Softening up while abroad. Soft skills and international student mobility*

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Abstract

Soft skills are important determinants of labour market outcomes and their relevance is growing over time. Existing studies have underscored their significance, emphasized their malleability during young adulthood and their persistent undersupply in the labour market. Despite these findings, the production function of soft skills remains under explored. This paper investigates whether international student mobility, during university studies, can work as an effective technology to produce soft skills. I compile a new data source at the graduate-occupation-employer level using administrative data augmented with the importance of both hard and soft skills across occupations. My identification strategy instruments the decision to become mobile by exploiting exogenous variation in exposure to past mobility through a fine degree by cohort level. My results show that international student mobility works as an effective technology to shape soft skills by allowing mobile graduates to sort themselves into jobs where soft skills are relevant. Being mobile during university studies helps graduates find jobs where communication (+9.7%), creativity (+13.1%), team working (+9.1%) and problem solving (+9.4%) skills are more important. I characterize the complier subgroup responding to my exposure instrument and show that my estimates refer to graduates coming from a negatively selected socio-economic background.

JEL Classification: I23, I26, J24

Keywords: economics of education, soft skills, labour market outcomes, tertiary education, instrumental variable

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1 Introduction

Soft skills are important predictors of success in the labour market by shaping earnings and the probability of obtaining a job (Heckman and Rubinstein, 2001, Heckman et al., 2006, Borghans et al., 2008, Heckman and Kautz, 2012, Lindqvist and Vestman, 2011). Recent evidence also documents how their importance is growing over time reflecting technological change, automation (Deming, 2017a, Edin et al., 2022) and pointing towards complementarities between hard and soft skills (Weinberger, 2014, Deming, 2017b, Börner et al., 2018). Employer's voracious demand for soft skills agrees with this argument, with communication, team working and collaboration skills frequently demanded by employers (Cunningham and Villaseñor, 2016) and appearing as essential requirements across job advertisements (Brenčič and McGee, 2023). Despite their importance very little is currently known in terms of their production and accumulation (Deming, 2022). These are particularly relevant issues given the evidence showing soft skills to be under-supplied by education institutions (Börner et al., 2018, Cunningham and Villaseñor, 2016). As argued by Heckman and Kautz (2012), there is ample need for policies aimed at fostering soft skills particularly because these policies are likely to exhibit high rates of returns given the ample set of life domains connected with these skills.

This paper studies whether international mobility, during tertiary education, works as an effective technology to produce soft skills. International Student Mobility allows students enrolled in tertiary education to spend some time abroad as part of their university program. In this paper I study credit mobility through which students enrolled in their home country can earn credits towards their degree by attending lectures and taking examination at an host institution. My identification strategy instruments the endogenous decision to be mobile with a measure of exposure to mobility. I exploit plausibly exogenous variation in exposure to mobility, through peer pressure, at a fine degree course by cohort level that is likely to influence the individual decision to go abroad without having any direct effect on soft skill accumulation.

I combine data from several sources. I first start with the Italian Labour Force Survey which I augment, by matching through occupational codes, with the importance of several hard and soft skills in each profession. Data on skill importance comes from the Italian National Institute for Policy Evaluation[1] which periodically surveys all professions classified by the Italian statistical office mapping out the required skillset for the Italian economy[2]. From the same institute I also obtain another dataset surveying employers on their needs to re-training staff across both hard and soft skills. I use these data to first show that both soft and hard skills explain sizeable proportions of total variability in earnings and how there is an undersupply of these skills in workforce. I then retrieve mandatory census survey data for all graduates from the University of Turin and merge it with an administrative regional archive detailing spells in the labour market. Similarly to above I augment the dataset with

[1] *Istituto Nazionale per l'Analisi delle Politiche Pubbliche* (INAPP).

[2] The resulting dataset closely replicates US O*NET for Italy.

survey data measuring the importance of several hard and soft skills in each profession. The resulting graduate-occupation-employer matched dataset will serve as the main basis for analysis throughout this paper. Finally I also acquired a mandatory survey developed by the University of Turin and administered to the first year intake of all students enrolling in the academic year 2020/ 2021. This last data source collects the initial stock of soft skills at enrolment and provides additional empirical evidence to corroborate the validity of the peer exposure instrument.

I provide novel empirical evidence confirming the role of soft skills for success in the labour market. I show that soft skills and hard skills seem to explain a similar proportion of variability in earnings. I then document how soft and hard skills explain different components of the total earning variability. Next, I show evidence of an unmet demand of soft skills. A survey of Italian employers documents the ample need to train staff on soft skills. The intention to develop training on soft skills strongly exceeds the need of training for hard skills. This finding suggests how the available stock of soft skills held by Italian professionals does not meet the demand of employers and calls for policies aimed at skills accumulation. This concern is not unique to the Italian economy, Börner et al. (2018) pool together data from uses millions of publications, course syllabi, and job advertisements and document a similar under-supply of soft skills.

My main result confirms that International Student Mobility works as an effective technology to produce soft skills. Tracking graduates into their first job after university, I am able to show that the importance of soft skills is higher in jobs held by mobile graduates compared to their non mobile peers. Effects are particularly pronounced for skills helping individuals to communicate, come up with new ideas, work with others and master problem solving. I interpret this finding as evidence of sorting into jobs where soft skills are important. My IV estimates identify a Local Average Treatment Effect (LATE) causal parameter which refers to the compliers subpopulation (Imbens and Angrist, 1994). I characterize the complier subgroup activated by the exposure instrument and show that students who respond to peer pressure are socially negatively selected. Compliers are more likely to come from less educated and less affluent households, they perform worse in terms of high school achievement, are less likely to have attended an academic high school track and have already been mobile within Italy to attend university.

This paper relates to studies across several strands of the literature. It contributes to the literature investigating the production of soft skills across the life cycle. Academic research has clearly shown how environments and life experiences play a key role in shaping individual stocks of soft skills (Heckman et al., 2013, Borghans et al., 2008). The exact timing along the individual life-cycle when these skills can best be improved has been subject to debate. Research shows that, unlike cognitive development, many personality traits and soft skills experience the highest mean level rise in young adulthood (Borghans et al., 2008, Chioda et al., 2021). However, the cost for public intervention to allow disadvantaged individuals to catch up is likely to be greater later in life because "early mastery of a range of cognitive, social, and emotional competencies makes learning at later ages more efficient and there easier and more likely to continue" (Heckman, 2006).

Importantly, while the technology to produce basic skills is relatively well understood, the technology for producing higher order skills, including soft skills, is currently not as well understood (Deming, 2022). The development of soft skills is currently largely under-investigated, with only an handful of examples from development economics. Adhvaryu et al. (2023) study the effects of a randomly assigned workplace soft skill training on Indian garment workers. Using data on productivity at the individual level their estimates report large gains driven from improved teamwork, collaboration and spillovers to untreated co-workers working alongside treated individuals. Chioda et al. (2021) investigate returns from an MBA training aimed at the development of both hard and soft skills for Ugandan students at the end of high school. The effects reported in Chioda et al. (2021) are particularly prolonged with clear benefits 3.5 years after program completion. Individuals assigned to a soft skill intense curriculum score higher on skills measures for self-efficacy, negotiation and persuasion. The training allows treated individuals to join higher earnings trajectories and become more frequently self-employed. Dimitriadis and Koning (2022) study the effect of introducing a short 2 hours soft skill session within a 2 day training for entrepreneurs in Togo. Their estimates show that even short sessions, but placed in productive environments, can help entrepreneurs develop more valuable connections to improve their business ventures pointing at the low stock of soft skills to explain the paucity of pre-existing business links. These papers demonstrate the sizeable returns to manipulating soft skills with successful interventions beyond early years and well into adulthood life.

I find sizeable improvements across many soft skills for highly skilled young adults, in a developed country, as they complete higher education and embark towards their first jobs. The estimates are likely driven by the very intensive nature of International Student Mobility uprooting individuals from familiar conditions and exposing them to a different environment. These findings resonate with the education literature which has put forward two theories to explain the role of mobility in shaping participants' knowledge and skills (Dolce et al., 2023). The Experimental Learning Theory (ELT, (Kolb, 2014)) considers student mobility as an opportunity for participants to experiment with new information. According to this theory, learning arises by a constant derivation and modification of concepts through experience. Skills are advanced as mobile students interact with the new environment they are placed in, face obstacles, unfamiliar situations and develop solutions to solve them. The Transformative Learning Theory (TLT, (Mezirow, 1997)) instead postulates that international mobility can help in changing the frame of reference of graduates. Frames of references are defined as the structures of assumptions through which individuals understand their experiences. In TLT, international mobility fosters learning by questioning students' perspectives and their frames of reference through exposure to different practices and habits.

This paper also speaks to the literature investigating returns to international student mobility. Despite the effects of International Student Mobility having been extensively studied across several disciplines (Roy et al., 2019), the literature that takes into account the endogenous decision to become mobile and estimate causal effects is more limited. These studies have shown that international student mobility enhances subsequent migration patters to find a job (Parey and Waldinger, 2011, Oosterbeek and Webbink, 2011, Di Pietro, 2012, Pinto, 2022), academic achievement (Granato et al., 2022, De Benedetto et al., 2023) and the accumulation of hard skills such as foreign language proficiency (Sorrenti, 2017). Other studies have established the causal link between International Student Mobility and labour market outcomes. Several studies, including those by (Di Pietro, 2015, d'Hombres and Schnepf, 2021, Iriondo, 2020), have demonstrated the positive impact of mobility on post-graduation employment prospects, highlighting both an increased likelihood of securing a job and a reduction in the duration needed to find suitable employment. Mobile graduates have also been found to earn higher salaries in their jobs (See Giorgio et al. (2022) for a review).

Advocates of student mobility have consistently contended that it enhances both hard and soft skills, influencing labor market outcomes significantly (Souto-Otero et al., 2019). However, while the more qualitative literature routinely reports a role of mobility in shaping soft skills (Roy et al., 2019, Varela, 2017), to the best of my knowledge there is no empirical evidence showing a causal link between studying abroad and the accumulation of these skills. The main difficulty arises of a lack of data (De Benedetto et al., 2023), an issue I circumvent in this paper by compiling a novel data source.

The remainder of this paper is organized as follows. Section 2 introduces the measure of soft skill I use, validates its importance for labour market success and present evidence of the under-supply of soft skills. Section 3 presents the data I collected while Section 4 outlines the identification strategy. Section 5 illustrates the main results, Section 6 discusses robustness checks and finally Section 7 concludes.

2 Soft skills and international student mobility

2.1 Soft skills

Despite the academic attention that soft skills have received, there is no agreement on a single definition of soft skills (Deming, 2017b) with studies typically referring to them as either "non-cognitive ability", "personality traits" or "socio-emotional skills". This paper refers to soft skills as "non-cognitive" abilities which, while being influenced by time invariant personality traits, can be expanded and modelled by individual life decisions. These skills are often compared to hard skills which instead refer to the technical or specialized knowledge that is required to perform a specific activity. Soft skills are not task-specific, they apply to any context and can be transferred across different activities.

I retrieve a list of 21 soft skills from a survey of workers administered by the Italian national institute for public policy evaluation (INAPP) to replicate O*NET for Italy (O*NET Italia). The choice of which soft skills to include is grounded on the qualitative literature on

International Student Mobility (Encinas and de la Torre, 2021, Souto-Otero et al., 2019). Mobile graduates frequently describe their mobility period as a profound and life changing opportunity that is likely to broaden their horizon by interacting with new and diverse cultures[3]. Table 1 below detail the list of 21 soft skills in scope for this project grouped into 6 dimensions together with their average importance values across all occupations. My skill importance measure ranges from 0 (not important at all) to 100 (very important). I also retrieve a list of 12 core hard skills that will serve both to decompose skill contribution in explaining earnings and as a falsification exercise in the robustness checks of the paper.

[3]European Commission (2024) report perceptions and experiences from former mobile students in Europe.

Table 1: Soft and Hard Skills

Domain	Skill name	Skill description
Communication and language	Written Expression	Ability to communicate in writing so others will understand
	Oral Expression	Ability to communicate in speaking so others will understand
	Foreign Language	Knowledge of the structure and content of a foreign language including meaning, spelling, composition, grammar, and pronunciation
Working with others	Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do
	Coordination	Adjusting actions in relation to others' actions
	Persuasion	Persuading others to change their minds or behavior
	Negotiation	Bringing others together and trying to reconcile differences
	Cooperation	Job requires being pleasant with others and displaying a good-natured, cooperative attitude
	Social Orientation	Job requires preferring to work with others rather than alone, and being personally connected with others on the job
Creativity	Fleuncy of Ideas	Ability to come up with a number of ideas about a topic
	Originality	Ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem
	Innovation	Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems
Fortitude	Persistence	Job requires persistence in the face of obstacles
	Initiative	Job requires a willingness to take on responsibilities and challenges
	Self-Control	Job requires maintaining composure, keeping emotions in check, controlling anger, and avoiding aggressive behavior, even in very difficult situations
	Stress Tolerance	Job requires accepting criticism and dealing calmly and effectively with high-stress situations
	Adaptability/ Flexibility	Job requires being open to change (positive or negative) and to considerable variety in the workplace
Problem solving	Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems
	Active learning	Understanding the implications of new information for problem-solving and decision-making
	Learning strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things
	Complex Problem Solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions
	Analytical thinking	Job requires analyzing information and using logic to address work-related issues and problems

Domain	**Skill name**	**Skill description**
Core Hard Skills	Mathemtics	Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications
	Physics	Knowledge and prediction of physical principles, laws
	Chemistry	Knowledge of the chemical composition, structure, and properties of substances
	Biology	Knowledge of plant and animal organisms, their tissues, cells, functions
	Psychology	Knowledge of human behavior and performance; individual differences in ability, personality
	Sociology & Anthropology	Knowledge of group behavior and dynamics, societal trends and influences
	Geography	Knowledge of principles and methods for describing the features of land, sea, and air masses
	Medicine & Dentistry	Knowledge of the info and techniques needed to diagnose and treat human injuries
	Therapy & Counselling	Knowledge of principles, methods, and procedures for diagnosis, treatment
	Education & Training	Knowledge of principles and methods for curriculum and training design, teaching
	Italian Language	Knowledge of the structure and content of the Italian language

Note: Table presents the list of soft and hard skills in scope for this project. I grouped skills across six domains. Foreign language proficiency, originally an hard skill, is grouped together with written and oral expression under the domain for communication and language skills. Skill name and skill description come from the 2013 *Indagine Campionaria sulle Professioni* (ICP) collected by *Istituto Nazionale Analisi Politiche Pubbliche* (INAPP) to mirror O*NET.

I next show that soft skills and hard skills are both important predictors of success in the labour market. Most of the empirical literature studies soft skills using individual level data by measuring them through a series of proxy variables (Lindqvist and Vestman, 2011, Deming, 2017b). In this paper I do not observe any stock of soft skills at the individual level but record how important soft skills are considered to be for each occupation[4]. This is an important part of the paper because it validates my empirical set up by confirming, through occupational level data, the role of soft skills in explaining labour market success in line with the literature (Lindqvist and Vestman, 2011, Heckman et al., 2006). The decision to ground soft skills through tasks adheres also with the literature bridging economics and psychology according to which tasks, in my set up occupations, can be informative of underlying individual traits (Borghans et al., 2008).

I run three different specification by estimating:

$$Salary_{io} = f(SK)_o + u_{io} \tag{1}$$

$$Salary_{io} = f(HK)_o + e_{io} \tag{2}$$

$$Salary_{io} = f(SK)_o + f(HK)_o + r_{io} \tag{3}$$

I use the Italian Labour Force data for 2013 matched with the importance of skills across occupations. In the data I measure the salary for each individual i and a measure of skill importance at the occupation level o from O*Net Italia. I specify a linear specification for both soft (SK) and hard (HK) skills across equations 1 - 3.

Table 2: Salary decomposition

Model	Dependent	Soft Skills	Hard Skills	Adj $\bar{R}^2$	R^2	R^2_{SS}	R^2_{HS}	N
A	Monthly salary	Yes	No	34.44	34.45			137,675
B	Monthly salary	No	Yes	30.72	30.72			137,675
C	Monthly salary	Yes	Yes	39.16	39.18	54.76%	45.24%	137,675

Notes: Table reports measures of goodness of fit from OLS estimates for salary equations 1 - 3. Model A includes only soft skills, model B only hard skills while model C includes both soft and hard skills. I decompose the overall R^2 from model C across soft and hard skills. I include all skills in Table 1, these are 21 soft skills and 12 hard skills. I specify a linear function for all skill types. The sample refers to all individuals reporting to be working in the 2013 Italian Labour Force Survey.

Table 2 below reports the R^2 across all three specifications and the decomposition of total explained variability between soft and hard skills for specification 3 following the shapley value decomposition (Shorrocks, 2013). Reading across models A and B I show that the proportion of earnings variability explained by soft and hard skills is similar at around 1/3 of the total variability in earnings with soft skills possibly explaining slightly more than the set of chosen hard skills. Estimates for model C show that combining both

[4]The data comes by a survey of workers employed across occupations.

skills raises the explained variability to nearly 40% with the relative contribution of soft and hard skills mirroring the previous results. These findings align with the empirical literature emphasizing the significance of both hard and soft skills for success in the labor market (Lindqvist and Vestman, 2011), thereby validating the approach employed in this paper, which involves the measurement of soft skills at the occupational level. Finally I test empirically if soft and hard skills explain a different proportion of the variability in earnings or whether they are picking up the same components. Formally this requires testing across non-nested specifications and I follow Greene (2003) in checking whether specification 1 encompasses specification 2. According to the encompassing principle, specification 1 would encompass specification 2 if the features of specification 1 can be explained by specification 2 but the reverse is not true. The test is implemented by augmenting specification 1 with all the additional regressors from specification 2. In my simple set up, where the two set of regressors are mutually exclusive, this is equivalent to running specification 3. The null of specification 1 encompassing specification 2 can be rejected by performing an F-test in the augmented model. I am able to reject the null of encompassing with a p-value of 0.000. The evidence allows me to conclude that hard and soft skills explain different proportions of success in the labour market and points towards skill complementarities mirroring similar findings from the literature (Deming, 2017a, Weinberger, 2014).

Despite their clear importance in explaining success in the labour market I find evidence of unmet demand of soft skills. A 2017 survey of employers carried out by the Italian national institute for public policy evaluation (INAPP)[5] reports that 42% of all Italian employers indicate the need to retrain their staff in the following year. Employers responding to the survey are asked to indicate a wide range of retraining needs across both hard and soft skills for up to 5 professions. For each skill I recode re-training needs across professions and compute needs at the employer level. The calculations provided in Table 3 report the proportion of employers indicating the need to retrain at least one of their professionals on each skill. Comparing hard to soft skills my findings show a strong need of upskilling for soft skills. The demand for training in hard skills ranges from 1.64% for geography, 11.90% for maths and peaks at 26.97% and 36.28% for Italian and Foreign Language skills respectively. Training for Soft Skills is much more frequently indicated. The least mentioned soft skill refers to "Learning Strategies" with 18.82% of employers and peaks at 45.26% and 46.20% for "Social Perceptiveness" and "Coordinating" respectively. Italian employers are not alone in facing an under supply of soft skills. A study by Börner et al. (2018) pools together millions of publication, course syllabi and job advertisements and paints a similar picture, soft skills for communication, negotiation and persuasion are found to be increasingly important among hard skill intense jobs yet their supply is limited though education.

[5] *Istituto Nazionale per l'Analisi delle Politiche Pubbliche.*

Table 3: Employers' training needs

Hard skills	Proportion	*Soft skills*	Proportion
Mathematics	11.90%	Written Expression	28.08%
Physics	5.47%	Oral Expression	36.51%
Chemistry	10.99%	Active Learning	26.44%
Biology	4.89%	Learning Strategies	18.82%
Psychology	10.38%	Social Perceptiveness	45.26%
Sociology & Anthropology	4.74%	Coordination	46.20%
Geography	1.64%	Persuasion	28.85%
Medicine & Dentistry	4.44%	Negotiation	26.18%
Therapy & Counselling	2.09%	Complex Problem Solving	38.88%
Education & Training	9.12%		
Italian Language	23.97%		
Foreign Language	36.28%		

Note: Table reports the proportion of employers who state the need to retrain their professionals across both hard and soft skills. Proportion are computed from the total number of employers who stated the need to retrain at least one staff across any skill. Data come from *Professioni e Competenze* (PEC), a survey collected by *Istituto Nazionale Analisi Politiche Pubbliche* (INAPP) in 2017.

2.2 International Student Mobility

International Student Mobility (ISM) allows students enrolled in tertiary education to spend some time abroad as part of their program. Students engaged in ISM can earn credits towards their degree by attending lectures and taking examination at an host institution.

In Italy where this study is set, and across Europe, the European Region Action Scheme for the Mobility of University Students (ERASMUS) is the main mobility scheme available to students in Europe. ERASMUS has been set up in 1987 by the European Commission and has grown to be one of the main successful EU programs having allowed, as of 2022, more than 13 million students to live and study abroad (European Commission and Culture, 2023). Erasmus students spend a period from 3 to 12 months at a partner institution that has established a bilateral agreement with the home university students are enrolled in. Partnerships are usually initiated by department staff through personal networks, they are long term contracts and are hence unlikely to be shaped by students' preferences and requests in the short-run. Anyone wishing to apply need to submit an application in response to a call released by their home institution every year. The call specifies the number of mobility scholarships on offer for each destination and the length of each mobility. Students cannot go on an Erasmus mobility without being first selected by their home institution and having been offered a scholarship. Once selected students enjoy a full tuition fee waiver at the host institution[6], a scholarship[7] and automatic recognition

[6]Students only pay their regular fees at their home university.

[7]The scholarship is usually only able to cover part of the costs. The European Commission pays between 250 and 700 euros depending on destination. National Erasmus agencies, or individual institutions, can allocate additional monetary resources to mobility. In the academic year 2023/2024 students from UniTO could apply for an additional grant ranging from 0 to 450 euros depending on household income.

of examination taken while abroad[8].

3 Data

I use data across multiple sources. My main dataset comes from combining AlmaLaurea microdata with an administrative employment archive collated by the region of Piedmont in Northern Italy. AlmaLaurea is a consortium of all major Italian universities that compiles microdata on graduates' academic and labour market performance. Data on academic performance is collected through a mandatory survey all graduates from UniTO have to complete before concluding their time at university. AlmaLaurea records a rich snapshot of graduates' backgrounds, detailing performance in high school, parental occupation and education together with academic achievement at university and job prospects upon completion. I handle multiple occurrences[9] in AlmaLaurea by keeping the last degree completed. I extend this data source with Comunicazioni Obbligatorie Piemonte (COP), an administrative archive detailing all job contracts signed, modified or terminated by anyone working in the region of Piedmont or legally resident in Piedmont and working anywhere else in Italy. COP is part of the mandatory notification (*Comunicazioni Obbligatorie*) of any labour market event concerning hiring, firing and conversion of job contracts that Italian employers are legally required to file with public employment authorities. The requirement was introduced by law in 2006[10] and came into force in 2008. The archive is a matched employer-employee database on job flows recording contract information (e.g.: start, termination, type), occupation (5 digits) and sector of employment but does not contain any information on earnings[11]. My combined dataset spans all graduates from 2007 until 2019. I augment this dataset with the importance of skills across occupations. Data on skill importance comes from a survey of workers administered by the Italian national institute for public policy evaluation (INAPP) to map out the entire skillset required by the Italian economy[12]. The data was collected in 2013 and closely replicates O*NET for Italy (hence O*NET Italia) by detailing a list of both hard and soft skills. The final dataset is a graduate-occupation-employer matched data source where for each graduate I observe jobs, the importance of hard and soft skills, and employers.

The Almalaurea-COP dataset only contains information on graduates who either find

[8]Selected students need to submit a learning agreement before leaving their home institution. Learning agreements are then approved by students' home department ensuring full recognition once they come back.

[9]Multiple occurrences arise whenever individuals complete more than one degree program at the same institution. This is typically the case for anyone completing both a bachelor and a master degree at the University of Turin.

[10]2007 Italian Budget Law 296/2006.

[11]Starting from September 2019 employers are also required to provide information on contractual pay, this information is unfortunately not available for the cohorts in scope for this study.

[12]The data refers to 796 occupations as defined by the Italian Statistical Office (ISTAT).

a job in Piedmont or who are legally resident in Piedmont and work anywhere else in Italy. Because UniTO is the main university of the region it is not surprising that about 78% of all 2007 - 2019 graduates in AlmaLaurea can be tracked back to COP at any given time. For each graduate, COP allows to retrieve the full working history of individuals provided they either work in the region or remain legally resident in the region and work anywhere else in Italy. In my main estimates I explore short term effects of ISM on soft skills. Hence, I find all labour market spells active at one year since graduation day[13] and select the dominant one for my estimates[14]. My final selection criteria leave me with 45,515 individuals who are working at one year since graduation day, corresponding to roughly 39% of all AlmaLaurea graduates for 2013 - 2019. A full comparison of socio-economic characteristics, available in Table A.2 in the Appendix alleviates concerns over sample selection. Individuals with an active labour market spell are remarkably similar to the the universe of graduates when it comes to age, gender and achievement at high school. There are some minor differences in terms of parental education and areas of geographic origin. Graduates in COP tend to come from slightly less educated households and, in line with expectations, slightly more from Turin and the region of Piedmont where the university is located.

I build the main variable of interest, *ISM*, as a dummy equal to one if an individual ever studied abroad as part of their university studies. My instrument is a measure of exposure to past student mobility at the degree by cohort. It comes from taking the ratio, for each degree course and graduation cohort, of the number of mobile graduates over the total of all graduates. The ratio for each cohort is computed by referring to total numbers from the previous cohort. This instrument hence captures exposure by exploiting variability in the proportion of fellow mobile students across different degrees courses and over time. Skill importance comes from O*NET Italia where workers are asked to indicate how important, from 1 (Not important) to 5 (Extremely important), each skill is in their current job. O*NET Italia then aggregated individual replies to produces an occupation-level measure of skill importance ranging from 0 to 100. I combine all soft skills in a given domain, grouped according to Table 1, and compute an index by taking the mean. My empirical analysis will first explore returns to soft skills at the domain level and will then investigate single soft skills driving the overall effects across each domain.

Table 4 presents descriptive statistics for variables included in my baseline estimates. About 13% of all graduates with an active spell in COB engaged in ISM during their studies and the average exposure to mobility was 15%. Roughly 19% of all graduates come an household with at least one tertiary educated parent and most individuals come from either Turin, 69%, or the rest of Piedmont 24%. Looking across occupation characteristics, skills for fortitude and communication are amongst the most important soft skills in graduates' jobs with average scores, out of 100 points, of 73.1 and 61.2 respectively. These skills are closely followed by team working skills with 59.6 points, Problem solving skills, 57.9 points,

[13]Figure A.1 in the Appendix shows that my results remain similar when using different selection windows in COP.

[14]I discuss methodological decisions on handling multiple spells in Section A.1 in the Appendix.

and eventually creativity skills with 45.8 points.

In the exploratory analysis presented in Section 2 I also leveraged data from the Italian Labour Force Survey (IT-LFS) for year 2013 augmented with O*NET Italia. I finally retrieved additional data, from INAPP, on a 2017 survey of employers[15] detailing their needs to retrain their staff across both hard and soft skills.

[15] *Professioni e Competenze* (PEC).

Table 4: Descriptive statistics

	N	Mean	SD	Min	Max	AlmaLaurea-COB	N	Mean	SD	Min	Max
Soft Skills						*Socio economic background, endogenous and IV*					
Communication skills - Index	45515	61.23	12.96	16.25	95.83	Age	45515	26.69	5.00	20.59	82.99
Written expression	45515	78.94	9.91	35.71	100.00	Female	45515	0.68	0.46	0.00	1.00
Oral expression	45515	67.52	18.98	5.00	98.81	High school: achievement (/100)	44787	80.07	11.87	60.00	100.00
Foreign language	45515	37.23	18.05	2.38	100.00	High school: classical studies	45508	0.10	0.30	0.00	1.00
Creativity skills - Index	45515	45.76	16.55	8.33	90.83	High school: scientific studies	45508	0.38	0.49	0.00	1.00
Fluency of Ideas	45515	40.26	15.33	1.32	90.00	High school: other academic	45508	0.20	0.40	0.00	1.00
Originality	45515	43.50	19.46	4.17	94.74	High school: technical	45508	0.26	0.44	0.00	1.00
Innovation	45515	53.53	17.76	9.52	94.32	High school: other/ foreign	45508	0.02	0.13	0.00	1.00
Fortitude skills - Index	45515	73.12	10.64	29.17	95.25	High school: vocational	45508	0.03	0.18	0.00	1.00
Persistence	45515	68.22	12.87	15.48	95.24	HH ED: Both parents tertiary	44763	0.06	0.25	0.00	1.00
Initiative	45515	68.82	14.52	23.81	96.43	HH ED: One parent tertiary	44763	0.13	0.34	0.00	1.00
Self-Control	45515	79.12	10.59	29.76	100.00	HH ED: Both parents hs	44763	0.50	0.50	0.00	1.00
Stress Tolerance	45515	77.38	10.07	25.00	98.75	HH ED: Both parents less than hs	44763	0.30	0.46	0.00	1.00
Adaptability/ Flexibility	45515	72.07	11.61	38.75	98.33	HH Jobs: High social class	44491	0.18	0.38	0.00	1.00
Problem solving skills - Index	45515	57.93	17.14	8.50	92.86	HH Jobs: Medium social class	44491	0.56	0.50	0.00	1.00
Critical Thinking	45515	60.08	18.85	0.00	97.50	HH Jobs: Low social class	44491	0.27	0.44	0.00	1.00
Active Learning	45515	58.75	17.92	5.26	96.43	Residency: Turin	45515	0.69	0.46	0.00	1.00
Learning strategies	45515	49.23	19.55	3.75	90.00	Residency: Turin not Piedmont	45515	0.24	0.43	0.00	1.00
Complex Problem Solving	45515	56.68	18.80	5.00	95.83	Residency: Italy not Piedmont	45515	0.06	0.25	0.00	1.00
Analytical thinking	45515	64.90	16.06	15.00	97.50	Residency: Abroad	45515	0.00	0.05	0.00	1.00
Team working skills - Index	45515	59.60	11.94	17.29	87.92	Endogenous: ISM	45425	0.13	0.34	0.00	1.00
Social Perceptiveness	45515	59.11	17.76	8.33	96.43	IV: Exposure ISM	44499	0.15	0.14	0.00	1.00
Coordination	45515	68.85	12.46	7.50	95.00						
Persuasion	45515	42.20	13.07	1.19	88.04						
Negotiation	45515	49.40	15.06	4.76	95.83						
Cooperation	45515	75.01	10.51	16.25	98.21						
Social Orientation	45515	63.05	13.94	3.75	100.00						

Note: Table reports descriptive statistics for 2007 - 2019 UniTO graduates with an active labour market spell at 1 year since graduation day. Data on socio-economic background retrieved from AlmaLaurea *Profilo dei Laureati*, a mandatory survey required before graduation. HH jobs refers to a recoding of parental jobs at the household level. In AlmaLaurea parental jobs are classified in high, mid and low social class jobs following Schizzerotto (2002). High social class jobs include directors, entrepeurs with more than 15 employees, academics and highly skilled self-employed individuals. Mid social class jobs feature team managers, employees, teachers, entrepreneurs with less than 15 employees and low skilled self-employed individuals. Low class jobs include workers and clerks. Information about social class is provided at the household level by taking the highest level of social class from either parent. Soft skills measured at the occupation level by *Istituto Nazionale per l'Analisi delle Politiche Pubbliche* (INAPP) in 2013.

4 Identification strategy

I estimate returns to International Student Mobility by running the following specifications:

$$y_{o_{(ijdac)}} = \beta_0 + \beta_1 ISM_{ijdac} + \boldsymbol{\beta_2'}\mathbf{X_i} + \beta_3'\mathbf{P_j} + \omega_a + \lambda_d + \delta_c + \epsilon_{o_{(ijdac)}} \tag{4}$$

where $y_{o_{(ijdac)}}$ measures the importance of a given soft skill in occupation o held by graduate i, enrolled in degree j, from department d, in subject area a and from graduation cohort c. ISM_{ijdac} is an indicator for students who have studied abroad at any time as part of their studies. $\mathbf{X_i}$ is a vector of individual level controls including performance and type of high school, gender, age, geographical area of origin, parental education and parental jobs. $\mathbf{P_j}$ is a vector of degree characteristics detailing information of type of degree, and separate dummies for degree courses with either an English or an international name. $\omega_a, \lambda_d, \delta_c$ refer to fixed effects for subject area, department and cohort.

Consistent estimation of the returns to international student mobility β_1 by OLS is difficult because of the likely presence of unobserved individual heterogeneity (Parey and Waldinger (2011)). Omitted variable bias would arise whenever the decision to become mobile is linked with individual characteristics I do not observe (e.g.: motivation, attitudes, past stock of soft skills) and that are also determinants of the stock of soft skills. The sign of the resulting endogeneity bias is likely to be ambiguous. OLS estimates might be biased upwards if students who have a higher stock of soft skills to begin with decide to become mobile. An alternative possibility, that would bias OLS downwards, is that students are aware of the potential benefits of international mobility and individuals with a low stock of these skills decide to leave to improve them. Existing evidence has shown both that mobile students tend to score higher than their non-mobile peers on psychometric measures before departure (Souto-Otero et al., 2019). At the same time ISM has a long tradition across Italian universities[16] and students frequently report ambitions towards personal and professional growth when asked about their motivations to engage in mobility (Lesjak et al., 2015).

The likely presence of endogeneity motivates the need to implement an instrumental variable identification strategy. I instrument the individual decision to go abroad with a measure of exposure to mobility by running the following system of equations:

$$ISM_{ijdac} = \alpha_0 + \alpha_1 \text{Exposure ISM}_{jdac} + \boldsymbol{\alpha_2'}\mathbf{X_i} + \boldsymbol{\alpha_3'}\mathbf{P_j} + \omega_a + \lambda_d + \delta_c + \rho_{ijdac} \tag{5}$$

$$y_{o_{(ijdac)}} = \mu_0 + \mu_1 \widehat{\text{ISM}}_{ijdac} + \boldsymbol{\mu_2'}\mathbf{X_i} + \boldsymbol{\mu_3'}\mathbf{P_j} + \omega_a + \lambda_d + \delta_c + \eta_{o_{(ijdac)}} \tag{6}$$

where *exposure ISM* is used as an instrumental variable for the decision to be mobile. My instrument is a measure for exposure to international student mobility by exploiting

[16] also thanks to the ERASMUS scheme being set up in 1987.

variation across degree courses and cohorts within subject areas, departments and academic years. In the Italian university system students enrol into degree courses for both bachelor and master programs. Degree courses are offered by a single combination of a department within a subject area. Departments offer degree courses across different, yet related subjects. This non-nested structure across departments and subject areas allows for separate estimation of FEs for departments and subjects[17].

For each degree course I measure the proportion of graduates from the previous cohort who have been mobile. The identification strategy is similar to those developed by Parey and Waldinger (2011), Di Pietro (2012) and Sorrenti (2017) but varies at a more granular level by exploiting a finer variability across degree courses and cohorts[18]. Moreover, given that I contrast exposure at the degree course level, and that mobility schemes are offered at the department or subject level, I isolate variation coming from peer pressure. This is different from previous research that exploited a combination of peer pressure and the supply of mobility scholarships[19]. Conditioning on FEs, my first stage specification shows that graduates who have been exposed to more mobile peers are more likely to go abroad. I cluster standard errors at the degree course by cohort level matching the level of variation of the instrument (Abadie et al., 2023).

The validity of the identification strategy rests on the assumptions of instrumental variable estimation (Angrist and Pischke (2009), Abadie (2003)). This requires an instrument that, once conditioning on covariates, is as good as randomly assigned (independence), operates on potential outcomes only through a single known causal channel (exclusion restriction), is strongly related to the endogenous variable (relevance) and affects all individuals in the same way (monotonicity).

Independence requires the previous exposure instrument not to proxy for any unobservable characteristics influencing potential outcomes or potential treatment status. In the context of this paper, this assumption would be violated, for instance, if students who are particularly motivated towards mobility, or have higher soft skills to begin with, are aware of the exposure measure and they base their degree enrolment decision on this information. I argue this is unlikely because ERASMUS slots are allocated either at the department or at the subject area level and the proportion of graduates who have been mobile at the degree course level is very difficult to observe. As argued by Sorrenti (2017), even the availability of ERASMUS slots at the broader department level is difficult to con-

[17]In a robustness check I impose a more restrictive specification by exploiting subject by department variation and show that results remain similar.

[18]See Appendix A.4 for a visual inspection of this variability.

[19]The ERASMUS program, the main mobility scheme available to students in Europe requires the award of a scholarship in order to study abroad. At UniTO scholarships are allocated at the department or subject area level. Candidates apply to a place at a foreign institution that has signed a partnership with the department or subject area students are enrolled in. Applicants are then ranked according to a merit based ranking process. Unfortunately data on rankings has only been centrally collected by the international office of UniTO starting from 2017 onwards and is not available for the cohorts of graduates I use in this paper.

sider for prospective students. This makes it even more unlikely for prospective students to be able to sort into degree courses on the basis of past exposure to mobility. Likewise, ranking of universities, that might take into account an internationalization component when producing their scores, are silent about the variability across degree courses within universities, departments and subject areas. A possible concern is that my instrument is picking up some departmental or subject level characteristics reflecting institutional efforts to promote mobility, and the accumulation of soft skills, by the department which also manages the availability of exchange programs. This concern is eased in my specification because I include a granular array of FEs and effectively compare exposure across degree courses but within departments and subject areas[20]. I also add a control to characterise single degree courses whose name is in the English language or have a name recalling internationalization to control for interest in international learning[21]. Moreover, across all specifications, I compute the selection on unobservables, relative to the observables included in the model, that would drive the estimated effect to zero (Oster, 2019). A relative selection greater than 1, meaning that unobservables would need to matter at least as much as my observables, is generally considered robust (Oster, 2019). Throughout Tables 6 - 7 I compute Oster's delta for the reduced form specifications and show that my IV results tend to be robust. In a robustness check I augment the main specification with a measure of soft skills[22] for the intake of UniTO students from the academic year 2020 - 2021. This information comes from a mandatory survey all first year students had to complete before taking any examination[23]. From this data source I retrieve a list of 139 degree courses that I am able to match back to my original dataset[24]. The inclusion of this additional measure for soft skills has little effects on my estimates.

The exclusion restriction instead requires the peer pressure instrument to only influence potential outcomes through the individual decision to be mobile. This requirement would be violated if high exposure to ISM also entails more foreign students coming to the University of Turin and students who are left home grow their soft skills by interacting with incoming foreigners. While this is possible because exchange programs are bi-directional, I consider this to be unlikely. Exchange program are managed at the subject, or departmental, level and incoming students usually take classes across many degree courses to fulfil the credit requirements set by their home institutions. My regression, by virtue of the FEs, compares students across degree courses within the same department or subject area, and it is unlikely that local students will spend large portion of time with the same incoming students.

[20]In a more restrictive specification I allow for department by subject area fixed effects and show that results remain qualitatively similar, see Table A.4 in the Appendix).

[21]See Section A.3 in the Appendix for the approach I used.

[22]See Section A.2 in the Appendix for on this measure of soft skills.

[23]The survey was introduced in the academic year 2017 - 2018 but was made a mandatory requirements for the intake of students enrolling in 2021 - 2021.

[24]See Section A.2 in the Appendix for more details on how this matching is carried out.

To tackle any outstanding potential issues with both independence and the exclusion restriction I employ a methodology developed by Conley et al. (2012) that assesses the robustness of my results to plausible violations of the conditions above. This approach requires the specification of the degree of violation of the assumptions by modelling the direct effect the instrument plays on the dependent variable. I implement this approach by allowing for a range of violations starting from zero (no violation) to the coefficient of the instrument in the reduced form and assess the robustness of my results.

Relevance, instead, requires the instrument to strongly explain the endogenous variable once conditioning on the FEs and the controls. I assess the strength of my instrument by reporting in Table 5 the estimated first stage and the associated F-statistics. Given the clustering nature of the error term all tables report the effective F-statistics together with the F-Critical values (Olea and Pflueger, 2013). Moreover, the Appendix also reports, in Table A.3, Anderson-Rubin p-values to confirm that inference is not plagued by weak instrument concerns even in the presence of large values for the F-statistics (Keane and Neal, 2023).

Monotonicity postulates that the effect of the instrument has the same sign across all individuals. This implies that student going abroad when experiencing low exposure would also leave in a high exposure environment. This is required in the LATE theorem to rule out defiers (i.e. individuals who go abroad when exposed to a low exposure environment but who would stay home if placed in a high exposure setting).

Under the assumptions above the 2SLS estimates a Local Average Treatment Effect (LATE) that is the effect for the subgroup in the population responding to the instrument (Imbens and Angrist, 1994). This group is known as the compliers, those whose treatment status follows the instrument. Compliers cannot be directly identified (Angrist and Pischke, 2009) but I can estimate the first moment of their observable characteristics through the Abadie's κ weighting scheme. According to Abadie (2003) we can retrieve conditional expectations for compliers by computing:

$$E[g(Y,D,X)|D_1 > D_0] = \frac{1}{D_1 > D_0} E[\kappa g(Y,D,X)] \tag{7}$$

where $g(.)$ is any measurable function such that $E[g(.)]$ is finite, D is the endogenous variable. Kappa is a weight defined as follows:

$$\kappa = 1 - \frac{D(1-Z}{Pr(Z=0|X)} - \frac{Z(1-D}{Pr(Z=1|X)} \tag{8}$$

Abadie's kappa allows to characterize expectations of covariates and untreated means for compliers. The methodology requires both the endogenous and the instrument to be binary variables so I recode my exposure instrument into a binary variable taking value 1 if the exposure is larger than the median at department and cohort year level and 0 otherwise[25]. I estimate the probability that the instrument is switched on conditioning on

[25] In the Appendix I replicate my main 2SLS results using this binary version of the instrument. I show

covariates by assuming a probit specification with all the covariates included in the first stage equation.

5 Results

5.1 First stage

Table 5 reports estimates for the first stage from Equation 5. Column (1) shows the estimated coefficient for the exposure instrument in a specification where I include subject, department and academic year FEs and also control for degree naming characteristics. The estimated effect of 0.478 is strong and highly statistically significant. The magnitude of this figure is noteworthy because it is extremely similar in size to 0.4490 and 0.4945 reported in Parey and Waldinger (2011) and Sorrenti (2017) respectively and corroborates the validity of my measure of exposure to mobility. Adding individual controls, in Column (2), hardly changes my estimated first stage and leaves the strength of the instrument virtually unaffected. Being exposed to past mobility has a similar and strong increase in the probability of going abroad in both specifications whether I condition on individual level characteristics or not. The coefficient for my individual controls show that students from more educated families, compared to the base category of both parents not having completed high school, are more likely to go abroad by 9 percentage points. The same pattern is observed when looking at parental jobs, compared to families from a low social class, high social class students are more likely to be mobile. The strength of the relationship is also confirmed by the large Effective F-stat above 100, mirroring the result in Sorrenti (2017), and well above the critical value of 37.42 computed to allow for clustering in the standard errors (Olea and Pflueger, 2013). Despite the first stage being strong, I follow Keane and Neal (2023) and provide[26] Anderson and Rubin values across all second stage results to confirm my estimates are not plagued by weak instruments even when the F-stat is large.

5.2 Second stage

Tables 6 and 7 report second stage estimates. Across both tables odd columns report OLS estimates while even columns show results from 2SLS. The OLS estimates point towards a positive, albeit modest, association between international student mobility and the importance of soft skills in jobs held 1 year after graduation. My IV estimates confirm this association and show that results are larger.

that while the first stage decreases the instrument remains strong. Second stage estimates grow larger but point in the same direction.

[26]See Table A.3 in the Appendix.

Table 5: First stage estimates

	(1) ISM	(2) ISM
IV: Exposure	0.49***	0.48***
	(0.04)	(0.04)
Age		-0.00**
		(0.00)
Female		-0.01
		(0.00)
HH ED: Both parents tertiary		0.09***
		(0.01)
HH ED: One parent tertiary		0.04***
		(0.01)
HH ED: Both parents hs		0.02***
		(0.00)
HH Jobs: High social class		0.05***
		(0.01)
HH Jobs: Medium social class		0.02***
		(0.00)
Year FE	Y	Y
Degree names FE	Y	Y
Department FE	Y	Y
Subject FE	Y	Y
Number of Obs.	44413	42641
Effective F-stat	192.67	176.94
Critical Effective F-stat	37.42	37.42

Note: Table reports First Stage estimates using COP-AlmaLaurea data for UniTO graduates in employment one year after graduation. All models include cohort, degree names, department, subject area, and type of degree completed FEs. Column 2 adds individual controls for age, gender, high school type, high school achievement, area of residence, parental education and parental occupation. Reference category for parental education is households where both parents did not complete high school. Reference for parental jobs is low socio-economic class, see footnote in Table 4 for more details on this variable. Standard errors are clustered at the degree by cohort level. Effective F-stat and critical values from Olea and Pflueger (2013) to allow for cluster robust inference. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 6: Second stage estimates - Index

	Communication		Creativity		Fortitude		Problem solving		Team working	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
ISM	1.49***	5.90***	1.73***	5.95**	0.52***	3.07*	1.22***	5.40*	0.57***	5.39***
	(0.19)	(2.17)	(0.26)	(2.94)	(0.16)	(1.57)	(0.24)	(2.79)	(0.17)	(1.81)
Oster's δ	1.11	2.34	0.54	0.79	0.29	1.21	0.70	1.79	0.23	1.51
Untreated mean	60.86	60.77	45.59	45.47	73.12	73.08	57.85	57.77	59.62	59.59
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Obs.	43603	42641	43603	42641	43603	42641	43603	42641	43603	42641

Note: Table reports OLS estimates (odd columns) and second stage 2SLS estimates (even columns) for returns to ISM using COP-AlmaLaurea data for UniTO graduates in jobs one year after graduation. The dependent variable is an index ranging from 0 to 100 and computed by taking the mean of all skills belonging to the dimensions identified in Table 1. All models include cohort, degree names, department, subject area, and type of degree completed FEs. All models also control for individual characteristics: controls for age, gender, high school type, high school achievement, area of residence, parental education, parental occupation, high school type and high school achievement. I also include Oster's δ computed using individual level controls, applied to reduced form equations for 2SLS specifications. Standard errors are clustered at the degree by cohort level. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

My 2SLS estimates are particularly strong for communication skills (+5.90 points), creativity (+5.95 points), problem solving (+5.40 points) and team working (+5.39 points). These effects correspond to an increase of 9.71% (communication), 13.09% (creativity), 9.35% (problem solving) and 9.05% (team working) respectively compared to the mean for the untreated group.

In Table 7 below, I investigate across each domain, reported in different panels, the relevant soft skills that are driving my effects. In line with expectations, the effect of communication skills, from panel A, are driven by the marked increase in oral expression (+11.65%) and foreign language proficiency (+19.33%) reflecting the skills that most mobile graduates need to pick up during their mobility spell in the host country.

Similarly, mobility plays a key role in shaping the creative skills of graduates in their future jobs as shown in Panel B. The effects are particularly evident for the ability to generate a large set of ideas (fluency of ideas, +15.89%), innovative thinking (+9.60%) and an improvement in the originality of ideas (+14.81%).

Table 7: Second stage estimates - Skills

Panel A: Communication skills												
	Written expression		Oral expression		Foreign language							
	(1)	(2)	(3)	(4)	(5)	(6)						
	OLS	IV	OLS	IV	OLS	IV						
ISM	0.50***	2.84*	1.16***	7.81**	2.80***	7.05**						
	(0.14)	(1.61)	(0.27)	(3.04)	(0.27)	(2.84)						
Oster's δ	0.67	13.75	0.88	113.99	0.98	0.76						
Untreated mean	78.82	78.76	67.18	67.06	36.57	36.48						
Panel B: Creativity skills												
	Fluency of Ideas		Originality		Innovation							
	(1)	(2)	(3)	(4)	(5)	(6)						
	OLS	IV	OLS	IV	OLS	IV						
ISM	1.33***	6.35**	2.10***	6.38*	1.77***	5.12*						
	(0.23)	(2.73)	(0.32)	(3.59)	(0.28)	(2.87)						
Oster's δ	0.56	1.37	0.50	0.64	0.47	0.50						
Untreated mean	40.06	39.97	43.23	43.08	53.48	53.36						
Panel C: Fortitude skills												
	Persistence		Initiative		Self-Control		Stress Tolerance		Adaptability Flexibility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)		
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV		
ISM	1.14***	5.45***	1.16***	5.63***	-0.15	-0.24	0.15	0.06	0.31*	4.45***		
	(0.19)	(2.11)	(0.21)	(2.18)	(0.16)	(1.43)	(0.15)	(1.46)	(0.17)	(1.68)		
Oster's δ	0.80	2.12	0.65	1.43	-0.08	0.07	0.07	0.08	0.20	2.90		
Untreated mean	68.04	68.00	68.74	68.70	79.29	79.26	77.48	77.45	72.05	72.00		
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Obs.	43603	42641	43603	42641	43603	42641	43603	42641	43603	42641	43603	42641

Continued on next page

Panel D: Problem solving skills												
	Critical Thinking		Active Learning		Learning Strategies		Complex problem Solving		Analytical Thinking			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)		
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV		
ISM	1.40***	4.82	1.26***	6.87**	0.96***	1.56	1.31***	7.03**	1.17***	6.73**		
	(0.27)	(3.09)	(0.26)	(2.97)	(0.26)	(3.13)	(0.27)	(2.93)	(0.23)	(2.67)		
Oster's δ	0.89	1.80	0.77	2.18	0.21	0.28	0.91	2.62	0.89	2.62		
Untreated mean	59.94	59.87	58.61	58.54	49.41	49.27	56.55	56.48	64.74	64.68		
Panel E: Team working skills												
	Social Perceptiveness		Coordination		Persuasion		Negotiation		Cooperation		Social Orientation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
ISM	0.39	2.24	0.35*	5.07**	0.90***	6.53***	1.39***	7.43***	0.23	6.11***	0.15	4.97**
	(0.24)	(2.69)	(0.18)	(1.97)	(0.21)	(2.02)	(0.24)	(2.19)	(0.15)	(1.68)	(0.19)	(1.94)
Oster's δ	0.09	0.60	0.25	-2.89	0.76	2.33	0.64	1.27	0.13	10.77	0.05	-0.77
Untreated mean	59.25	59.21	68.91	68.88	42.01	41.97	49.13	49.07	75.08	75.07	63.35	63.33
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Obs.	43603	42641	43603	42641	43603	42641	43603	42641	43603	42641	43603	42641

Note: Table reports OLS estimates (odd columns) and second stage 2SLS estimates (even columns) for returns to ISM using COP-AlmaLaurea data for UniTO graduates in jobs one year after graduation. Dependent variables range from 0 to 100 and refer to individual skills building dimensions across panels. Panel A shows communication skills, Panel B looks at creativity skills, Panel C refers to Fortitude skills, Panel D delves into Problem solving skills and Panel E features Team working skills. All models include cohort, degree names, department, subject area, and type of degree completed FEs. All models also control for individual characteristics: controls for age, gender, high school type, high school achievement, area of residence, parental education, parental occupation, high school type and high school achievement. I also include Oster's δ computed using individual level controls, applied to reduced form equations for 2SLS specifications. Standard errors are clustered at the degree by cohort level. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Mobility shapes soft skills connected with fortitude as shown in Panel C. Columns (2), (4) and (6) report how mobile graduates work in jobs where persistence (+8.01%), initiative (+8.20%) and adaptability (+6.18%) are more important. There is evidence of no effects for soft skills for self-control and stress tolerance, instead, with the estimated coefficients being statistically insignificant, small in magnitude and close to zero.

Likewise Panel D shows that ISM improves skills associated with active learning (+11.68%), problem solving (+12.45%) and analytical thinking (+10.41%). These results possibly reflect the need to adjust to a difference in teaching methods used in the host institution or the ability graduates had to develop to solve everyday problems arising in the host country.

Finally, effects are particularly pronounced for soft skills tied with the ability of working with others in Panel E. Mobile graduates sort themselves into jobs where the ability to coordinate (+7.36%), persuade (+15.56%), negotiate (+15.14%), cooperate with others (+8.14%) is starkly higher than non mobile individuals. More surprisingly, the estimated effect for the importance of social perceptiveness, defined as the ability of being aware of others' reaction and understanding why they react as they do, is much lower and imprecisely estimated. This is a new finding that challenges the theory that the importance of soft skills in working with others works mainly through the "reading of the mind" ability (Deming, 2017a). My results seem to indicate more an overall ability to effectively work in groups as reflected by the effects found for social orientation (+7.85%) that measures the preference for working with others rather than alone.

5.3 Complier analysis

My IV estimates refer to the complier subpopulation activated by the exposure instrument (Angrist and Pischke, 2009, Abadie, 2003). In my set-up, compliers are individuals who respond to the surrounding environment and ground their individual decision of going abroad on their peers. These are individuals on the margin who would leave when exposed to more mobile peers and who would stay home when placed in contexts with less mobile peers. Similarly to Sorrenti (2017) this subgroup of students is likely less prone to having been exposed to international mobility and might reap larger returns from spending time abroad.

In this subsection I explicitly investigate who compliers are in my setting. I show that they tend to be negatively selected when compared to the average graduate in the population. Table 8 reports estimated means of background characteristics for compliers (column 1), the entire population (column 2) and the ratio of the two (column 3). Compared to the average graduate, compliers are less likely to come from households with at least one tertiary educated parent (6% vs 19%) and more likely to come from parents whose jobs refer to lower socio-economic status (33% vs 27%). Similarly, compliers tend to perform worse in high school achievement (77.91 vs 80.07 out of 100), do not come from the classical high school track[27] (0% vs 10%) by having completed more frequently technical (43%

[27]Classical high schools are commonly referred as the most prestigious high school track in Italy and

vs 26%) and vocational education (10% vs 3%). Regarding area of residence, those who respond to exposure tend to come less frequently from the region of Piedmont (21% vs 24%) but are nearly twice more likely to come from the rest of Italy (10% vs 6%). This finding suggests that my exposure instrument, through peer pressure, pushes towards ISM socially negatively selected individuals who have already experienced some mobility within the country to attend university. Finally, compliers are slightly older than the average graduate (28.18 vs 26.69) but in line with the overall population instead when it comes to gender (66% vs 68% are women).

Table 8: Characteristics of compliers.

Variable	Mean for compliers $E[X \mid Complier]$	Mean for sample $E[X]$	Ratio: compliers/ sample $\frac{E[X \mid Complier]}{E[X]}$
HH ED: Both parents tertiary	0.03	0.06	0.44
HH ED: One parent tertiary	0.03	0.13	0.25
HH ED: Both parents hs	0.47	0.50	0.94
HH ED: Both parents less than hs	0.47	0.30	1.56
HH Jobs: High social class	0.15	0.18	0.84
HH Jobs: Medium social class	0.52	0.56	0.94
HH Jobs: Low social class	0.33	0.27	1.24
HS: Achievement	77.91	80.07	0.97
HS: Classical studies	0.00	0.10	0.00
HS: Scientific studies	0.32	0.38	0.84
HS: Other academic	0.16	0.20	0.81
HS: Technical studies	0.43	0.26	1.69
HS: Vocational	0.10	0.03	2.99
HS: Other foreign	0.00	0.02	0.00
Residency: Turin	0.69	0.69	1.00
Residency: Piedmont not Turin	0.21	0.24	0.88
Residency: Italy not Piedmont	0.10	0.06	1.51
Residency: Abroad	0.00	0.00	0.00
Age	28.18	26.69	1.06
Female	0.66	0.68	0.96

Note: Table reports estimated characteristics for compliers (Column 1), the average graduate in the sample (Column 2) and the ratio between compliers and the average graduate in the sample (Column 3). Characteristics for complies computed following Abadie (2003). Binary version of the exposure instrument by recoding the share version of the exposure instrument into a binary variable taking value 1 if the exposure is larger than the median at department and cohort year level and 0 otherwise.

6 Robustness checks

My main results remain similar after a series of robustness checks. First I show that my 2SLS estimates remain stable with and without adding controls on individual level characteristics as reported in Table A.4 in the Appendix. This check provides reassurance that my 2SLS are not conditional on the choice of control variables I use. Similarly, results

have raised concerns over social mobility (Cardinale and Sinigaglia, 2014).

remain similar when I modify my fixed effects to exploit variation within department by subject combinations as shown in Table A.4 in the Appendix.

I also follow a procedure developed by Oster (2019) to quantify the importance of confounders. Oster's delta measures the relative degree of selection on unobservables, relative to selection on observables, that would be needed to drive my estimates to zero. This approach relies on the assumption that selection on observables is informative of selection on unobservables. I compute Oster's delta for all reduced form equation and report the estimated results across both Table 6 and Table 7. A value of delta greater than one, meaning that there needs to be at least as much selection on unobservables than there is in observables, is usually considered robust especially given the wealth of controls I included in my baseline specification. Across all indexes analyzed in Table A.3, the Oster test supports the validity of my results but for creativity skills where it falls below the threshold of one.

An additional concern in my set-up is that students are aware of the exposure measure before deciding in which degree they enroll in and ground their enrolment decision based on the previous level of soft skills. As argued above this is highly unlikely because exposure is very difficult to observe and mobility scholarships are allocated at the departmental level. I anyway assess this possibility by retrieved a mandatory survey of soft skills (PassPortU) all first year students at UniTO had to complete before being able to enroll for examinations in the academic year 2020 - 2021. I collapsed microdata at the degree course level and computed soft skills as measured in PassPortU[28]. Table A.5 in the Appendix shows that the inclusion of these degree-level measure of soft skills barely alters my results.

I also explore whether my exposure instrument is picking up some degree-level component of teaching quality. I assess this by investigating whether international student mobility helps graduates grow their hard skills. Figure A.2 in the Appendix shows that mobile graduates do not sort themselves into jobs where hard skills are more important. For a few hard skills[29] I even find some evidence of a negative effect between international mobility and hard skills.

I then investigate the sensitivity of my estimates to different lags of exposure to mobility [30]. I replicate my analysis for two alternative lags: exposure (t-2) and exposure (t-3). Table A.8 in the Appendix reports the first stage and shows that results remain very similar, across all specifications my instrument remains strong and exhibits the same pattern as in Sorrenti (2017). Table A.9, also in the Appendix, reports second stage estimates across different specifications. Overall, second stage estimates decrease in magnitude and become more imprecisely estimated as the sample size shrinks. My depiction of the instrument variability, in Figure A.4 of the Appendix, reports evidence of sharp spikes of exposure across adjacent cohorts. This pattern might explain the relatively poor performance of

[28]see Section A.2 in the Appendix for a more detailed discussion.

[29]These are Biology, Psychology, Medicine & Dentistry and Therapy & Counselling.

[30]This sensitivity analysis is also helpful to alleviate concerns over spurious peer effects when linking group averages to individual outcomes (Angrist, 2014).

2SLS estimation when taking further lags and allays concerns over the quasi-random nature of exposure to past mobility. Noteworthy, using exposure computed at (t-3), my estimates for communication skills remain similar in magnitude while effects for creativity skills seem to increase.

In addition to this, I also replicate my analysis using different windows to select labour market spells in COP. In my main specification I compute the importance of skills using jobs active at exactly one year since graduation date. The administrative nature of my data, tracking all spells in the labour market, allows me to investigate how results would change as I draw different time windows around the one year cutoff. Widening the window I use to select active spells has the additional advantage of increasing my sample size. Figure A.1 in the Appendix shows that my results are virtually unaffected when extending the analysis to a window of +/- 90 days around the one year cutoff. Estimated effects tend to go down when enlarging the window to +/- 180 and +/- 365 days although there remains considerable overall overlap in confidence intervals.[31]

Lastly, I investigate how my results change by relaxing the exclusion restriction. I follow a methodology developed by Conley et al. (2012) and allow for a direct effect of my instrument on each soft skill I use. This robustness checks also allays concerns over my instrument being invalid due to common shocks effecting students in a given degree program (Angrist, 2014). I model a gamut of direct effects ranging from 0 to the estimated beta in the corresponding reduced form equation (Intention To Treat, ITT) of my IV estimates. As I show in Figures A.3a - A.3b in the Appendix, my results for the ability to communicate and to work with others are particularly robust. Even allowing for an unlikely direct effect of the instrument on the importance of communication and team working skills of a third of the ITT I am still able to estimate a positive effect of International Student Mobility.

7 Conclusions

This paper studies the impact of international student mobility (ISM) during tertiary education on the development of soft skills. I compile a unique graduate-occupation-employer matched dataset where I connect all graduates from a large university in Italy with regional administrative data on labour market spells and the importance of hard and soft skills across occupations. My data allows me to leverage on differential exposure to past levels of student mobility at a fine degree by cohort level as a source of plausibly exogenous variation to instrument the individual decision to become mobile.

My findings document how international student mobility works as an effective technology to produce soft skills. Effects are particularly pronounced for skills connected with communicating, being creative, working with others and mastering problem solving. The

[31] This pattern of results is likely driven by either the short run nature of my results or the possibility of picking up labour market spells initiated before graduating. A future version of this paper will explore this matter in more detail by investigating long run effects.

substantial effects I find resonate with the literature across economics and psychology (Borghans et al., 2008) emphasizing the malleability of soft skills in young adults aged 20 to 30. My estimates contribute to the existing literature on accumulation of soft skills by showing that previous results, largely focused on developing countries and low-skilled workers, also carry for high-skilled individuals. Noteworthy, I report large increases in persuasion, negotiation and coordination corroborating the substantial gains in communication and team working skills found in Adhvaryu et al. (2023).

The large effects I unearth apply to the population of compliers responding to my exposure instrument. As I show in Table 8, compliers are more likely to perform worse in high school, come from less academic high school tracks and lower educated households. This is also the group likely to benefit the most from international student mobility for two reasons. First, they probably hold a lower stock of soft skills due to their backgrounds and would benefit the most from ISM if training in soft skills is a substitute for low baseline stocks as argued in Adhvaryu et al. (2023). Second, soft skills are difficult and costly to observe for employers, international student mobility can help this type of individuals by providing them with an informative signal they might not be able to acquire otherwise.

It the current version, my results are silent on the mechanisms through which international student mobility fosters soft skills development. It remains unclear whether students grow their soft skills thanks to being exposed to more distant cultures, differences in teaching methods or longer spells abroad. At the same time, my current results only show effects for first jobs held 1 year after graduation day. To the extent that ISM promotes the accumulation of skills, instead of merely acting as a signal, estimated effects should also persist in subsequent jobs. Future research as part of this project will try to shed light on these topics.

The findings of this paper provide policy implications to policymakers and university administrators. Soft skills are important predictors of success in the labour market and their demand is likely to rise with automation. At the same time, employers struggle with the level of soft skills in the employees they recruit. A survey of Italian employers finds the ample need to provide training opportunities to improve the soft skills of new hires. Despite the effective role of international student mobility to produce soft skills only 13% of all university students in Italy[32] embark on one of these opportunities. It is well known in the literature of ISM that barriers to mobility remain present (Souto-Otero et al., 2013). Policymakers and university officials should hence consider the important benefits of soft skills and the strong potential international student mobility plays when designing university curricula, informing students about mobility schemes, and deciding future allocation of funding for international mobility.

[32]Figures refer to all 2018 pre-COVID graduates from universities providing data in AlmaLaurea, see (Timoteo et al., 2019) for more details.

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A Appendix

A.1 Data preparation

The main data source used in this paper comes from combining a census dataset for all graduates from the University of Turin (AlmaLaurea UniTO) with a regional administrative archive (*Communicazione Obbligatorie Piemonte*, COP) on labour market spells.

AlmaLaurea is a consortium of 80 Italian universities set up in 1994 with the aim of monitoring the academic and labour market performance of university graduates. All graduates, from any participating institution, need to complete a mandatory survey on individual characteristics, their achievements at university and labour market prospects. The data is collected right before concluding university studies and is augmented with administrative records held by universities. This procedure applies for every degree students complete and might give rise to multiple records as students are observed separately for every degree they are awarded.

I obtained access to microdata for the University of Turin from 2003 onwards. From this set of data I handle multiple graduations by keeping the last degree ever completed. I then restrict the data to graduation years from 2007 - 2019. This is necessary for three reasons. First, COP data became mandatory from 2008 onward. Second, my COP data was extracted from the region of Piedmont in May 2021. Third, I want to exclude from the analysis all graduates who could not travel abroad due to the mobility restrictions put forth to curb the COVID-19 pandemic.

COP is an administrative archive held by the region of Piedmont, where the University of Turin is based. The archive collects information on all spells in the labour market for all individuals working in Piedmont or legally resident in Piedmont and working anywhere else in Italy. The data comes from mandatory notifications each employer has to submit to public authorities every time they sign, modify or terminate an employment contract. This requirement was introduced by law in 2006 (2007 Italian Budget Law 296/2006) and entered into force in 2008 across all Italian regions. COP is equivalent to a matched employer-employee dataset on job flows recording: contract information (start, termination, type), occupation codes, sector of employment and an identifier for each employer. There is no data on earnings[33]. The mandatory requirement applies to all employees, including interns, but excludes self-employed individuals.

I start with a total of 117,524 UniTO graduates from 2007 - 2019 and merge them with COP. Combining this two datasets I am able to retrieve information on 91,419 graduates for a total of 627,046 spells in the labour market. The large proportion of merges (77.8%) can be traced back to the regional role played by the University of Turin and by the not enforced requirement, also due to the long bureaucratic process, of legally changing residency when moving across Italy to live, study or work in a different region. The labour

[33]Starting from September 2019 employers are also required to provide information on contractual pay, this information is unfortunately not available for the cohorts in scope for this study

market spell nature of the data allows me to find, for every matched graduate, any active labour market spell at the cutoff I choose. In my main estimates I study short term effects of international student mobility and focus on spells ongoing at exactly one year since graduation date. I find a total of 45,515 graduates with an active labour market spell since graduation day corresponding to about 38.7% of all 2007 - 2019 graduates. in the l In this dataset I observe a total of 368 degrees courses offered by 28 departments and affiliated with 16 subject areas. Degrees are coded by hand based on their title and their level distinguishing between bachelor, master and single cycle degrees. I compared degree titles with an administrative file provided by the University of Turin listing name and administrative codes[34] for the full set of degree courses offered by UniTO over time. I regrouped together degrees with misspells who did not have separate degree codes from the University of Turin. Degrees with similar names but different codes were considered separate.

I find the dominant spell, to handle multiple active labour market spells when setting a time cutoff, in the following way. I compute spell length for any ongoing contract at the cutoff I choose. For open ended spells I proceed in two ways depending on whether these are full time or part time contracts. For open ended full time contracts I search for any subsequent contract, starting after the open ended full time I am considering, I retrieve the starting date and apply it as termination date of the previous full time open ended. For open ended part time contracts, I search for any subsequent full time spell starting after the open ended part time I am considering, I retrieve the starting date and apply it as termination date of the previous part time open ended contract. For all open ended contracts, both part time and full time, which are not followed by any other contract I assign 31/12/2099 as termination date when computing spell length. This procedure allows for multiple part time contracts active at the same time but does not allow for a full time contract to overlap with any other spell. I find the dominant spell in the analysis by looking at the longest spell. In the rare case of duplicates, labour market spell active at the cutoff with the same length, I rank contracts based on occupational codes (from higher to lower) and keep the first observation.

Table A.2 compares all AlmaLaurea graduates (column 1) with graduates appearing in the AlmaLaurea-COP matched dataset (column 2) and finally with graduates with an active labour market spell one year after graduation date (column 3). The similarity of individuals across datasets allays concerns over sample selection and it is likely to originate from several factors. First, UniTO is mostly a regional university[35], as shown in Table A.2

[34]Administrative identifiers are not available in AlmaLaurea datasets

[35]The University of Turin is the main university in Piedmont, centered in Turin and with local campuses scattered across neighbouring provinces. There are two other academic tertiary institutions active in Piedmont: The Polytechnic of Turin (PoliTO) and the University of Eastern Piedmont. PoliTO is amongst the most famous technical universities in Italy and specializes in engineering degrees which are not offered by UniTO. The University of Eastern Piedmont is a smaller general purpose university active in the Eastern area of Piedmont and was set up in 1998 from a series of detached departments originally from UniTO.

with nearly 84% of all UniTO graduates legally resident in Piedmont during university studies. In addition to this, the short term cutoff used in the main specification, that looks at active labour market spells one year since graduation day, makes it unlikely for anyone from Piedmont to have changed their legal residency even if working somewhere else. Lastly, Piedmont is located in Northern Italy, one of the most economically dynamic areas of the country allowing for students coming from the rest of Italy to find employment locally and hence appearing in COP regardless of where they are legally resident in Piedmont.

A.2 PassPortU: Soft skills

In recognition of the importance of soft skills, the University of Turin designed a dedicated project, PassPortUnito (PassPortU), to assess and promote the development of soft skills among its students. PassPortU was designed in 2016 by a team of psychologists from the University of Turin (Ricchiardi and Emanuel, 2018). The project includes an online tool to evaluate and promote training for soft skills. PassPortU identified 12 soft skills belonging to 4 domains with each domain containing 3 soft skills. I use these measures of soft skills as a robustness check in Section 6 to allay concerns over a possible correlation between my instrument and the initial stock of soft skills held by students.

Students self-report their soft skills through 136 survey items using Likert scales ranging from 1 (strongly disagree) to 6 (strongly agree) with an expected completion time of about 30 minutes[36]. Table A.1 below maps soft skills against domains and the survey items available in PassPortU. The first domain, "Task Orientation", focuses on soft skills measuring how individuals approach problems, make decision and manage their time and work. The second domain refer to "Self-Awareness" and maps skills capturing how individuals assess themselves, take initiative, manage and control their emotions. The third domain, "Motivational Area" is made of skills taking stock of how individuals deal with stressful situations, process their experiences and approach their goals. The final domain refers to the "Interpersonal Relations Area" and includes skills measuring how individuals relate with their peers, understand their responsibility, handle conflict and communicate with others. After completing a first assessment PassPortU offers all students and staff at UniTO an online course, lasting between 20-30 hours, aimed at improving the soft skills identified above[37]. PassPortU was made a mandatory requirement for all incoming students enrolling at UniTO in the academic year 2020 - 2021. Incoming students had to take the initial assessment test, the online course and then a follow up test before being able to sit for any examination.

I obtained data on all assessment tests taken by all first year students, including bachelor, master and single cycle programs, from 01/10/2020 until 31/12/2021 when testing was

[36] Emanuel et al. (2022) provides an in-depth description of the assessment tool together with the theoretical constructs along which soft skills are measured and the psychometric description of the test

[37] See Emanuel et al. (2021) for a more detailed discussion of the training and an evaluation of its effect on perceived soft skills

Table A.1: Soft skills in PassPortU

Area	*Soft skill*	*Survey item*
Task orientation	Problem solving and decision making	15
	Time management	13
	Adaptive strategies to tackle tasks	7
Self-Awareness	Self-valorisation	13
	Stress tolerance and emotional self-regulation	12
	Proactivity	14
Motivational	Objective guidance	15
	Locus of control	6
	Resilience	10
Interpersonal relations	Teamwork	12
	Communication	9
	Conflict management	10
Total		136

Note: Table reports, for each area, soft skills and the number of survey items eliciting them. See Ricchiardi and Emanuel (2018) for a thorough definition of soft skills as defined in PassPortU.

a mandatory requirement. For each individual I compute the set of soft skills mentioned above from the 136 survey items available in the PassPortU test. I then collapse the microdata at the degree level. In this dataset students self-reported their degree names and I use a fuzzy matching technique to connect them back with my AlmaLaurea-COB matched dataset using the reported degree name and the type of degree completed[38]. I am able to retrieve 139 degrees out of a total of 368 degree courses available in the AlmaLaurea-COB matched dataset corresponding to about 38% of all degrees completed. My AlmaLaurea-COB matched dataset includes all degree courses completed by anyone graduating from 2007 until 2019, as many of these degrees were discontinued over the years they could not merge with study programs offered by UniTO in 2020 - 2021 explaining the result of my partial merge. The proportion of successful merges increases from 38% to 81% when looking only at degrees completed in 2019 in my AlmaLaurea-COB matched dataset.

[38]Concatenating degree names with their type helps me distinguish between study programs with the same name but offered both at Bachelor and Master level. Doing so also reduces the likelihood of incorrectly merging degrees with similar names but offered at different levels.

A.3 Degree names

I characterize degree programs based on their titles to capture degrees taught in English and degree with an international naming. I build a first dummy taking value of one for degrees with an English name as a proxy for programs taught in English. I find 10 degrees with an English title spanning subjects in economics, science, biology and political sciences. I then create a separate dummy that takes value one for degrees containing an international related word in their title. I flag degrees containing the words: "binational", "foreign", "international", "intercultural", "global", "trasnational", "world", "European", "cooperation". I find a total of 37 degrees that match my keywords. These degrees belong to subjects in economics, political sciences, law, literature and language.

Table A.2: Descriptive statistics: AlmaLaurea and AlmaLaurea-COP

	(1) AlmaLaurea			(2) AlmaLaurea-COP			(3) AlmaLaurea-COP 1Y		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
ISM	117302	0.16	0.37	91258	0.15	0.36	45425	0.13	0.34
Age	117524	26.47	5.07	91419	26.37	4.68	45515	26.69	5.00
Female	117524	0.65	0.48	91419	0.67	0.47	45515	0.68	0.46
High school: achievement (/100)	114767	80.62	12.04	89679	80.31	12.02	44787	80.07	11.87
High school: classical studies	117513	0.15	0.35	91410	0.13	0.34	45508	0.10	0.30
High school: scientific studies	117513	0.41	0.49	91410	0.40	0.49	45508	0.38	0.49
High school: other academic	117513	0.18	0.38	91410	0.19	0.39	45508	0.20	0.40
High school: technical	117513	0.21	0.40	91410	0.22	0.42	45508	0.26	0.44
High school: other/ foreign	117513	0.02	0.15	91410	0.02	0.14	45508	0.02	0.13
High school: vocational	117513	0.03	0.16	91410	0.03	0.17	45508	0.03	0.18
HH ED: Both parents tertiary	115526	0.10	0.30	89874	0.09	0.28	44763	0.06	0.25
HH ED: One parent tertiary	115526	0.17	0.37	89874	0.15	0.36	44763	0.13	0.34
HH ED: Both parents hs	115526	0.48	0.50	89874	0.50	0.50	44763	0.50	0.50
HH ED: Both parents less than hs	115526	0.25	0.43	89874	0.26	0.44	44763	0.30	0.46
HH Jobs: High social class	114824	0.23	0.42	89327	0.21	0.40	44491	0.18	0.38
HH Jobs: Medium social class	114824	0.55	0.50	89327	0.55	0.50	44491	0.56	0.50
HH Jobs: Low social class	114824	0.23	0.42	89327	0.24	0.43	44491	0.27	0.44
Residency: Turin	117524	0.63	0.48	91419	0.68	0.47	45515	0.69	0.46
Residency: Turin not Piedmont	117524	0.21	0.41	91419	0.23	0.42	45515	0.24	0.43
Residency: Italy not Piedmont	117524	0.16	0.36	91419	0.09	0.28	45515	0.06	0.25
Residency: Abroad	117524	0.01	0.08	91419	0.00	0.06	45515	0.00	0.05

Note: Table reports descriptive statistics for all UniTO graduates (column 1), UniTO graduates matched with COB (column 2) and UniTO graduates with an active labour market spell in COB one year since graduation day (column 3). Data for graduates comes from AlmaLaurea *Profilo dei Laureati* and refers to 2007 - 2019 graduates. AlmaLaurea-COB refers to the subsample of AlmaLaurea matched with *Communicazione Obbligatorie Piemonte* (COP), a regional archive detailing labour market spells for anyone working in Piedmont or those legally residing in Piedmont and working anywhere else in Italy. All figures refer to 2007 - 2019 graduates.

Table A.3: Reduced Form and Second Stage Estimates

	Communication skills		Creativity skills		Fortitude skills		Problem solving skills		Team working skills	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IV: Exposure - t-1	2.82***		2.85**		1.47**		2.57*		2.58***	
	(1.03)		(1.39)		(0.75)		(1.34)		(0.85)	
ISM		5.90***		5.95**		3.07*		5.40*		5.39***
		(2.17)		(2.94)		(1.57)		(2.79)		(1.81)
Exact p-value	0.00		0.00		0.00		0.00		0.00	
AR p-value		0.01		0.04		0.05		0.05		0.00
Oster's delta	2.34	2.34	0.79	0.79	1.21	1.21	1.79	1.79	1.51	1.51
Untreated mean	59.23	60.77	44.56	45.47	70.85	73.08	56.08	57.77	56.84	59.59
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Obs.	42696	42641	42696	42641	42696	42641	42696	42641	42696	42641

Note: Table replicates IV estimates from main specification in Table 6. Odd columns report reduced form (ITT) estimates while even column show 2SLS estimates. The table also includes Anderson-Rubin (AR) and exact p-values obtained from 1,000 replications. Standard errors are clustered at the degree by cohort level. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A.4: Second stage estimates: Sensitivity analysis

Panel A:Communication & Creativity skills												
	Communication skills				Creativity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)				
ISM	5.90***	6.08***	7.48***	5.50***	5.95**	6.26**	8.63**	5.25**				
	(2.17)	(2.13)	(2.42)	(1.81)	(2.94)	(2.88)	(3.35)	(2.44)				
Oster's δ	2.34		2.64	1.82	0.79		1.03	0.63				
Untreated mean	60.77	60.71	60.77	60.77	45.47	45.40	45.47	45.47				
Individual controls	Y	N	Y	Y	Y	N	Y	Y				
Year FE	Y	Y	Y	Y	Y	Y	Y	Y				
Degree names FE	Y	Y	Y	N	Y	Y	Y	N				
Department FE	Y	Y	N	Y	Y	Y	N	Y				
Subject FE	Y	Y	N	Y	Y	Y	N	Y				
Sub by Dep FE	N	N	Y	N	N	N	Y	N				
Number of Obs.	42641	44413	42640	42641	42641	44413	42640	42641				
Panel B: Fortitude, Problem solving & Team working skills												
	Fortitude skills				Problem solving skills				Team working skills			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11	(12)
ISM	3.07*	2.97*	4.25**	2.66**	5.40*	5.41**	8.46***	3.83*	5.39***	5.21***	7.12***	4.58***
	(1.57)	(1.54)	(1.76)	(1.36)	(2.79)	(2.73)	(3.06)	(2.31)	(1.81)	(1.76)	(2.05)	(1.54)
Oster's δ	1.21		1.60	0.76	1.79		2.33	1.08	1.51		1.96	0.90
Untreated mean	73.08	73.07	73.08	73.08	57.77	57.72	57.77	57.77	59.59	59.56	59.59	59.59
Individual controls	Y	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y	N
Department FE	Y	Y	N	Y	Y	Y	N	Y	Y	Y	N	Y
Subject FE	Y	Y	N	Y	Y	Y	N	Y	Y	Y	N	Y
Sub by Dep FE	N	N	Y	N	N	N	Y	N	N	N	Y	N
Number of Obs.	42641	44413	42640	42641	42641	44413	42640	42641	42641	44413	42640	42641

Note: Table shows sensitivity for second stage estimates from main specification. Across each skill domain, the first column replicates 2SLS estimates from Table 6, the second column removes individual level controls, the third column includes department by subject fixed effects while the last column drops fixed effects for international degree names (see Annex A for a discussion about this). All models include cohort and type of degree completed FEs. Individual controls refer to age, gender, high school type, high school achievement, area of residence, parental education, parental occupation. Oster's δ computed using individual level controls applied to reduced form equations. Standard errors are clustered at the degree by cohort level. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A.5: Second stage estimates: Controlling for soft skills

Panel A:Communication & Creativity skills

	Communication skills					Creativity
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	COB - All	COB - SK	COB - SK	COB - All	COB - SK	COB - SK
ISM	6.08***	9.62***	9.84***	6.40**	11.15***	3.68
	(2.18)	(2.48)	(2.60)	(2.94)	(3.51)	(3.27)
Untreated mean	60.77	60.03	60.03	45.47	44.69	44.69
Individual controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y	Y
Soft skills		N	Y		N	Y
Number of Obs.	42641	30222	30222	42641	30222	30222

Panel B: Fortitude, Problem solving & Team working skills

		Fortitude skills			Problem solving skills			Tean working skills	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	COB - All	COB - SK	COB - SK	COB - All	COB - SK	COB - SK	COB - All	COB - SK	COB - SK
ISM	3.15**	5.35***	4.05**	5.52**	10.59***	9.58***	5.39***	7.24***	7.00***
	(1.57)	(1.88)	(1.95)	(2.79)	(3.26)	(3.43)	(1.80)	(2.12)	(2.24)
Untreated mean	73.08	73.00	73.00	57.77	57.57	57.57	59.59	59.62	59.62
Individual controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Soft skills		N	Y		N	Y		N	Y
Number of Obs.	42641	30222	30222	42641	30222	30222	42641	30222	30222

Note: Table shows sensitivity for second stage estimates from main specification once conditioning on initial stock of soft skills. Across each skill domain, the first column replicates 2SLS estimates from Table 6, the second column estimates the same model for the sample of degrees for which soft skills are available (see Appendix A for a discussion) and the third column adds controls for soft skills measured at the degree level. Standard errors are clustered at the degree by cohort level. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A.6: First stage estimates: Binary and continuous instruments

	(1) ISM	(2) ISM
IV: Continuous Exp	0.48***	
	(0.04)	
IV: Binary Exp		0.04***
		(0.01)
Age	-0.00**	-0.00***
	(0.00)	(0.00)
Female	-0.01*	-0.01**
	(0.00)	(0.00)
HH ED: Both parents tertiary	0.09***	0.09***
	(0.01)	(0.01)
HH ED: One parent tertiary	0.04***	0.04***
	(0.01)	(0.01)
HH ED: Both parents hs	0.02***	0.02***
	(0.00)	(0.00)
HH Jobs: High social class	0.05***	0.05***
	(0.01)	(0.01)
HH Jobs: Medium social class	0.02***	0.02***
	(0.00)	(0.00)
Year FE	Y	Y
Degree names FE	Y	Y
Department FE	Y	Y
Subject FE	Y	Y
Number of Obs.	42641	42641
Effective F-stat	176.83	54.29
Critical Effective F-stat	37.42	37.42

Note: Column 1 reports first stage estimates using my continuous instrument replicating Table 5. Column 2 refers to specification with binary instrument. I recode the continuous instrument in a binary variable for all degree by cohort values greater than department by cohort median. Standard errors are clustered at the degree by cohort level. Effective F-stat and critical values from Olea and Pflueger (2013) to allow for cluster robust inference. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A.7: Second stage estimates with continuous and binary instruments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Communication		Creativity		Fortitude		Problem solving		Team working	
	Continuous	Binary	Continuous	Binary	Continuous	Binary	Continuous	Binary	Continuous	Binary
ISM	5.90***	14.17**	5.95**	53.17***	3.07*	8.16*	5.40*	5.53	5.39***	10.35*
	(2.17)	(5.60)	(2.94)	(12.63)	(1.57)	(4.93)	(2.79)	(6.75)	(1.81)	(5.48)
Oster's delta	2.34	1.99	0.79	1.96	1.21	0.83	1.79	0.67	1.51	0.87
Untreated mean	60.77	60.77	45.47	45.47	73.08	73.08	57.77	57.77	59.59	59.59
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sub by Dep FE	N	N	N	N	N	N	N	N	N	N
Number of Obs.	42641	42641	42641	42641	42641	42641	42641	42641	42641	42641

Note: Odd columns report second stage estimates using my continuous instrument. Even columns refer to specifications with binary instrument. I recode the continuous instrument in a binary variable for all degree by cohort values greater than department by cohort median. Standard errors are clustered at the degree by cohort level. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A.8: First stage estimates: Time lags

	(1) ISM	(2) ISM	(3) ISM
IV: Exposure - t-1	0.48***		
	(0.04)		
IV: Exposure - t-2		0.45***	
		(0.04)	
IV: Exposure - t-3			0.41***
			(0.05)
Age	-0.00**	-0.00**	-0.00***
	(0.00)	(0.00)	(0.00)
Female	-0.01*	-0.01	-0.01
	(0.00)	(0.00)	(0.00)
HH ED: Both parents tertiary	0.09***	0.09***	0.10***
	(0.01)	(0.01)	(0.01)
HH ED: One parent tertiary	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)
HH ED: Both parents hs	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
HH Jobs: High social class	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)
HH Jobs: Medium social class	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
Year FE	Y	Y	Y
Degree names FE	Y	Y	Y
Department FE	Y	Y	Y
Subject FE	Y	Y	Y
Number of Obs.	42641	37492	32485
Effective F-stat	176.83	135.68	77.76
Critical Effective F-stat	37.42	37.42	37.42

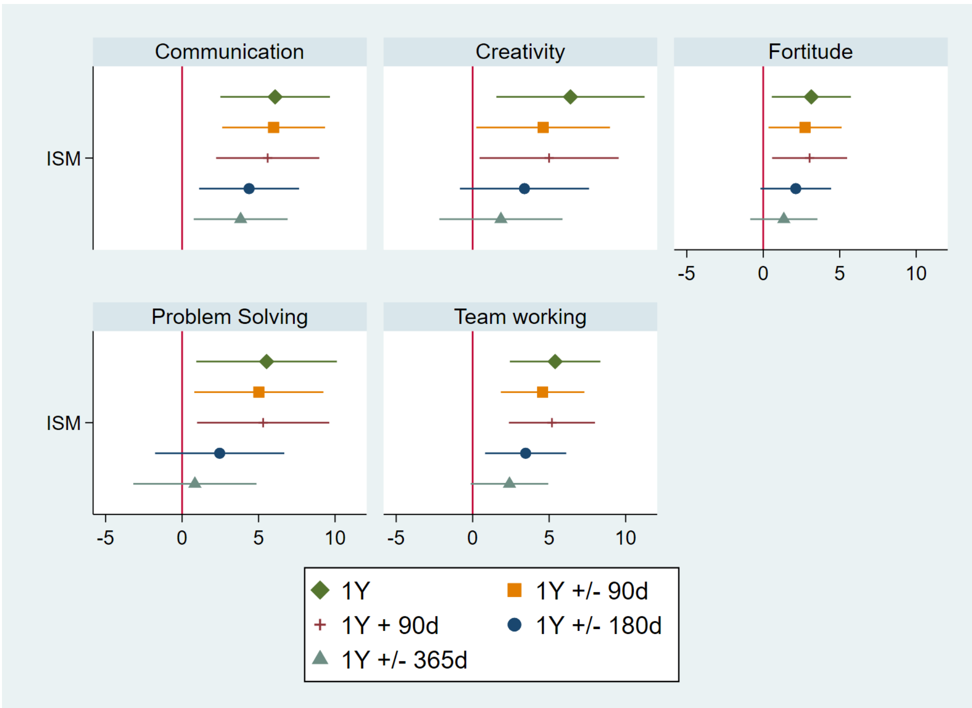
Note: Table reports first stage estimates using different lagged versions of the continuous exposure instrument. Standard errors are clustered at the degree by cohort level. Effective F-stat and critical values from Olea and Pflueger (2013) to allow for cluster robust inference. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A.9: Second Stage Estimates: Time lags

	(1) Communication	(2) Creativity	(3) Fortitude	(4) Problem solving	(5) Team working
Panel A: Exposure: t - 1					
ISM	5.90***	5.95**	3.07*	5.40*	5.39***
	(2.17)	(2.94)	(1.57)	(2.79)	(1.81)
Oster's delta	2.34	0.79	1.21	1.79	1.51
Untreated mean	60.77	45.47	73.08	57.77	59.59
Number of Obs.	42641	42641	42641	42641	42641
Panel B: Exposure: t - 2					
ISM	3.98	4.10	1.17	2.46	3.41*
	(2.48)	(3.32)	(1.75)	(3.22)	(2.01)
Oster's delta	1.75	0.49	0.39	0.89	0.83
Untreated mean	60.63	45.43	73.05	57.70	59.62
Number of Obs.	37492	37492	37492	37492	37492
Panel C: Exposure: t - 3					
ISM	5.25*	8.39**	0.87	2.64	2.70
	(2.71)	(3.85)	(2.03)	(3.64)	(2.28)
Oster's delta	2.08	0.96	0.26	1.07	0.41
Untreated mean	60.45	45.31	73.00	57.55	59.62
Number of Obs.	32485	32485	32485	32485	32485
Year FE	Y	Y	Y	Y	Y
Degree names FE	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y

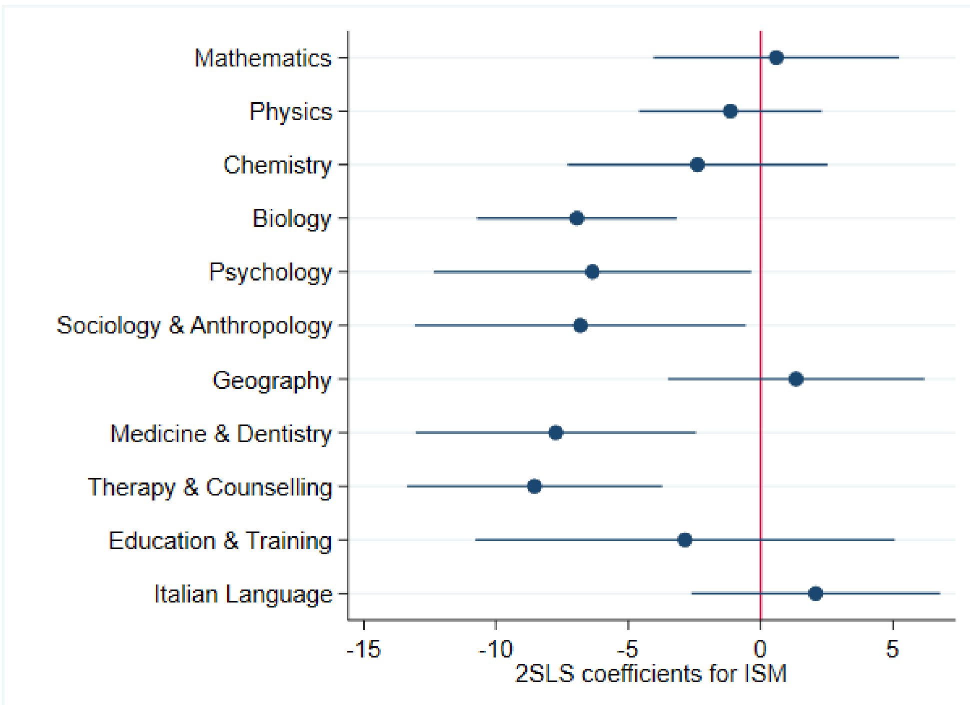
Note: Table replicates IV estimates from main specification in Table 6 using different lags to exposure across panels. All models include cohort, degree names, department, subject area, and type of degree completed FEs. All models also control for individual characteristics: controls for age, gender, high school type, high school achievement, area of residence, parental education, parental occupation, high school type and high school achievement. I also include Oster's δ computed using individual level controls, applied to reduced form equations for 2SLS specifications. Standard errors are clustered at the degree by cohort level. *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Figure A.1: Sensitivity to different windows to select spells in the labour market



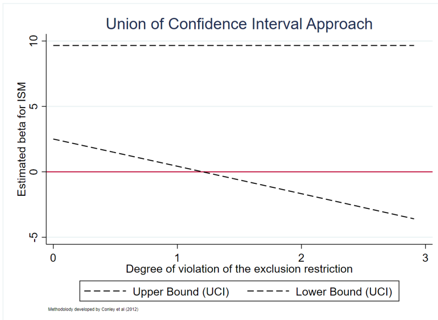
Notes The figure replicates the main specification from equations 5 - 6 using different windows to select active labour market spells around graduation dates. For each skill index, I first replicate my main 2SLS results from Table 6 selecting spells active exactly at one year since graduation day. I then expand this selection window by considering +/ - 90 days, + 90 days, +/ - 180 days and finally +/ - 365 days. This last window maps every labour market spell already active at graduation day up to two years since then. See Section A.1 in the Appendix for a discussion on the methodology used to choose between multiple spells within each window.The figure plots 95% confidence intervals for second stage estimates. For all regressions, the dependent variable is an index ranging from 0 to 100 and computed by taking the mean of all skills belonging to the dimensions identified in Table 1. All models include cohort, degree names, department, subject area, and type of degree completed FEs. All models also control for individual characteristics: controls for age, gender, high school type, high school achievement, area of residence, parental education, parental occupation. Standard errors are clustered at the degree by cohort level. Sample sizes are: 42,641 for 1Y, 52,062 for 1Y +/- 90 days, 48,130 for 1Y + 90 days, 57,195 and 1Y +/- 180 days and 64,027 for 1Y +/ - 365 days.

Figure A.2: Falsification check: Hard skills

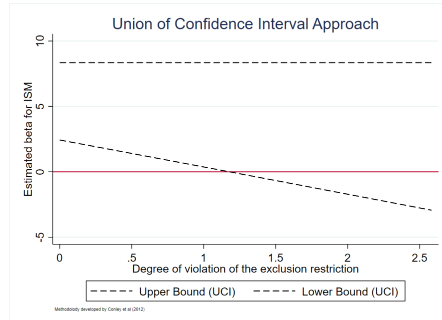


Notes The figure performs a falsification check by replicating the main specification from equations 5 - 6 and plotting 95% confidence intervals. Dependent variables refer to hard core skills from Table 1 except for foreign language proficiency which is instead part of my main results in Table 7. For all regressions, the dependent variable is an index ranging from 0 to 100. All models include cohort, degree names, department, subject area, and type of degree completed FEs. All models also control for individual characteristics: controls for age, gender, high school type, high school achievement, area of residence, parental education, parental occupation. Standard errors are clustered at the degree by cohort level.

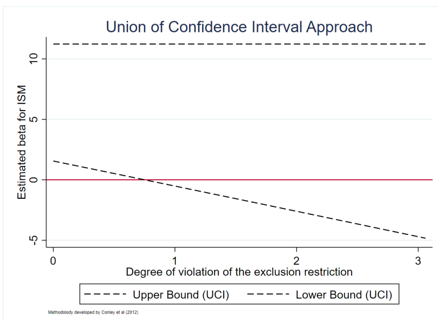
Figure A.3: Relaxing the exclusion restriction



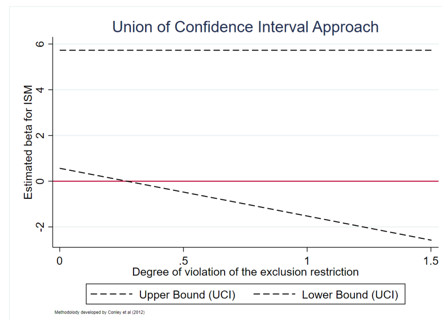
(a) Communication and language



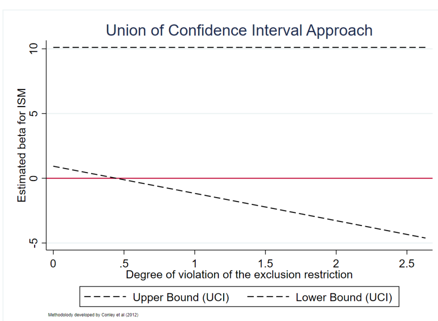
(b) Team working



(c) Creativity



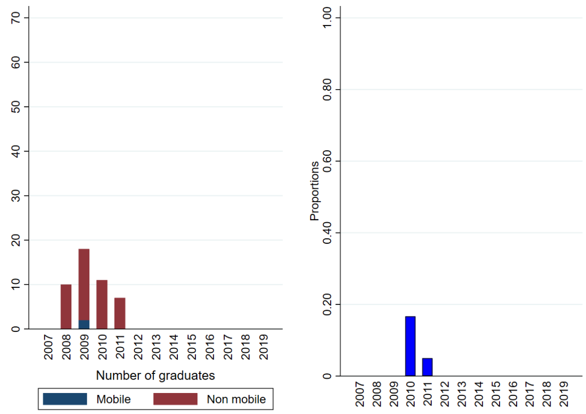
(d) Fortitude



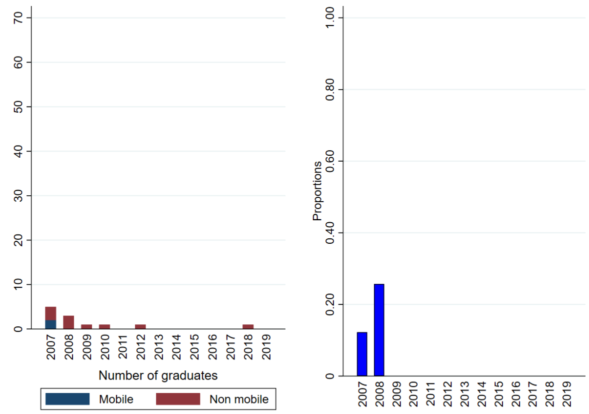
(e) Problem solving

Notes The graphs show results from applying a procedure developed by Conley et al. (2012) on second stage estimates for each skill dimension. The x-axis measures the degree of violation of the exclusion restriction allowed in the estimation, the y-axis shows the estimated coefficient of ISM for each degree of violation. I allow for different estimates with violations from 0 to the full effect found in our reduced form estimated in Table A.3. Setting the degree of violation to zero replicates my main result. The red horizontal line shows the maximum violation of the exclusion restriction allowed before the estimated set includes zero. The graph is based on the union of 90% confidence intervals. Standard errors are clustered at the degree by cohort level.

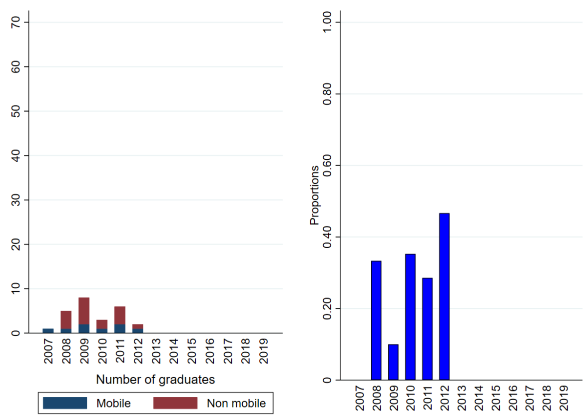
Figure A.4: Visualising instrument variability



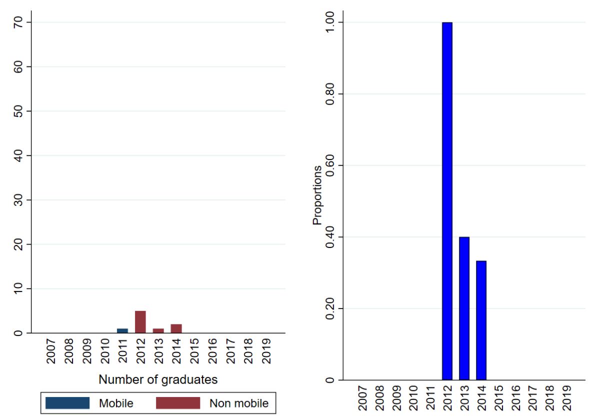
(a) Degree ID 60



(b) Degree ID 102



(c) Degree ID 103



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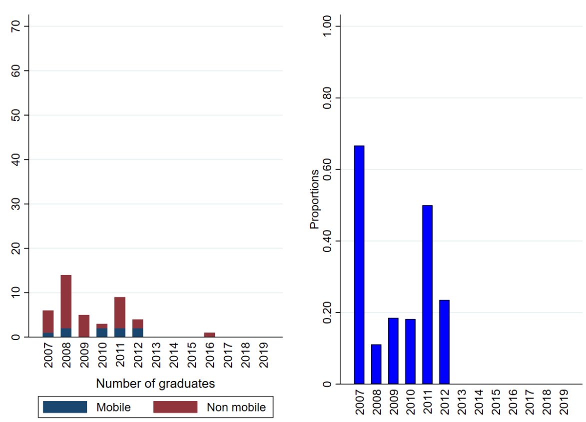
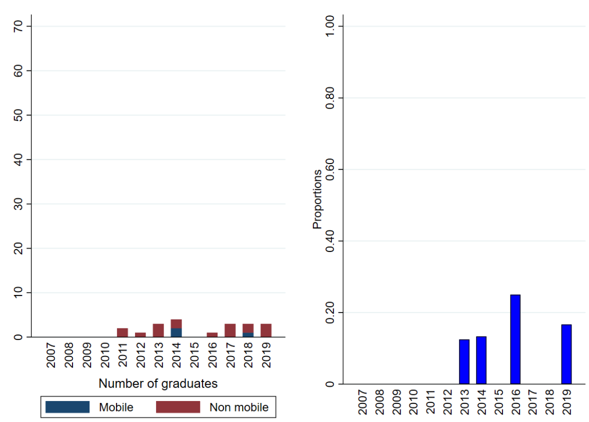
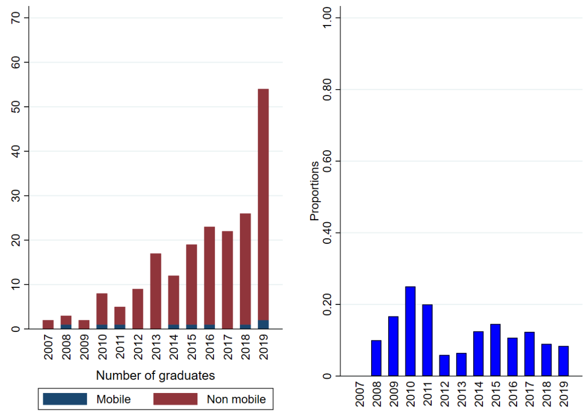


(e) Degree ID 108

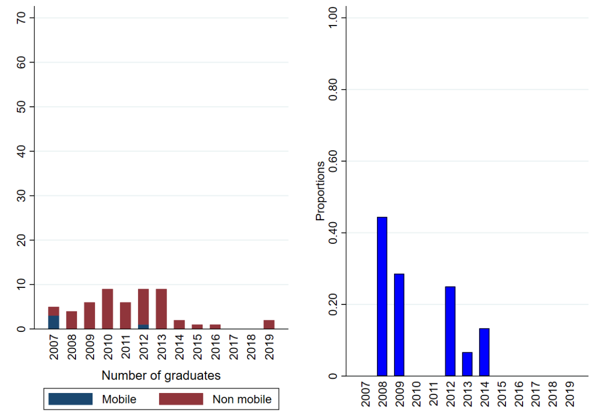


(f) Degree ID 109

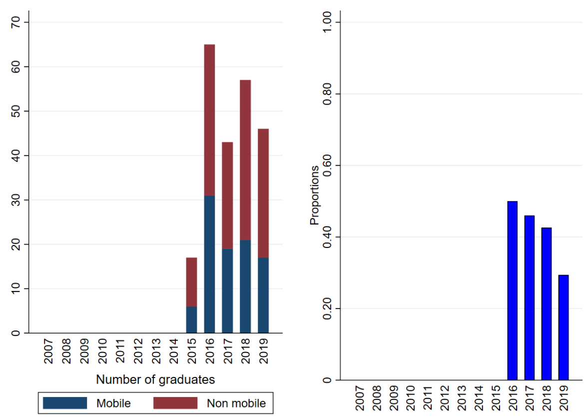
Figure A.4: Visualising instrument variability (continued)



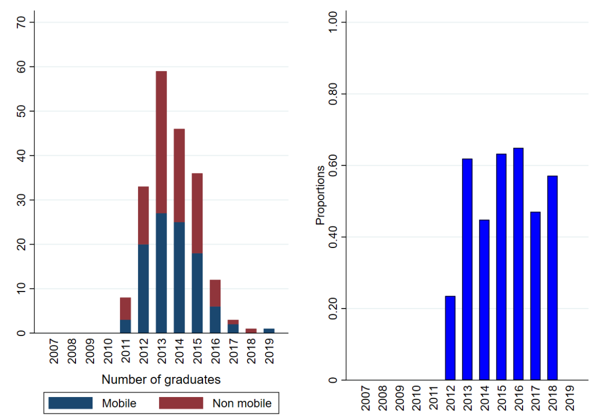
(g) Degree ID 110



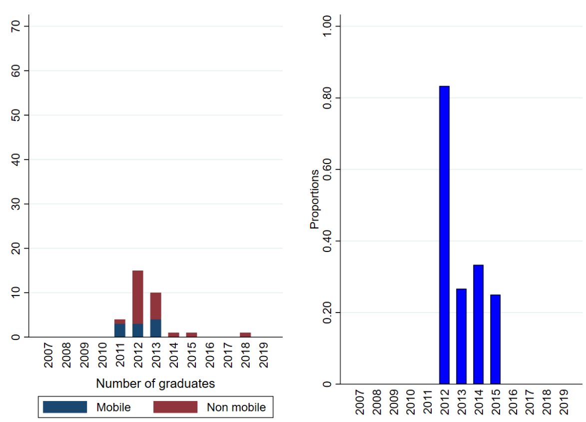
(h) Degree ID 115



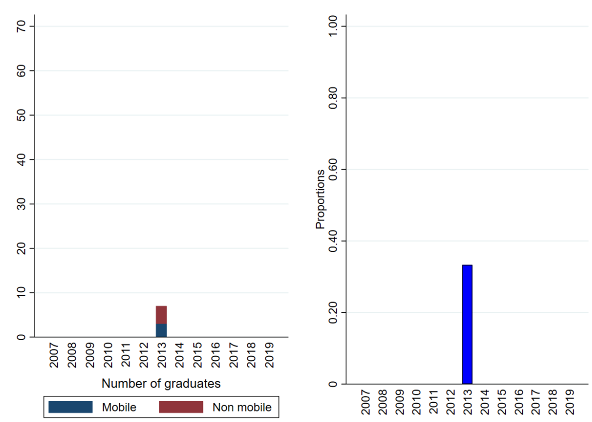
(i) Degree ID 118



(j) Degree ID 119

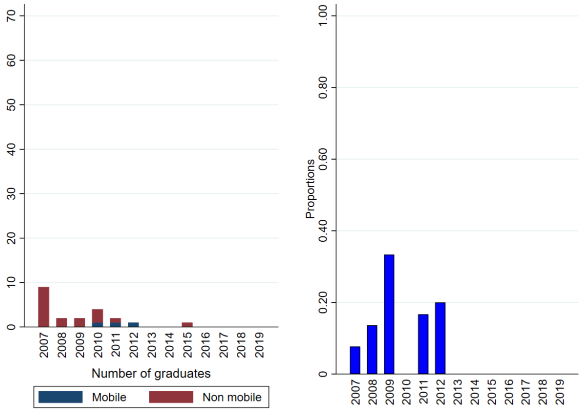


(k) Degree ID 122

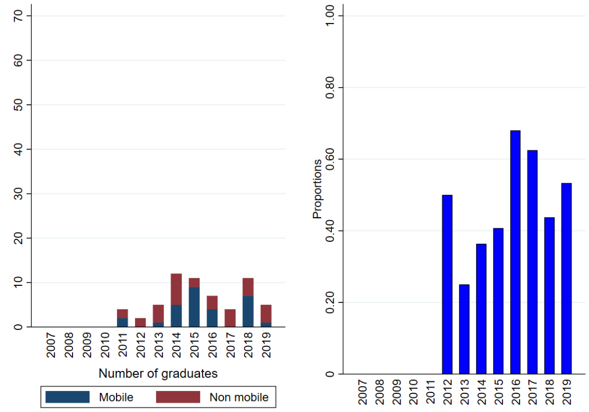


(l) Degree ID 123

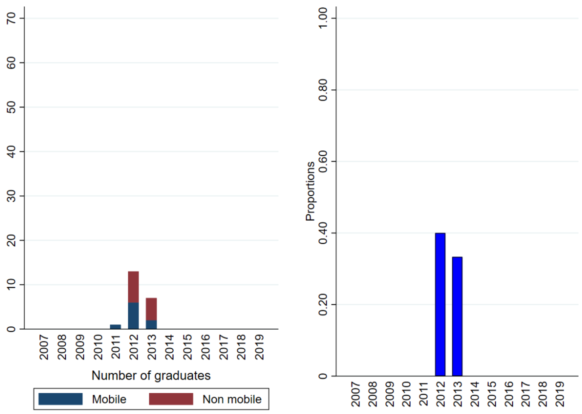
Figure A.4: Visualising instrument variability (continued)



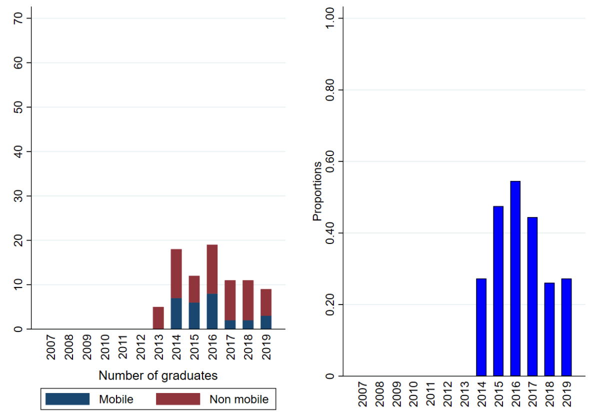
(m) Degree ID 124



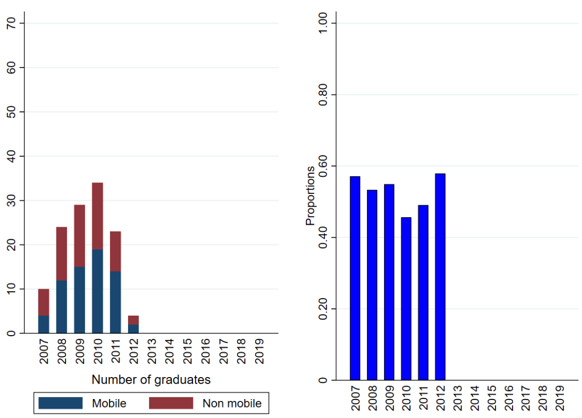
(n) Degree ID 125



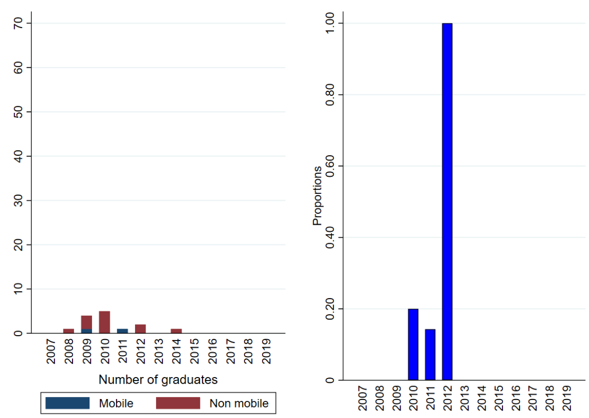
(o) Degree ID 138



(p) Degree ID 229



(q) Degree ID 233



(r) Degree ID 244

Notes The graphs show the total number of mobile and non mobile graduates (left panel) and the value of my instrument exposure to past mobility (right panel). Total number of graduates refer to those with an active labour market spell one year since graduation day in the AlmaLaurea-COB matched dataset. Exposure to past mobility is computed as a proportion from the full AlmaLaurea dataset for all graduates of the University of Turin. All measures are reported by graduation cohorts for each degree. This figure shows, as an example, degrees affiliated with the Economics, Mathematics and Statistics (ESOMAS) department of the University of Turin. Graphs for degrees affiliated with other departments are available upon request.