order to have a higher level of job characteristic $\tilde{X}^a_{jt}$ abroad. We do this separately for each job attribute $\tilde{X}^a_{jt}$ in vector $\tilde{\mathbf{X}}_{\mathbf{jt}}$.

5 Results

5.1 Willingness to pay for job location

5.1.1 Main results

Table 4 shows the estimated WTPs from the mixed logit model outlined in Equation 3. Column (1) reports the estimated means of the distribution of job attributes' WTPs, and Column (2) reports the estimated SDs. The first result of the paper is that future doctors display a negative and significant WTP for jobs located abroad. On average, they would be willing to give up on €13,515/year for a job located in Italy instead of their favourite European country, the highest WTP estimated among all job attributes. However, this average result hides significant heterogeneity due to unobservable factors, as among all attributes, job location WTP also has the highest SD, equal to €17,216. Figure 1 shows the distribution of the posterior individual level WTPs for going abroad, estimated using the method proposed by Revelt and Train (2000). On the basis of these estimates, we can trace out two groups of students: those who would be willing to pay to stay in Italy and those who would be willing to pay to go abroad. In particular, we find that 84.2% of the students have a mean WTP of €17,562 to stay back in Italy and 15.8% of the students have a mean WTP of €7,841 to move to their favorite European country.

5.1.2 Heterogeneity by observed factors

Figure 2 reports the means of the WTP distribution for jobs located in respondents' favourite European country and their 95% confidence interval estimated by individual background variables (panel a) and personality traits (panel b). The results are obtained from estimating Equation 4, and each row is for a different trait. Characteristics for which the mean WTP difference across groups is significant are marked with significance stars.[9]

When start by analysing the role of background characteristics. First, within our sample of highly-educated medical students we find no evidence of a gender gap in migration intentions, as measured by students' WTP to move abroad (the absolute value of the WTP difference, ΔWTP, is equal to €170, p-value>0.1). This is consistent with findings by Docquier et al. (2009), who argue that the observed gender differences in brain drain should mostly be attributed to unequal access to higher education by gender, and by Docquier et al. (2012), who show that skilled women are not more internationally migratory than skilled men.

Moreover, we do not find evidence that attending medical schools outside of the region of birth is a predictor of migration intentions (ΔWTP=€13, p>0.1), suggesting that early internal migration for obtaining a medical degree is not a good proxy of migration intentions for working abroad. We also fail to find statistically significant differences in migration intentions among students with high and low family income (ΔWTP=€864, p>0.1), implying that resource constraints do not seem to matter very much to shape migration intentions. In line with Grogger and Hanson (2013), we instead find that students with highly educated parents are more willing to migrate than those with low educated parents (ΔWTP=€3858, p>0.1). The WTP difference among the two groups is large, but as few medical students have low-educated parents the gap is not significant. Consistent with Botezat (2022), we also find that students who report that they want to become a doctor to keep a family tradition alive are significantly more willing to migrate than the others (ΔWTP=€5217, p<0.05). So long as valuable occupation-specific knowledge is transmitted within the family, this finding implies a negative selection of the pool of left-behind doctors. Contrarily, we estimate no statistically significant difference in the mean WTP for future doctors willing to specialise in clinical or surgical specialties

[9]Significance levels are not adjusted for multiple comparisons. The corresponding SDs are reported in Appendix Figure A2. The Figure shows scant evidence of heterogeneous effects on the dispersion of these WTP distributions.

(ΔWTP=€2440, p>0.1), reassuring for the balance of the skill composition of future doctors willing to remain in Italy.

Furthermore, we find that individual-level push and pull factors, as well as correlates of migration preferences, are strong predictors of migration intentions. For instance, students with a partner (see e.g. Mincer, 1978) have a far more negative WTP for jobs located abroad (ΔWTP=€4275, p<0.05), and so do students willing to specialise in their own university (ΔWTP=€7968, p<0.01), while students who know the language spoken in their favourite foreign European country (ΔWTP=€6824, p<0.05) or have personal ties there (ΔWTP=€4415, p<0.05) are more willing to migrate.

Finally, we investigate whether individual cognitive abilities also matter for migration intentions. Consistent with the assignment mechanism described in Appendix D, students scoring higher at the national standardised entry test are those who choose first, and eventually the best students choose to attend the best universities, that end up having a higher minimum entry score. Several Italian research institutes provide measures of medical degree course quality in Italy, and the most well-known one is produced yearly by CENSIS - a think tank. We take attendance of a university with a CENSIS score above vs. below the median as an indicator of high vs. low cognitive abilities of students. Consistent with Bütikofer and Peri (2021), we find that students with higher cognitive abilities (i.e., enrolled in the best Italian medicine schools) are more willing to migrate (ΔWTP=€5165, p<0.05), with potentially relevant implications for the skill composition of the pool of remaining doctors.[10] Instead, we do not find significant differences in WTP by students' GPA within university (ΔWTP=€2227, p>0.1). This is likely due to the fact that there is limited variation in the skill composition of students within universities after the initial selection by ability, so that GPA is a poor proxy of cognitive abilities.

Moving to the distinctions by personality traits, the small existing literature in economics on the association between the big-5 personality traits and migration (Ayhan et al., 2020; Fouarge et al., 2019; Bütikofer and Peri, 2021) finds that openness to experiences, extraversion and adaptability are positively associated with migration intentions and actual migration outcomes.[11] While our results also suggest that future doctors with higher openness and extraversion are more likely to migrate, the differences are

[10]This finding could also suggest that the best universities shape the migration intentions of students. While we are not able to distinguish between these two stories, their implications for the skill composition of remaining doctors is rather comparable.

[11]Additional studies in the psychological literature include Jokela et al. (2008), and (Jokela, 2009)

not significant(ΔWTP=€2366, p>0.1, for openness, and ΔWTP=€1597, p>0.1 for extraversion).

Moreover, consistent with Caliendo et al. (2019), we find that individuals with higher internal (external) locus of control scores are more (less) willing to migrate, and we also see that individuals with higher self-efficacy are more willing to migrate (Hoppe and Fujishiro, 2015). However, even in these cases the uncovered differences are too small to be significant (ΔWTP=€1366, p>0.1 for internal locus of control; ΔWTP=€1900, p>0.1 for external locus of control; ΔWTP=€1984, p>0.1 for self-efficacy). Finally, consistent with Winter-Ebmer (1994), and Polavieja et al. (2018), we find no statistically significant evidence that intrinsic vs. extrinsic motivation to become a doctor matters for migration intentions (ΔWTP=€1178, p>0.1 for intrinsic motivation and ΔWTP=€2724, p>0.1 for extrinsic motivation).

The limited impacts of personality on migration intention estimated by our DCE in comparison with some other studies in the literature may depend on our research design, that prompts students to choose between Italy and their favourite foreign European country. As shown by Fouarge et al. (2019), personality plays a central role to explain migration to culturally distant locations, while it has a lower impact for destination countries that are percevied as close by subjects. In addition, we are investigating heterogeneous effects by personality within a sample of highly-skilled and highly educated individuals, where there may be less variation in personality than in the general population.

Despite these limitations, there are, however, some traits for whom we do find economically and statistically significant heterogeneous effects. First, consistent with Jaeger et al. (2010), we find that risk tolerance is positively related with migration intentions (ΔWTP=€5723, p<0.01).[12] Moreover, more altruistic medical students are more willing to migrate (ΔWTP=€10273, p<0.01), and so do students with higher levels of competitiveness (ΔWTP=€4405, p<0.1). On the one hand, altruistic doctors are more likely to forego personal benefits for the sake of patients' benefits (see Galizzi et al., 2015, for a review of the economic literature on altruism in the medical profession). On the other hand, Buser et al. (2021) find that competitiveness is a strong and consistent predictor of labour market success in terms of both income and occupation quality. Our findings

[12]Medical migration decisions also depend on the relative career and clinical uncertainty faced by physicians across countries. For instance, using data from the MABEL survey, van der Pol et al. (2019) conclude that more risk averse British GPs migrate to Australia due to lower career and clinical uncertainty in Australia than the UK.

may suggest that migration is one of the means by which the more competitive reach success. Overall, these results deliver important and somewhat worrisome implications for the quality of the pool of doctors that are willing to remain in Italy.

5.2 Willingness to pay for other job attributes

5.2.1 Baseline results

The WTP estimates for the other job characteristics included in our job descriptions are also reported in Table 4.

In terms of effects on the mean of the preference distribution, we find a positive and significant coefficient of 0.126 on income, which suggests that the probability of choosing a job increases with higher salary. We also estimate that future doctors have a mean WTP of €6,572 for having some development opportunities and a much higher WTP of €10,998 for having good development opportunities with respect to the baseline of poor development opportunity jobs. Job security is also important: compared to the reference level of a fixed-term two-year job contract with no renewal chance, a two-year contract with a 50% renewal chance has a higher valuation amongst the students, with a mean WTP of €11,800 and €8,878 for that of a permanent contract. When it comes to skill mismatch, we see that - with respect to other job attributes - students have a low willingness to pay for avoiding a job for whom they are overskilled. This may partly depend on the fact that we are offering jobs as medical specialists, and students may perceive that there is limited potential for skill mismatch. Finally, we see that working conditions are highly valued, and students are willing to pay a high sum of €12,740 to have a job with adequate workload with little overtime work and night shifts as opposed to having a high workload with frequent overtime work and night shifts.

We also estimate that there is substantial unobserved heterogeneity in preferences for these job attributes, as witnessed by the significant and sometimes very large SDs. The heterogeneity in WTPs also emerges clearly in Figure 3, where we plot the posterior distributions of the individual-level WTPs.

5.2.2 WTPs by home and abroad

The large unobserved heterogeneity of future doctors' WTPs for several job attributes depicted in Figure 3 deserves further investigation. For instance, it is remarkable to see

that individuals' WTP for a permanent job is markedly heterogeneous, and spans a large range of positive and negative values. In this Section, we investigate whether part of this unobserved variability depends on the heterogeneity of future doctors' preferences for the attributes of jobs located in Italy or in their favourite foreign European country.

Thus, in Table 5, we report the WTP estimates of job characteristics for jobs located in Italy and abroad obtained from Equation 5, and test whether the differences are statistically signficant. Apart from good working conditions, which is valued equally in home and foreign countries, we find significant WTP differences between home and abroad in every job attribute level. We see that future doctors have a very high WTP for a permanent job contract in Italy , but would prefer a temporary job contract with renewal possibility in their favourite foreign European country. We also see that, consistently, professional development opportunities are highly valued by them for jobs located in Italy, but not as much for jobs located abroad. And finally, we see that they do not mind being low skill-matched in jobs located in Italy, but are really averse to this in foreign countries.

Taken together, these results suggest that Italian medical students are more prone to permanently settling down in Italy than in their favorite foreign European country. They are instead willing to go abroad for a short period of time in jobs that do not seem too challenging for them, to explore the life and work conditions there, with the option of settling there for the long-term. These are important findings, as they suggest that Italian medical students look for different jobs in Italy and abroad, and although they are willing to give up on a considerable share of their salary to stay in Italy (see Section 5.1), they may choose to move abroad at least for a period if they cannot find jobs with desirable characteristics in Italy.

6 Robustness Checks

In Appendix E we report the results of several sensitivity tests. First, Appendix Tables A3 and A4 report results when we exclude respondents whose favourite European country is the UK - not any longer a EU member since 2020. Second, Appendix Tables A5 and A6 report the estimates obtained without the use of sampling weights. Third, Appendix Tables A7 and A8 show the estimates using a conditional logit model - that overlooks the heterogeneity of individual preferences - instead of the mixed logit one. As can be

seen, our main qualitative conclusions remain unchanged.[13] Finally, given that our choice task requires students to trade off among several attributes, in Appendix F we investigate the potential role played by attribute non-attendance using the approach based on latent class models championed by Scarpa et al. (2009). The results analysis broadly confirms our main findings.

7 Conclusion

In this study, we have used a Discrete Choice Experiment to investigate the migration intentions of medical students in Italy. We have allowed students to choose among jobs characterised by multiple attributes, including location, income, job security, professional development opportunities, working conditions and skill match. Analysing the resulting choices through a mixed logit model, we have assessed that future doctors have on average a large and positive willingness to pay to work in Italy, but there is also substantial heterogeneity.

We have related this unobserved heterogeneity to background characteristics of students and to their personality traits. Our findings provide evidence of positive selection into migration on the basis of several background characteristics (including attendance of a high-quality medical school and willingness to become a doctor due to a family tradition) and personality traits (including altruism, risk aversion and competitiveness) that are generally associated with positive long-run outcomes as doctors and in the labour market. These findings bring new and perhaps worrisome news in terms of the selection of migrating young doctors.

We have also analysed students' willingness to pay for other job attributes, and whether attributes' attractiveness depends also on job location. Our results suggest that future doctors prefer permanent contracts in Italy and temporary contracts with renewal possibilities abroad. Consistently, good professional development opportunities matter for them more in Italy than abroad. In addition, future doctors would not like to be underskilled abroad - as they may already be facing other difficulties correlated with settling in a new environment - but do not mind it in Italy - where they are inclined to settle for the

[13]Following Equation 1, we have also estimated our baseline mixed logit model in the preference space instead of the WTP space, and obtained the distribution of the implied WTPs using simulations. The results are consistent with the ones obtained from the estimation in WTP space, although slightly larger in magnitude in line with findings by Hole and Kolstad (2012), and are not reported.

long-term and might be willing to undergo training. On the contrary, their preferences for good working conditions (workload, overtime work, night shifts) are comparable across jobs located both in Italy and abroad.

These findings have implications for the design of job contracts for retaining young physicians. Although future Italian doctors are willing to forego a non-negligible share of their salary to work in Italy, the data tell us that many migrate to find jobs abroad. As shown in the counterfactual simulations developed in Appendix G, this share of migration would increase substantially as the quality of the Italian job declines. Considering that future doctors are very keen on obtaining jobs in Italy with good working conditions and professional development opportunities, these findings suggest that the jobs they could get in Italy may lack these features - suggesting a potential area of intervention in order to help retain young doctors.

Future doctors in our sample also prefer fixed-term renewable jobs aborad and permanent jobs in Italy, and consistently have lower WTP for professional development opportunities abroad than in Italy. One possible interpretation of these findings suggests that prospective doctors who plan to migrate may initially view their migration as a temporary arrangement. However, their preferences may shift once they settle in their new country, and they may decide to remain there.[14] Considering that the doctors in our study display a preference for well-paying jobs and that salary adjustments are relatively easier to make compared to other job aspects, policies that offer tax incentives to expatriates who return to their home country could facilitate the process of returning migration.[15]

With the recent occurrence of the global Covid-19 pandemic and a projected shortage in medical personnel in many countries in the near future, this paper offers important guidelines for framing policy in order to retain medical doctors and incentivise those who have already emigrated to return.

[14]For instance, Adda et al. (2022) show that roughly 50% of Turkish immigrants in Germany are still in the country after 15 years from migration, Jensen and Pedersen (2007) report that 30% of EU-12 immigrants in Denmark have not left the country after 10 years, and according to OECD (2008) only 18% of immigrants in the US have left the country after 5 years.

[15]An example of such policies is the "Controesodo" scheme established by the Italian Government in 2010 (see e.g. Bassetto and Ippedico, 2022; Creanza, 2023). This specific policy granted a large tax discount for college-graduate emigrants *returning* in Italy. Eligibility was conditional on residence abroad for at least 2 years and pre-migration residence in Italy for at least 2 years. As a result, the policy itself may have generated incentives for temporary migration. However, our finding that future doctors prefer 2-year *renewable* jobs abroad over 2-year *fixed term* ones seems to suggest that their preferences are not solely shaped by the eligibility conditions for this policy. Otherwise, we should have detected no difference in their WTPs for 2-year renewable and non-renewable jobs abroad.

References

Adda, J., C. Dustmann, and J.-S. Gorlach (2022). The Dynamics of Return Migration, Human Capital Accumulation, and Wage Assimilation. *The Review of Economic Studies 89*(6), 2841–2871.

Adovor, E., M. Czaika, F. Docquier, and Y. Moullan (2021). Medical brain drain: how many, where and why? *Journal of Health Economics 76*, 102409.

AMWAC (2005). Doctors in vocational training: rural background and rural practice intentions. *Australian Journal of Rural Health 13*(1), 14–20.

Anelli, M. (2019). University to work transition. *IGIER policy brief*.

Anelli, M. and G. Peri (2017). Does emigration delay political change? evidence from italy during the great recession. *Economic Policy 32*(91), 551–596.

Ayhan, S. H., K. Gatskova, and H. Lehmann (2020). The impact of non-cognitive skills and risk preferences on rural-to-urban migration in ukraine. *Journal of Comparative Economics 48*(1), 144–162.

Bassetto, J. and G. Ippedico (2022). The effects of returenees' tax schemes on high-skilled migration in italy. Mimeo, University of Trento.

Batista, C. and D. J. McKenzie (2021). Testing classic theories of migration in the lab. Discussion paper 16469, CEPR.

Becker, S. O., A. Ichino, and G. Peri (2004). How large is the "brain drain" from italy? *Giornale degli economisti e annali di economia*, 1–32.

Bhargava, A. and F. Docquier (2008). Hiv pandemic, medical brain drain, and economic development in sub-saharan africa. *The World Bank Economic Review 22*(2), 345–366.

Bhargava, A., F. Docquier, and Y. Moullan (2011). Modeling the effects of physician emigration on human development. *Economics & Human Biology 9*(2), 172–183.

Botezat, A. (2022). Socio-economic drivers of migration intentions among romanian medical students: what is the role of the intergenerational transfer of the medical profession? Mimeo, Romanian Academy.

Botezat, A. and R. Ramos (2020). Physicians' brain drain-a gravity model of migration flows. *Globalization and Health 16*(1), 1–13.

Brunello, G. and P. Wruuck (2021). Skill shortages and skill mismatch: A review of the literature. *Journal of Economic Surveys 35*(4), 1145–1167.

Buser, T., M. Niederle, and H. Oosterbeek (2021). Can competitiveness predict education and labor market outcomes? evidence from incentivized choice and survey measures. Working paper, National Bureau of Economic Research.

Bütikofer, A. and G. Peri (2021). How cognitive ability and personality traits affect geographic mobility. *Journal of Labor Economics 39*(2), 559–595.

Caliendo, M., D. A. Cobb-Clark, J. Hennecke, and A. Uhlendorff (2019). Locus of control and internal migration. *Regional Science and Urban Economics 79*, 103468.

Campbell, D., W. G. Hutchinson, and R. Scarpa (2008). Incorporating discontinuous preferences into the analysis of discrete choice experiments. *Environmental and Resource Economics 41*(3), 401–417.

Chen, G., S. M. Gully, and D. Eden (2001). Validation of a new general self-efficacy scale. *Organizational research methods 4*(1), 62–83.

Cleland, J. A., P. Johnston, V. Watson, N. Krucien, and D. Skåtun (2017). What do uk medical students value most in their careers? a discrete choice experiment. *Medical Education 51*(8), 839–851.

Clemens, M. A. (2007). Do visas kill? health effects of african health professional emigration. *Center for Global Development Working Paper* (114).

Clemens, M. A. and G. Pettersson Gelander (2006). A new database of health professional emigration from africa. *Center for Global Development Working Paper* (95).

Creanza, P. P. (2023). 'returning brains': tax incentives, migration and scientific productivity. Mimeo, Princeton University.

Datta, N. (2019). Willing to pay for security: a discrete choice experiment to analyse labour supply preferences. Working Paper 1632, Centre for Economic Performance, LSE.

Docquier, F., B. L. Lowell, and A. Marfouk (2009). A gendered assessment of highly skilled emigration. *Population and Development Review 35*(2), 297–321.

Docquier, F., A. Marfouk, S. Salomone, and K. Sekkat (2012). Are skilled women more migratory than skilled men? *World Development 40*(2), 251–265.

Docquier, F. and H. Rapoport (2012). Globalization, brain drain, and development. *Journal of Economic Literature 50*(3), 681–730.

Falk, A., A. Becker, T. J. Dohmen, D. Huffman, and U. Sunde (2016). The preference survey module: A validated instrument for measuring risk, time, and social preferences.

Fouarge, D., M. N. Özer, and P. Seegers (2019). Personality traits, migration intentions, and cultural distance. *Papers in Regional Science 98*(6), 2425–2454.

Galizzi, M. M., T. Tammi, G. Godager, I. Linnosmaa, and D. Wiesen (2015). Provider altruism in health economics. Working Paper 4-2015, THL.

Gallego, G., A. Dew, K. Bulkeley, C. Veitch, M. Lincoln, A. Bundy, and J. Brentnall (2015). Factors affecting retention of allied health professionals working with people with disability in rural new south wales, australia: discrete choice experiment questionnaire development. *Human Resources for Health 13*(1), 1–11.

Grogger, J. and G. Hanson (2013). The scale and selectivity of foreign-born phd recipients in the us. *American Economic Review 103*(3), 189–92.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis 20*(1), 25–46.

Hanson, K. and W. Jack (2010). Incentives could induce ethiopian doctors and nurses to work in rural settings. *Health Affairs 29*(8), 1452–1460.

Heidenreich, S., V. Watson, M. Ryan, and E. Phimister (2018). Decision heuristic or preference? attribute non-attendance in discrete choice problems. *Health Economics 27*(1), 157–171.

Hellemans, A. (2001). Beating the european brain drain. *Nature 414*(6862), 4–5.

Hensher, D. A. (2006). Revealing differences in willingness to pay due to the dimensionality of stated choice designs: an initial assessment. *Environmental and Resource Economics 34*(1), 7–44.

Hole, A. R. (2011). A discrete choice model with endogenous attribute attendance. *Economics Letters 110*(3), 203–205.

Hole, A. R. and J. R. Kolstad (2012). Mixed logit estimation of willingness to pay distributions: a comparison of models in preference and wtp space using data from a health-related choice experiment. *Empirical Economics 42*(2), 445–469.

Hoppe, A. and K. Fujishiro (2015). Anticipated job benefits, career aspiration, and generalized self-efficacy as predictors for migration decision-making. *International Journal of Intercultural Relations 47*, 13–27.

Horn, L., K. Tzanetos, K. Thorpe, and S. E. Straus (2008). Factors associated with the subspecialty choices of internal medicine residents in canada. *BMC Medical Education 8*(1), 1–8.

Jaeger, D. A., T. Dohmen, A. Falk, D. Huffman, U. Sunde, and H. Bonin (2010). Direct evidence on risk attitudes and migration. *The Review of Economics and Statistics 92*(3), 684–689.

Jensen, P. and P. J. Pedersen (2007). To stay or not to stay? out-migration of immigrants from denmark. *International Migration 45*(5), 87–113.

Jokela, M. (2009). Personality predicts migration within and between us states. *Journal of Research in Personality 43*(1), 79–83.

Jokela, M., M. Elovainio, M. Kivimäki, and L. Keltikangas-Järvinen (2008). Temperament and migration patterns in finland. *Psychological Science 19*(9), 831–837.

Kahneman, D. (1973). *Attention and effort*, Volume 1063. Citeseer.

Kolstad, J. R. (2011). How to make rural jobs more attractive to health workers. findings from a discrete choice experiment in tanzania. *Health Economics 20*(2), 196–211.

La Colla, L. (2019). Health worker gap in italy: the untold truth. *The Lancet 394*(10198), 561–562.

Lumpkin, J. R. (1985). Validity of a brief locus of control scale for survey research. *Psychological reports 57*(2), 655–659.

Malhotra, N. K. (1982). Information load and consumer decision making. *Journal of Consumer Research 8*(4), 419–430.

Mandeville, K. L., M. Lagarde, and K. Hanson (2014). The use of discrete choice experiments to inform health workforce policy: a systematic review. *BMC Health Services Research 14*(1), 1–14.

Mandeville, K. L., G. Ulaya, M. Lagarde, A. S. Muula, T. Dzowela, and K. Hanson (2016). The use of specialty training to retain doctors in malawi: a discrete choice experiment. *Social Science & Medicine 169*, 109–118.

Mas, A. and A. Pallais (2017). Valuing alternative work arrangements. *American Economic Review 107*(12), 3722–59.

Mayr, K. and G. Peri (2009). Brain drain and brain return: theory and application to eastern-western europe. *The BE Journal of Economic Analysis & Policy 9*(1).

McFadden, D. et al. (1973). Conditional logit analysis of qualitative choice behavior.

McFadden, D. and K. Train (2000). Mixed mnl models for discrete response. *Journal of Applied Econometrics 15*(5), 447–470.

McKenzie, D. (2015). Learning about migration through experiments. *Migration: Economic Change, Social Challenge 68*.

Mincer, J. (1978). Family migration decisions. *Journal of political Economy 86*(5), 749–773.

Non, A., I. Rohde, A. de Grip, and T. Dohmen (2022). Mission of the company, prosocial attitudes and job preferences: A discrete choice experiment. *Labour Economics 74*, 102087.

OECD (2008). *International Migration Outlook* (2008 ed.). OECD. Paris.

Paterlini, M. (2019). Italy calls on retired doctors to fill health worker gap. *The Lancet 393*(10180), 1492.

Paterlini, M. (2022). Warnings over doctor shortages amid italian health reforms. *The Lancet 399*(10341), 2093.

Payne, J. and J. Bettman (2001). Preference choice and adaptive strategy use. In *Bounded rationality: The adaptive toolbox - Dahlem Workshop Reports*, pp. 103–121. The MIT Press, Cambridge.

Polavieja, J. G., M. Fernández-Reino, and M. Ramos (2018). Are migrants selected on motivational orientations? selectivity patterns amongst international migrants in europe. *European Sociological Review 34*(5), 570–588.

Revelt, D. and K. Train (2000). Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier.

Riccò, M., L. Vezzosi, and F. Balzarini (2020). Challenges faced by the italian medical workforce. *The Lancet 395*(10229), e55–e56.

Ryan, M., J. R. Kolstad, P. C. Rockers, and C. Dolea (2012). How to conduct a discrete choice experiment for health workforce recruitment and retention in remote and rural areas: a user guide with case studies. Working paper, The World Bank.

Ryan, M., V. Watson, and V. Entwistle (2009). Rationalising the âirrationalâ: a think aloud study of discrete choice experiment responses. *Health Economics 18*(3), 321–336.

Ryan, R. M. and E. L. Deci (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology 25*(1), 54–67.

Scarpa, R., T. J. Gilbride, D. Campbell, and D. A. Hensher (2009). Modelling attribute non-attendance in choice experiments for rural landscape valuation. *European Review of Agricultural Economics 36*(2), 151–174.

Scarpa, R., R. Zanoli, V. Bruschi, and S. Naspetti (2013). Inferred and stated attribute non-attendance in food choice experiments. *American Journal of Agricultural Economics 95*(1), 165–180.

Sivey, P., A. Scott, J. Witt, C. Joyce, and J. Humphreys (2012). Junior doctorsâ preferences for specialty choice. *Journal of Health Economics 31*(6), 813–823.

Szawlowski, S., B. Harrap, A. Leahy, and A. Scott (2020). Medicine in australia: balancing employment and life (mabel). mabel user manual: wave 11 release. *Melbourne: Melbourne Institute: Applied Economic and Social Research, The University of Melbourne*.

Theodoropoulos, D., A. Kyridis, C. Zagkos, and Z. Konstantinidou (2014). Brain drain phenomenon in greece: Young greek scientists on their way to immigration, in an era of âcrisisâ. attitudes, opinions and beliefs towards the prospect of migration. *Journal of Education and Human Development 3*(4), 229–248.

Train, K. and M. Weeks (2005). Discrete choice models in preference space and willingness-to-pay space. In *Applications of simulation methods in environmental and resource economics*, pp. 1–16. Springer.

van der Pol, M., A. Scott, and A. Irvine (2019). The migration of uk trained gps to australia: Does risk attitude matter? *Health Policy 123*(11), 1093–1099.

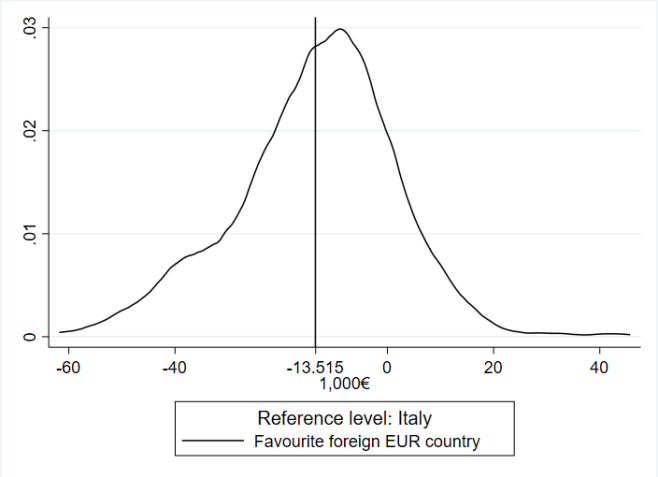
Vicarelli, G. and E. Pavolini (2015). Health workforce governance in italy. *Health Policy 119*(12), 1606–1612.

Winter-Ebmer, R. (1994). Motivation for migration and economic success. *Journal of Economic Psychology 15*(2), 269–284.

Xie, S., J. Wu, X. He, G. Chen, and J. E. Brazier (2020). Do discrete choice experiments approaches perform better than time trade-off in eliciting health state utilities? evidence from sf-6dv2 in china. *Value in Health 23*(10), 1391–1399.

Figures and Tables

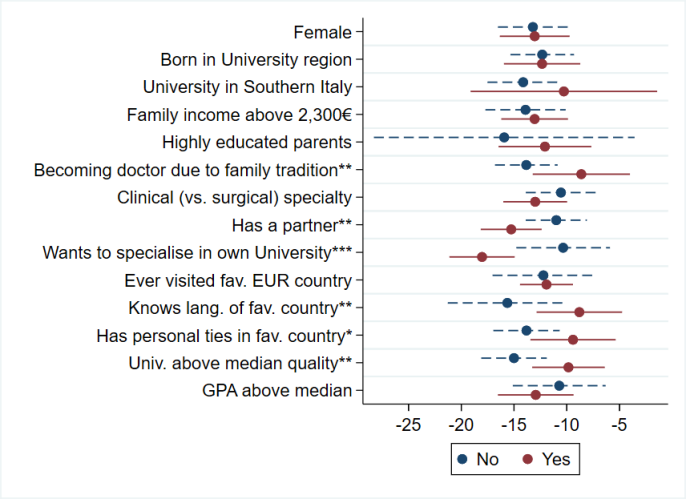
Figure 1: WTP distribution for jobs located in respondents' favourite European country.



Notes: The vertical bar indicates the mean of the distribution.

Figure 2: Mean of WTP distribution for jobs located in respondents' favourite foreign European country, by individual background variables and personality traits.

a. Background variables



b. Personality traits

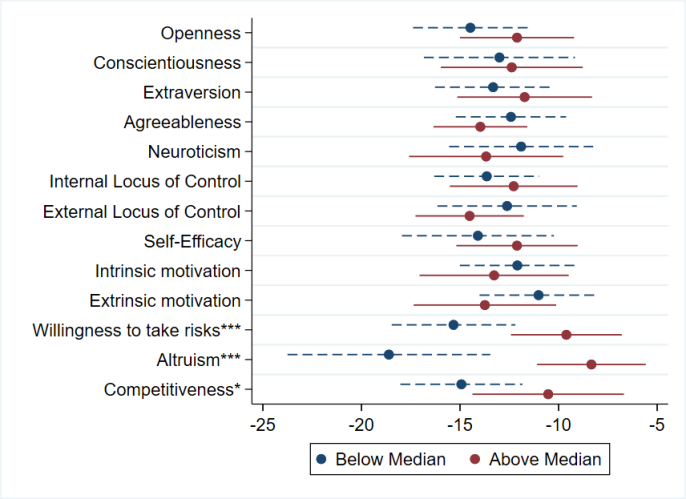
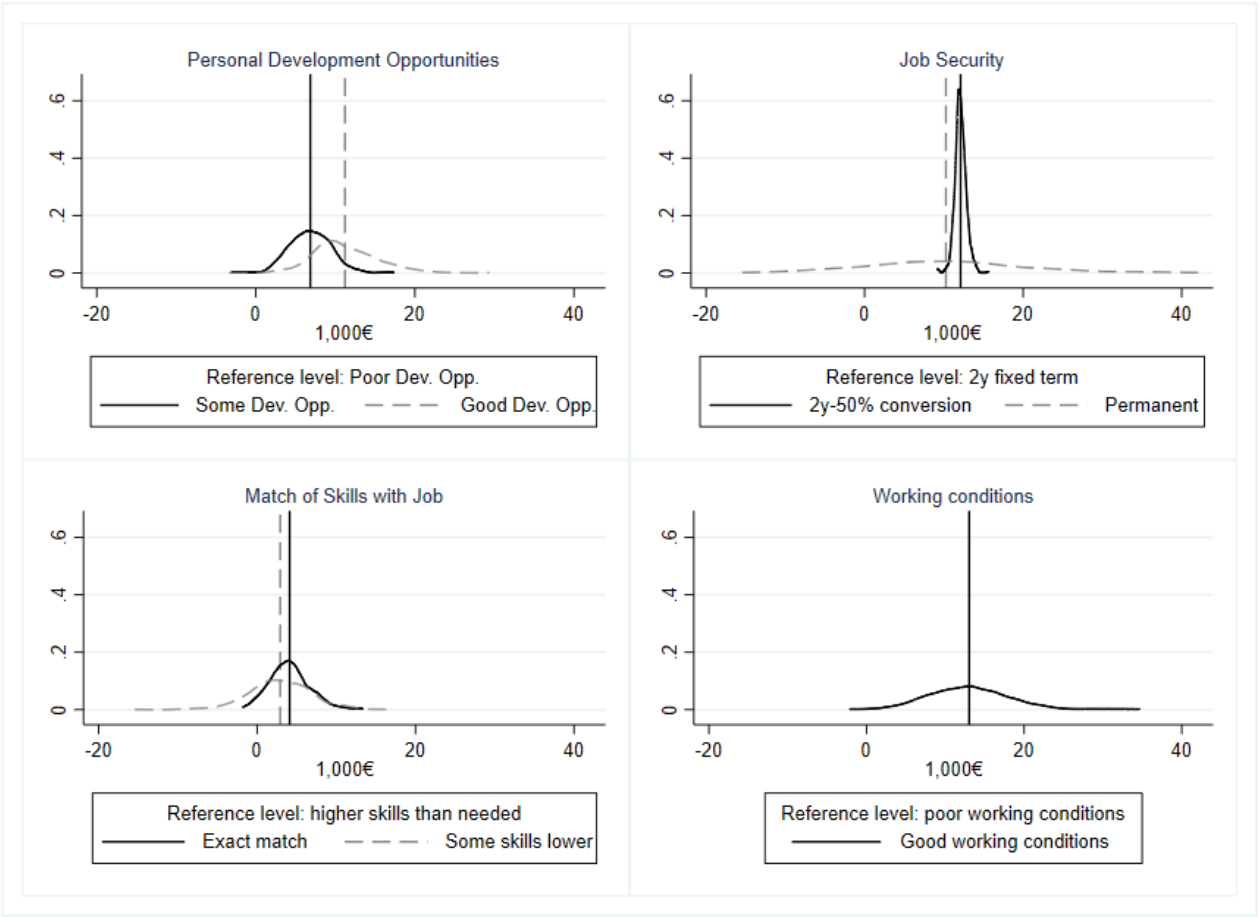


Figure 3: WTP distribution for non-monetary and non-geographical job attributes.



Notes: Vertical bars indicate the mean of each distribution.

Table 1: Job attributes and their levels

Attribute	Levels
Location	Italy Your favourite European foreign country
Annual net income (PPP adjusted)	€20.000 €30.000 €40.000 €50.000 €60.000 €75.000
Job security	2-year fixed term contract, non-renewable 2-year fixed term contract with 50% renewal probability Permanent job
Professional development opportunities	Limited opportunities for research and training Some opportunities for research and training Good opportunities for research and training
Working conditions	High workload with frequent overtime work and nightshifts Adequate workload with little overtime work and nightshifts
Match of skills with job content	Your skills are higher than required by the job Your skills are exactly matched to what is required by the job Some of your skills are lower than required by the job and need further development

Table 2: Sample representativeness

Variable	Population mean	Sample mean	Reweighted sample mean
Female	0.524	0.588	0.525
Age	23.90	24.73	23.91
Student shares by region			
North-East	0.284	0.402	0.284
North-West	0.172	0.175	0.171
Centre	0.379	0.228	0.379
South	0.165	0.195	0.165
Observations	6,599	527	527

Table 3: Descriptive statistics

Variable	Sample mean	Reweighted sample mean
Female	0.588	0.525
Born in the university's region	0.571	0.606
Parents have a secondary education degree or higher	0.705	0.726
Family income above €2,300	0.590	0.619
Has a partner	0.619	0.602
GPA above median by university	0.410	0.444
Wants to specialise in own university	0.353	0.371
Clinical (vs.) surgical specialty	0.624	0.631
Ever visited fav. EUR country	0.729	0.744
Knows lang. of fav. country	0.324	0.324
Has personal ties in fav. country	0.264	0.259
Observations	527	

Table 4: Baseline WTP-space mixed logit estimates. Mean and SD.

Variable	Mean	SD
Income (α_i)	0.126***	0.106***
	(0.009)	(0.008)
Job location WTP - reference: Italy		
Favourite foreign EUR country	-13,515***	17,216***
	(1,298)	(1,501)
Professional development opportunities WTP - reference: poor dev. opp.		
Some dev. opp.	6,572***	8,182***
	(947)	(1,122)
Good dev. opp.	10,998***	7,641***
	(941)	(934)
Job security WTP - reference: fix-term,non-renewable job		
Fixed-term job, 50% renew prob.	11,800***	4,920***
	(838)	(1,185)
Permanent job	8,878***	13,071***
	(1,009)	(971)
Working conditions WTP - reference level: poor		
Good working conditions	12,740***	8,408***
	(830)	(996)
Match of skills with job content WTP - reference: higher than needed		
Exactly matched	3,711***	5,809***
	(905)	(1,539)
Lower than needed	3,002***	8,849***
	(925)	(919)
ASC_1	-37,686***	5,115***
	(1,658)	(791)
ASC_2	-39,961***	2,931***
	(1,761)	(854)
Choices	8,432	
Subjects	527	

Notes: This table reports estimates obtained from Equation 3. Observations are weighted to match the population level statistics of the share of females, age and share of students by macro-regions. Robust standard errors in parentheses. *, p<.10, ** p<.05, *** p<.01.

Table 5: Mean WTP estimates for non-monetary,non-geographical job attributes across jobs located in Italy and in respondents' favourite foreign European country (abroad).

Variable	Home	Abroad	Difference
Professional development opportunities WTP - reference: poor dev. opp.			
Some dev. opp.	13,563***	-2,031	-15,594***
	(2,098)	(1,977)	(3,320)
Good dev. opp.	11,269***	7,137***	-4,132 ***
	(2,090)	(1,546)	(2,434)
Job security WTP - reference: fix-term,non-renewable job			
Fixed-term job, 50% renew prob.	3,866***	20,978***	17,111***
	(1,441)	(1,275)	(1,934)
Permanent job	13,979***	1,888	-12,091***
	(1,834)	(1,877)	(2,809)
Working conditions WTP - reference level: poor			
Good working conditions	13,243***	12,086***	-1,157
	(1,243)	(1,391)	(1,999)
Match of skills with job content WTP - reference: higher than needed			
Exactly matched	8,219 ***	-2,165*	-10,384***
	(1,545)	(1,279)	(2,118)
Lower than needed	9,085***	-4,209***	-13,294***
	(1,453)	(1,542)	(2,351)
Choices		8,432	
Subjects		527	

Notes: This table reports estimates obtained from Equation 5. Observations are weighted to match the population level statistics of the share of females, age and share of students by macro-regions. Robust standard errors in parentheses. *, p<.10, ** p<.05, *** p<.01.

Appendices

A Additional figures and tables

Figure A1: Choice task introduction and example

We now ask you to imagine that you have just completed your preferred specialization course and are looking for a job as a hospital doctor in your field of specialization. The next section will present a series of hypothetical scenarios. We will ask you to choose from some hypothetical job offers. Each scenario will contain two jobs, called "Offer A" and "Offer B". You will be asked to choose whether you prefer Offer A, Offer B, or neither. Each offer will be described using six characteristics, which we present below. Please read this information before proceeding.

1. Professional development opportunities. It refers to the opportunities for further research and training. Possible levels: Limited, Some, Good .

2. Annual net income. For open-ended contracts, the reported income is for the first two years, then assumes an increasing profile of about 5% every 2 years. If the work refers to a foreign country where the cost of living is higher (lower) than in Italy, assume to earn proportionally more (less) in order to maintain your purchasing power equal to what you would have in Italy with that sum. Possible levels: €20, 000, €30, 000, €40, 000, €50, 000, €60, 000, €75, 000.

3. Job security. It refers to contract duration. Possible levels: 2-year fixed-term contract non-renewable; 2-year fixed-term contract with 50% probability of a permanent position afterwards; Permanent position.

4. Working conditions. Possible levels: High workload, with overtime, availability and very frequent night shifts; Adequate workload, with overtime, availability and infrequent night shifts.

5. Match of skills with job content. Possible levels: Some of your skills are lower than those required by this job and need to be developed; Your skills are in line with those required by this job; Your skills are higher than those required by this job.

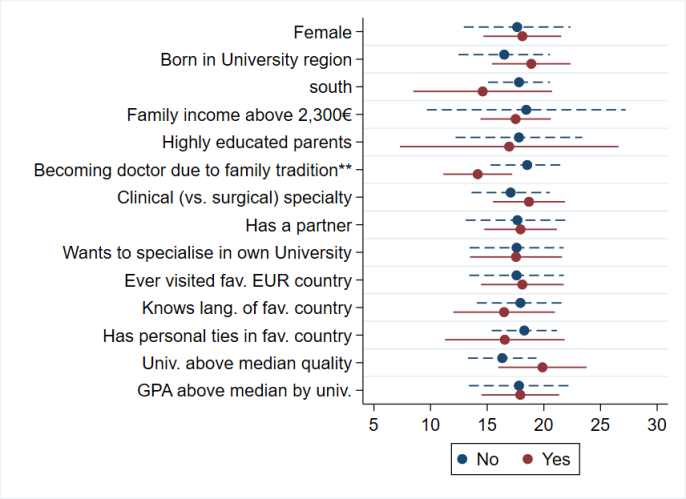
6. Country. Possible levels: Italy; Your favorite European foreign country.

Imagine that you have just completed your preferred specialization course and are faced with the following job offers for hospital doctor positions in your specialization. Which would you choose: A, B, or neither of the two?

	Job A	Job B	Opt-Out
Professional development Opportunity	Good opportunities for further research and training	Limited opportunities for further research and training	
Income (PPP adjusted)	€40,000	€40,000	
Job security	Permanent position	2-year temporary contract with 50% chance of a permanent position afterward	
Working Conditions	High workload with frequent overtime work and night shifts	Adequate workload with little overtime work and night shifts	
Match of skills with job content	Your skills are exactly matched to what is required by the job	Some of your skills are lower than required by the job and need further development	
Country	Your favourite foreign European country	Italy	
Which would you choose?	○	○	○

Figure A2: SD of WTP distribution for jobs located in respondents' favourite foreign European country, by individual background variables and personality traits.

a. Background variables



b. Personality traits

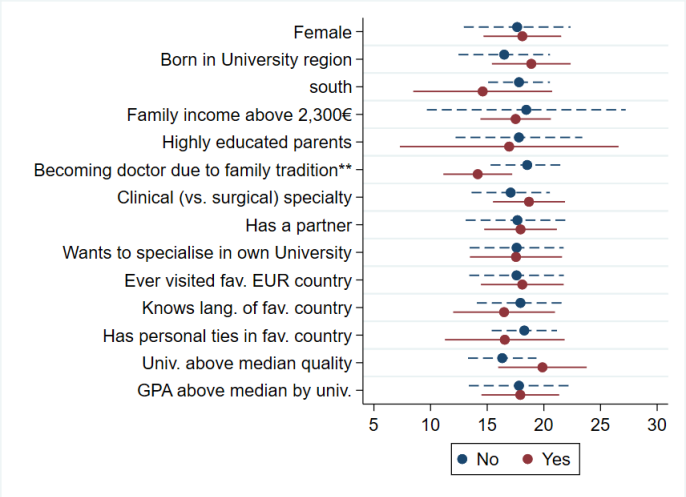


Table A1: Distribution of favourite foreign European countries in the final sample

Country	Sample share
United Kingdom	21.25
Spain	18.98
Switzerland	11.76
France	10.63
Germany	10.06
Netherlands	6.83
Portugal	3.23
Denmark	2.85
Ireland	2.66
Norway	2.66
Austria	2.47
Sweden	1.9
Belgium	1.52
Finland	1.33
Greece	0.57
Poland	0.38
Croatia	0.19
Cyprus	0.19
Luxembourg	0.19
Malta	0.19
Slovenia	0.19
Observations	527

Table A2: Distribution of respondents in the final sample by region and university

University	Sample size	Sample share
North-east		
Bologna	7	1.3
Ferrara	80	15.2
Padova	88	16.7
Udine	37	7.0
North-west		
Genova	37	7.0
Milano Statale	55	10.4
Centre		
Pisa	92	17.5
Roma "Campus biomedico" (private)	17	3.2
Roma "Sapienza"	11	2.1
South		
Bari	50	9.5
Catanzaro	5	1.0
Molise	48	9.1
Total	527	100.0

B Income levels definition

We decided the income levels based on data from the OECD (2019) on the average specialists' net income levels in European countries. After adjusting for PPP between Italy and the other countries, the observed average salaries vary from €31,600/year to €115,400/year, and the average Italian doctor's salary is €45,500/year. The key limitation of the OECD data is that they refer to the whole population of MDs, and therefore they do not represent starting salaries of medical school graduates immediately after finishing their specialisations. Anelli (2019) used Social Security (INPS) data for Italy to trace the earnings profiles of medical doctors. According to his data, the ratio of the earnings of doctors right after the end of specialisation and doctors at the middle of their career is roughly equal to two-thirds. In the absence of better data regarding the starting salaries of specialists in the different European countries, we use this principle to deflate the average salaries reported in the OECD data and compute reasonable starting salaries offered to newly specialised doctors. Under these assumptions, we use a lower bound for net entry yearly salary equal to €20,000 and the upper bound of €75,000. These income levels are all PPP adjusted using Italy as a benchmark. We also assumed that these PPP adjusted net income levels could appear across all countries considered in the study even though at the time of our survey the top (or low) end income levels may be more common in some countries than the others. Nevertheless, in Italy, the €75,000 income level is uncommon but nothing unheard of. For example, Anelli (2019) reports that among newly-specialised medical graduates there is a positive probability of being even in the top 1% of the income distribution in Italy. The relatively large income range also provides sufficient room for the elicitation of the underlying valuation of desirable jobs which may be not often seen at the time. This strategy is commonly used in the DCE studies for the purpose of product or policy design. In the meantime, to obtain a design with good properties such as efficiency and balance, we should refrain from imposing constraints to the experimental design unless certain combinations are *absolutely* implausible, which were not identified in our case.

C Survey instruments

This Appendix describes the survey instrument used to measure personality traits of respondents. Unless otherwise stated, answers to each item had to be reported on a 5-point ordinal Likert scale, with 1 meaning "strongly disagree" and 5 meaning "strongly agree". For each trait, we obtained a single index measure by standardizing the answers to each item in the final sample and then summing across items. Trait measures obtained with this simple method were highly correlated to the ones we estimated with polychoric principal component analysis (PPCA), but we preferred the former method because of convergence problems for the PPCA in some cases. We now turn to describe the survey instruments in detail.

- *Self-Efficacy*: We use three questions from Chen et al. (2001)
    1. I will be able to achieve most of my goals that I have set for myself
    2. Compared to other people, I can do most tasks very well

3. I try to avoid competition with others (reversed)

The original scale consists of 14 items. Non et al. (2022) exploit data collected on the full scale from university students (N=240) in a laboratory experiment and select three items that jointly have the highest correlation with the full scale (0.94 for the three mentioned items). In order to reduce survey length, we follow their selection.

– *Competitiveness*: We again follow Non et al. (2022) and use the following three (out of fourteen) items from the Revised Competitiveness Index:

1. I try to avoid competition with others (reversed)
2. I don't like competing against other people (reversed)
3. I like competition

– *Locus of control*: We use a six-item scale as described in Lumpkin (1985)

1. When I make plans, I'm almost sure that I'm going to make them work
2. Getting people to do the right thing is a matter of skill, luck has nothing to do with it
3. What happens to me depends only on my choices
4. Many of the sad things in people's lives depend in part on bad luck
5. Getting a good job mostly depends on being in the right place at the right time
6. Many times, I feel that I have little influence on the things that happen to me

– *Big-5 personality traits*: We use an 11-item scale as used in the Survey of Health, Ageing and Retirement in Europe (SHARE). The following items are included in the scale.
I see myself as a person...

1. ...who is reserved
2. ...who usually trusts
3. ...who usually tends to be lazy
4. ...relaxed, who handles stress well
5. ...who has few artistic interests
6. ...extroverted, sociable
7. ...who tends to be laughed at by others
8. ...who works accurately
9. ...who gets nervous easily
10. ...who has an active imagination
11. ...caring and kind to almost everyone

Items 5 and 10 relate to Openness; items 3 an 8 to Conscientiousness; items 1 and 6 to Extraversion; items 2, 7 and 11 to Agreeableness; items 4 and 9 to Neuroticism.

- *Intrinsic and extrinsic motivation*: We framed the following 7 questions after a detailed literature review on intrinsic and extrinsic motivation (Ryan and Deci, 2000; **?**). Items 1 to 4 refer to intinsic motivation, 5 to 7 to extrinsic motivation.
  What is your motivation for becoming a doctor?

  1. ... Sense of calling
  2. ... Personally rewarding work
  3. ... For doing well to others
  4. ... Intellectual curiosity
  5. ... Financial rewards
  6. ... Social status
  7. ... Family tradition

- *Risk attitude*: We used the following four items as used by the MABEL survey (Szawlowski et al., 2020): Please indicate your willingness to take risks... (1 representing "not at all willing" and 5 "very willing")

  1. ... in general
  2. ... in the financial sector (e.g. investing with uncertain results)
  3. ... professionally (e.g. publicly doubting a colleague)
  4. ... clinically (e.g. recommending controversial treatment)

- *Altruism*: We used the following two questions from Falk et al. (2016)

  1. "Are you inclined to donate to a good cause without expecting anything in return?" (1 represents "not at all inclined" and 5 "very inclined")
  2. Suppose you unexpectedly received €1,000. How much would you give to charity?

D Institutional background

Medical education and access to the medical profession in Italy are highly regulated. The degree course in medicine lasts 6 years. During years 1-3 students spend most of their time in class and cover the basics of medical theory. During years 4-6, they combine theoretical classes with medical practice in hospital wards.

In total, 40 Italian universities offer degree courses in medicine - 35 are public and 5 are private. The number of medical school seats available in every university is set every year by a decree of the Ministry of

Education after consultations with the universities. Given severe oversubscription, seats are offered on a competitive ground on the basis of the outcomes of an entry test. The test assesses general competences in logical reasoning, biology, chemistry, physics and math, and is standardized across all public universities, while each private university has its own test. Among public medical schools, the assignment mechanism is akin to a serial dictator. Before taking the test, applicants are asked to rank-order all public medical school and are then assigned to the highest choice with remaining seats, with students scoring higher at the tests being assigned first. Private universities instead admit students on the basis of the ranking at their own test.

According to data for 2019 from Almalaurea, a think-thank collecting information on universities and college-to-work transition[16], this selective access procedure makes it such that medical students are positively selected with respect to the general population of college students in terms of their family background and are more likely to come from academic high schools (the so-called *licei*).

In order to work as general practitioners (GPs) or specialists, medical graduates need to obtain a specialization degree.[17] Access to specialty courses is restricted and the number of available seats is set by law. Vicarelli and Pavolini (2015) report that a severe oversubscription problem exists also at this level, as the ratio of specialty training places over medical graduates is far below one, and close to 0.7. Access depends on a weighted average of a national test (that covers general topics commonly covered during medical degree courses and is common for both public and private universities) and applicants' CV (the evaluation concerns their final grade at the medical degree, their grade point average, and the quality of their dissertation). The assignment is again similar to a serial dictator, and the best candidates are allocated first. Specialisation courses last between 3 and 5 years, depending on the specialty of choice, and during their specialty training students receive a salary. The training of GPs is instead organized by regions in dedicated schools. As a result, we exclude those students who plan to become GPs from our analysis.

After specialisation, medical graduates start seeking jobs as specialists in private or public hospitals. According to Almalaurea data for 2020[18], five years after graduation, more than 93% of the medical school graduates are either already working as doctors or enrolled in a specialty course, and less than 1% report to be unemployed.

[16]https://www.almalaurea.it/universita/profilo/profilo2020

[17]In addition, until 2020 those medical graduates willing to work as physicians needed to pass a national qualification exam. This exam has then been abolished.

[18]https://www.almalaurea.it/universita/occupazione/occupazione18

E Robustness tests

Table A3: Baseline WTP-space mixed logit estimates. Excluding respondents listing UK as their favourite foreign European country. Mean and SD.

Variable	Mean	SD
Income (α_i)	0.125***	0.105***
	(0.010)	(0.008)
Job location WTP - reference: Italy		
Favourite foreign EUR country	-13,439***	17,575***
	(1,571)	(1,484)
Professional development opportunities WTP - reference: poor dev. opp.		
Some dev. opp.	6,145***	8,040***
	(1,016)	(1,449)
Good dev. opp.	9,950***	6,638***
	(1,016)	(1,331)
Job security WTP - reference: fix-term,non-renewable job		
Fixed-term job, 50% renew prob.	11,237***	6,523**
	(1,123)	(2,615)
Permanent job	9,467***	12,798***
	(1,591)	(1,171)
Working conditions WTP - reference level: poor		
Good working conditions	13,040***	8,862***
	(977)	(1,153)
Match of skills with job content WTP - reference: higher than needed		
Exactly matched	3,277***	6,071***
	(1,028)	(2,104)
Lower than needed	2,675***	7,438***
	(1,055)	(1,326)
ASC_1	-37,258***	5,169***
	(2,109)	(1,118)
ASC_2	-39,093***	3,988***
	(2,268)	(1,949)
Choices	6,640	
Subjects	415	

Notes: This table reports estimates obtained from Equation 3. Observations are weighted to match the population level statistics of the share of females, age and share of students by macro-regions. Robust standard errors in parentheses. *, p<.10, ** p<.05, *** p<.01.

Table A4: Mean WTP estimates for non-monetary,non-geographical job attributes across jobs located in Italy and in respondents' favourite foreign European country (abroad). Excluding respondents listing UK as their favourite foreign European country.

Variable	Home	Abroad	Difference
Professional development opportunities WTP - reference: poor dev. opp.			
Some dev. opp.	11,988***	-1,823	-13,811***
	(2,480)	(1,889)	(3,497)
Good dev. opp.	9,542***	7,621***	-1,921
	(1,991)	(1,575)	(2,745)
Job security WTP - reference: fix-term,non-renewable job			
Fixed-term job, 50% renew prob.	3,800***	19,840***	16,039***
	(1,725)	(1,459)	(2,245)
Permanent job	13,875***	1,229	-12,647***
	(2,071)	(2,711)	(3,356)
Working conditions WTP - reference level: poor			
Good working conditions	13,284***	12,292***	-992
	(1,509)	(1,552)	(2,059)
Match of skills with job content WTP - reference: higher than needed			
Exactly matched	8,344 ***	-2,394*	-10,738***
	(2,028)	(1,827)	(2,493)
Lower than needed	8,635***	-3,752***	-12,387***
	(1,461)	(1,536)	(2,306)
Choices		6,640	
Subjects		415	

Notes: This table reports estimates obtained from Equation 5. Observations are weighted to match the population level statistics of the share of females, age and share of students by macro-regions. Robust standard errors in parentheses. *, p<.10, ** p<.05, *** p<.01.

Table A5: Baseline unweighted WTP-space mixed logit estimates. Mean and SD.

Variable	Mean	SD
Income (α_i)	0.107***	0.075***
	(0.005)	(0.004)
Job location WTP - reference: Italy		
Favourite foreign EUR country	-13,473***	19,149***
	(996)	(959)
Professional development opportunities WTP - reference: poor dev. opp.		
Some dev. opp.	6,644***	7,291***
	(822)	(1,160)
Good dev. opp.	11,479***	8,330***
	(799)	(827)
Job security WTP - reference: fix-term,non-renewable job		
Fixed-term job, 50% renew prob.	12,435***	3,198
	(727)	(2,855)
Permanent job	10,131***	14,481***
	(917)	(904)
Working conditions WTP - reference level: poor		
Good working conditions	13,113***	8,661***
	(653)	(667)
Match of skills with job content WTP - reference: higher than needed		
Exactly matched	3,852***	6,093***
	(828)	(1,140)
Lower than needed	2,835***	7,060***
	(756)	(849)
ASC_1	-38,952***	5,383***
	(1,112)	(747)
ASC_2	-40,764***	849***
	(1,220)	(2,290)
Choices	8,432	
Subjects	527	

Notes: This table reports estimates obtained from Equation 3. Robust standard errors in parentheses. *, p<.10, ** p<.05, *** p<.01.

Table A6: Unweighted mean WTP estimates for non-monetary,non-geographical job attributes across jobs located in Italy and in respondents' favourite foreign European country (abroad).

Variable	Home	Abroad	Difference
Professional development opportunities WTP - reference: poor dev. opp.			
Some dev. opp.	13,235***	-942	-14,177***
	(1,499)	(1,525)	(2,336)
Good dev. opp.	12,556***	7,338***	-5,217 ***
	(1,477)	(1,430)	(2,376)
Job security WTP - reference: fix-term,non-renewable job			
Fixed-term job, 50% renew prob.	3,821***	22,129***	18,309***
	(1,149)	(1,225)	(1,884)
Permanent job	15,499***	3,113*	-12,387***
	(1,441)	(1,705)	(2,498)
Working conditions WTP - reference level: poor			
Good working conditions	14,207***	11,250***	-2,957
	(1,207)	(1,246)	(2,092)
Match of skills with job content WTP - reference: higher than needed			
Exactly matched	9,082***	-2,055	-11,137***
	(1,327)	(1,306)	(2,014)
Lower than needed	9,439***	-4,714***	-14,153***
	(1,264)	(1,493)	(2,292)
Choices		8,432	
Subjects		527	

Notes: This table reports estimates obtained from Equation 5. Robust standard errors in parentheses. *, p<.10, ** p<.05, *** p<.01.

Table A7: Baseline WTP conditional logit estimates.

Variable	WTP
Job location WTP - reference: Italy	
Favourite foreign EUR country	-10,894***
	(1,046)
Professional development opportunities WTP - reference: poor dev. opp.	
Some dev. opp.	8,947***
	(958)
Good dev. opp.	12,750***
	(1,005)
Job security WTP - reference: fix-term,non-renewable job	
Fixed-term job, 50% renew prob.	13,130***
	(922)
Permanent job	11,161***
	(1,022)
Working conditions WTP - reference level: poor	
Good working conditions	13,898***
	(758)
Match of skills with job content WTP - reference: higher than needed	
Exactly matched	4,843***
	(1,027)
Lower than needed	4,278***
	(987)
ASC_1	-37,609***
	(2,118)
ASC_2	-40,006***
	(2,217)
Choices	8,432
Subjects	527

Notes: Observations are weighted to match the population level statistics of the share of females, age and share of students by macro-regions. Robust standard errors in parentheses. *, p<.10, ** p<.05, *** p<.01.

Table A8: Conditional logit WTP estimates for non-monetary,non-geographical job attributes across jobs located in Italy and in respondents' favourite foreign European country (abroad).

Variable	Home	Abroad	Difference
Professional development opportunities WTP - reference: poor dev. opp.			
Some dev. opp.	17,537***	-2,696	-20,234***
	(1,839)	(1,764)	(2,879)
Good dev. opp.	12,388***	8,068***	-4,319*
	(1,769)	(1,473)	(2,532)
Job security WTP - reference: fix-term,non-renewable job			
Fixed-term job, 50% renew prob.	6,606***	20,645***	14,039***
	(1,598)	(1,460)	(2,361)
Permanent job	20,000***	2,443	-17,557***
	(2,045)	(1,891)	(3,301)
Working conditions WTP - reference level: poor			
Good working conditions	15,901***	11,925***	-3,976
	(1,528)	(1,406)	(2,512)
Match of skills with job content WTP - reference: higher than needed			
Exactly matched	10,014***	-1,062	-11,076***
	(1,656)	(1,359)	(2,256)
Lower than needed	13,911***	-7,124***	-21,035***
	(1,594)	(1,687)	(2,658)
Choices		8,432	
Subjects		527	

Notes: Observations are weighted to match the population level statistics of the share of females, age and share of students by macro-regions. Robust standard errors in parentheses. *, p<.10, ** p<.05, *** p<.01.

F Attribute non-attendance

An important assumption behind our results is that respondents consider all the attributes while making their choices between the job offers. There is a growing body of literature that focus on the importance of attribute non-attendance (ANA) - that is, how the results change if some individuals do not consider some of the attributes in the choice sets (Scarpa et al., 2009). ANA occurs for two main reasons (Heidenreich et al., 2018). First, it can occur when respondents need to simplify complex choice tasks with many different attributes due to limited cognitive capacity (Kahneman, 1973; Malhotra, 1982; Payne and Bettman, 2001). This heuristic approach to decision making violates the assumption of continuous preference on which consumer behaviour theory works (Campbell et al., 2008). Second, it can occur if respondents consider one or more attributes to be unimportant. ANA that occurs due to the deeming of some attributes to be unimportant represents preferences and is in line with consumer theory (Hensher, 2006; Ryan et al., 2009). Considering that respondents in our sample are high-ability medical students, it is unlikely that limited cognitive capacity applies to our context. As a result, in what follows we will assume that ANA occurs if respondents deem attributes as non-important and attach them zero value.

The existing studies generally use two different approaches to measure ANA – stated and inferred. Stated ANA methods ask respondents which attributes they did not consider while making their choice decisions. Inferred ANA methods, on the other hand, use econometric methods (usually some variant of a latent class logit model) to estimate ANA strategies probabilistically (Hole, 2011; Scarpa et al., 2013; Heidenreich et al., 2018). These approaches constrain the coefficients of the attributes that are considered to be non-attended to zero. As our survey does not include state measures of attribute non-attendance, we adopt one of the most widely utilised inferred ANA approaches, pioneered by Scarpa et al. (2009). This approach exploits a latent class logit (LCL) model which assumes that there are C different classes of respondents with one class following a full attendance strategy and each of the other (C-1) classes following some kind of attribute non-attendance strategy. We assume that the income attribute is always attended as it is unlikely that respondents do not consider the salary level of the job contract and also because it is the numeraire attribute essential for calculating WTPs. That leaves 5 attributes and hence a total of 2^5 or 32 attribute non-attendance strategies. Examples of ANA strategies include any one of the attributes (say personal development opportunity) being non-attended, any two being non-attended and so on. We further assume, following Scarpa et al. (2009) that the non-zero attribute coefficients across the C classes are equal.

Mathematically, a utility function is used to represent each ANA strategy for individual i for alternative j at choice situation t:

$$U_{ijt}(\delta_c) = (\beta \cdot \delta_c)' x_{ijt} + \epsilon_{ijt} \tag{1}$$

where β is a vector of marginal utilities or coefficients of the attributes to be estimated. They are constant across the C classes. The vector x_{ijt} represents the attribute levels and ϵ_{ijt} is an extreme value distributed random error term. The vector δ_c contains only ones and zeros and multiplied with the vector β, they represent different ANA strategies.

We ran into maximum log-likelihood convergence problems while running the 32-class (31 ANA

strategies and 1 fully attended strategy) model. We even tried assuming that the working conditions attribute is always attended based on other supporting evidence, bringing down the number of classes in the LCL model to 16. Unfortunately, the model still did not converge. This is not surprising given that we only have 527 respondents in our final sample.

Hence we decided to run several smaller LCL models with each non-attendance strategy separately (always maintaining the full-attendance strategy as one of the classes in each of these LCL models). Specifically, we ran 5 different LCL models:

1. Any one attribute is non-attended (6-class model with one attribute being non-attended in each class and one class with all attributes being attended).
2. Any two attributes are non-attended (11-class model with 10 of the classes assuming any two attributes being non-attended in some combination and one full-attendance class).
3. Any three attributes are non-attended (11-class model with 10 of the classes assuming any three attributes being non-attended in some combination and one full-attendance class).
4. Any four attributes are non-attended (6-class model with 5 of the classes assuming any four attributes being non-attended in some combination and one full-attendance class).
5. Five attributes are non-attended (2-class model with one class assuming all five attributes to be non-attended and the other class assuming full attendance).

Table A9 shows the results from these 5 models. The columns show the average WTPs of each attribute from the above mentioned models and their corresponding probabilities of being non-attended or skipped. For example, in the 1-ANA model, where any one of the attributes are allowed to be non-attended, the average WTP of going abroad is -€13,039 and the probability that the country attribute is skipped is 0.364. The average WTPs are obtained as the non-zero attribute WTP (which is equal across the classes where the attribute is attended) times the total probability that the attribute is attended to (or $1 - the\ probability\ of\ non - attendance$). The non-attendance probabilities are calculated as the sum of the class shares where the attribute is considered to be non-attended. The results show that regardless of the ANA strategies assumed, the WTPs are quite stable across the models and in line with our main results. Country of work seems to be the attribute that is most susceptible to being non-attended with non-attendance probability reaching as high as 70% suggesting that they are highly susceptible to move abroad if amply compensated by other job attributes. Working conditions seems to be the attribute with the lowest non-attendance probabilities across the models suggesting that respondents really care about their workload, much in line with our home-abroad model (see Table 5).

Table A9: Average WTPs by ANA model with corresponding attribute non-attendance probabilities

Attribute	1-ANA WTPs (1)	ANA prob (2)	2-ANA WTPs (3)	ANA prob (4)	3-ANA WTPs (5)	ANA prob (6)	4-ANA WTPs (7)	ANA prob (8)	5-ANA WTPs (9)	ANA prob (10)
Job location WTP - reference: Italy										
Favourite foreign EUR country	-13,039	0.364	-11,378	0.67	-11,545	0.70	-12,906	0.502	-12,408	0.261
Professional development opportunities WTP - reference: poor dev. opp.										
Some dev. opp.	8,053	0.112	6,623	0.265	4,848	0.384	5,151	0.520	8,303	0.261
Good dev. opp.	12,395	0.112	10,603	0.265	9,046	0.384	7,733	0.520	11,429	0.261
Job security WTP - reference: fix-term,non-renewable job										
Fixed-term job	12,557	0.04	11,942	0.232	11,701	0.460	9,158	0.516	11,417	0.261
Permanent job	11,565	0.04	11,483	0.232	12,630	0.460	7,297	0.516	9,669	0.261
Working conditions WTP - reference level: poor										
Good working conditions	13,722	0.26	14,163	0.153	11,999	0.424	11,488	0.429	13,228	0.261
Match of skills with job content WTP - reference: higher than needed										
Exactly matched	4,516	0.20	2,296	0.426	-248	0.575	2,711	0.557	4,837	0.261
Lower than needed	3,347	0.20	2,620	0.426	-124	0.575	3,145	0.557	4,368	0.261

Notes: This table reports estimates obtained from the latent class logit model used to identify attribute non-attendance (ANA) patterns. The columns show the average WTPs of an attribute from the relevant ANA model and its corresponding non-attendance probability.

G Counterfactual simulations

To quantify the average impact of each job attribute on students' migration intentions, we conduct simulations by using the estimates[19] from our main-effects model, reported in Table 4. We predict the share of students who would prefer to pick a job in Italy vs. in their favourite foreign European country as we change the characteristics of jobs. Our results are presented in Table A10. We start with a base-case scenario that compares two jobs with the features that may resemble those of good entry-level jobs in Italy according to Almalaurea data (good development opportunities, fix-term with 50% chances of conversion, good working conditions, exact skill match, and €40,000 net annual income), one located in Italy and one abroad. In this base-case scenario, only 30% of students would pick the job abroad. However, this share increases substantially as the quality of the Italian job declines. As expected, working condition is the job attribute that triggers a large change in migration probability, as around 49% of students would leave if the Italian job had poor instead of good working conditions, all else being equal. This is followed by poor job security (47% would leave if the Italian job was fixed-term with zero probability of conversion), poor development opportunities (46% of students would leave Italy if it offered poor instead of good development opportunities), while skill mismatch only plays a secondary role. Income is also relevant, as around 45% of students would move abroad if the job in Italy paid €30,000 instead of €40,000. The probability of migration would further increase to around 60% if the net annual income dropped to €20,000.[20]

[19] Both point and covariance estimates are used in the simulations with the latter accounting for parameter estimates uncertainty.

[20] We obtain qualitatively comparable results if we start from two equally undesirable jobs and improve the quality of the job located abroad. Results are available from the authors.

Table A10: Counterfactual simulations. Probability of choosing a job abroad as the quality of the Italy job declines.

Location	Abroad	Italy								
	Base case	Base case	Case1	Case2	Case3	Case4	Case5	Case6	Case7	Case8
Poor dev.opp.	0	0	0	1	0	0	0	0	0	0
Some dev.opp.	0	0	1	0	0	0	0	0	0	0
Good dev.opp.	1	1	0	0	1	1	1	1	1	1
Fix-term,non-ren.	0	0	0	0	1	0	0	0	0	0
Fix-term,50% ren.	1	1	1	1	0	1	1	1	1	1
Perm. job	0	0	0	0	0	0	0	0	0	0
Poor work.cond.	0	0	0	0	0	1	0	0	0	0
Good work cond.	1	1	1	1	1	0	1	1	1	1
Overskilled	0	0	0	0	0	0	1	0	0	0
Matched skills	1	1	1	1	1	1	0	0	1	1
Underskilled	0	0	0	0	0	0	0	1	0	0
Income (€1,000)	40	40	40	40	40	40	40	40	30	20
% choosing abroad		0.3014	0.3759	0.4625	0.4735	0.4884	0.3561	0.3269	0.4451	0.5989
Std.err		0.0183	0.0238	0.0242	0.0234	0.0238	0.0232	0.0185	0.0202	0.0225