Emigration prospects and educational choices: Evidence from the Lorraine-Luxembourg corridor.*

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Abstract

An extensive literature has documented the incentive effect of emigration prospects in terms of human capital accumulation in origin countries. Much less attention has been paid to the impact on specific educational choices. Using novel data from graduates from the University of Lorraine (France) we find that students who paid attention to the foreign labor market at the time of enrollment tend to choose topics that lead to occupations that are highly valued in Luxembourg, a booming economy across the border. These results hold when accounting for heterogeneous substitution patterns and when accounting for the potential endogeneity of the interest for the foreign labor market.

JEL Classification: C25, F22, J61.

Keywords: Brain gain, Emigration prospects, Educational choices, Discrete choice modelling, Labor markets.

1 Introduction

Over the last decades, there has been a significant increase in the observed international mobility of skilled workers. While migration has long been the missing piece of globalization, the emigration rate of workers with a college degree has been multiplied by a factor of three over the last 30 years (Docquier and Rapoport (2012)). This increase first reflects a strong rise in the demand for skills in developed economies, spurred by many factors including skill-biased technological progress. Firms located in industrialized countries are nowadays in great competition to attract the talented

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workers and have increasingly searched beyond the domestic labor market. This increase in labor demand has been matched by the higher propensity of skilled individuals to move abroad over time. Today, college graduates are better informed about foreign work opportunities, as technology makes it easier to obtain information about job offers abroad and tends to reduce physical and psychological moving costs.

The international migration of skilled workers, especially between developing and developed countries, has been coined the "brain drain" phenomenon. In the 1970s, the traditional view was that the brain drain was detrimental to the origin countries, as it led to a depletion of their human capital. This traditional view inspired the proposed Baghwati tax through which destination countries would compensate the origin countries for the loss incurred by the brain drain (Bhagwati (1976)). However, this view has been nuanced over time through the identification of several additional effects generated by the brain drain. An important effect is the so-called incentive effect of migration in terms of human capital investment.

The incentive effect of migration in terms of human capital level arises from the greater opportunities offered to individuals by the foreign labor market. The attractiveness of foreign opportunities are higher for educated individuals, basically for two complementary reasons. First, the wage premium between the domestic and foreign labor markets is clearly increasing with respect to the skill level. Second, immigration policies that act as powerful sorting devices in many destination countries are more favorable to skilled individuals. In turn, compared with an autarkic situation in which foreign options are unavailable, emigration prospects lead a larger number of individuals to invest in education, raising the global level of human capital in the source countries before emigration takes place. Whether the ex-post level of human capital increases or not, i.e., whether the brain drain results in a brain gain, depends on a set of country-specific factors. These factors include the quality of the higher education system, and the quality of economic institutions (Beine et al. (2008)).

The precise nature of the incentive effect of the brain drain was clarified at the end of the 1990s in a set of theoretical works (Stark et al. (1997), Mountford (1997), Vidal (1997), Beine et al. (2001)). Subsequently, these theoretical results have received some empirical support, initially based on macroeconomic data (Beine et al., 2008) and confirmed by more recent works (Bocquier et al. (2024), Cha'ngom et al. (2023)). These empirical macroeconomic studies have also been complemented by analyses based on individual data, showing that the incentive effect is much more than an academic curiosity (Batista et al. (2012), Abarcar and Theoharides (2024) among others). However, this literature has focused on one specific type of incentive effect, namely the impact on the global human capital level, but has neglected to consider the impact in terms of the type of acquired skills. The incentive effect implies that individuals should not only increase their education level, but also invest more in the skills that are relatively more rewarded abroad compared with the domestic market. In this paper, we bring evidence in favour of such an effect.

To this aim, we take advantage of an original survey that covers students from the University of Lorraine after graduation.[1] The University of Lorraine is one of the most important universities in France and offers a comprehensive selection of subjects and degrees. The Lorraine region is located in the northeast of France and is contiguous with the Grand-Duchy of Luxembourg, one of the richest countries in the world with a booming labor market based on the development of financial services and technological products. Luxembourg, due to its geographical and linguistic proximity, the absence of mobility restrictions for French citizens, and the existence of convenient bilateral agreements in the area of income taxation and social security, has been by far the preferred foreign option for fresh college graduates originating from this region. The survey data include precise information about the topics studied by the graduates of the university, as well as a rich set of individual characteristics. Combining this information with data capturing the relative attractiveness of corresponding professional occupations in the Luxembourgish and the French labor markets, we investigate whether the students internalized that information when choosing their subject at the start of their higher education studies. The attractiveness of each occupation is measured through average wages as well as through its employability rate in both countries' markets. An interesting aspect of the survey that we exploit is that it includes an explicit question about the attention the students paid to the foreign labor market in general, and to Luxembourg in particular, when deciding on their study subject.

Our findings can be summarized as follows. We provide evidence of an effect of emigration

[1]The survey is conducted by the OVU (Observatoire de la vie universitaire), which is an operational unit within the University of Lorraine. OVU conducts annual surveys in order to assess the quality of integration of graduates of the university in the labor market.

prospects on the investment on skills that are relatively more rewarded abroad. More specifically, students at the University of Lorraine tend to enroll more in degree programs that lead to higher employability in Luxembourg. We also find an effect related to higher wages, although employability seems to be the driving factor of attractiveness. The incentive effect of emigration is observed for students stating that they paid some attention to the foreign markets in general, and to Luxembourg in particular at the time of enrollment. In line with the theoretical expectations, students who did not consider these options are not subject to an incentive effect of emigration. These results suggest that acquiring information about foreign options is key to generating an incentive effect of emigration prospects on human capital investment. Our results are robust to several phenomena. The findings hold when we capture in our estimations the fact that some set of topics are more alike than others, implying a higher degree of substitutability in the educational choices. They are also similar when we account for the possibility that the interest shown for Luxembourg might be related to factors driving the education choices.

Our paper is directly related to three separate existing strands of literature. First, we contribute to the empirical literature on the brain gain in general and then on the incentive effect in terms of human capital accumulation in particular. Following early evidence based on macroeconomic data (Beine et al. (2008)), a set of contributions has assessed the existence of the incentive effect based on individual data.[2] Batista et al. (2012) bring the first causal evidence in the case of emigration from Cape Verde, showing that an increase in the individual probability of emigration tended to boost educational achievement at the secondary education level. Shrestha (2017) takes benefit of a change in the educational requirements of recruitment of Nepali citizens for the British Army and shows that this change led to an increase in the proportion of men completing their secondary education. This resulted in a net increase in the ex post human capital level, which in turn generated beneficial effects for the local economy. Chand and Clemens (2019) exploit a quasi-natural experiment in which a sudden surge in discrimination against islanders of Indian ethnicity in Fiji led to a large emigration wave of this group of individuals and to an important investment in skills on their side, resulting ultimately in a brain gain.

[2]While most papers look at the impact of emigration prospects on contemporaneous levels of human capital levels, some studies focus also on the inter-generational effects of such emigration shocks. See, for instance, Theoharides (2018) or Dinkelman and Mariotti (2016).

There is also a limited number of contributions suggesting that emigration prospects induce investment in specific skills in origin countries. Abarcar and Theoharides (2024) exploit variations in U.S. visa restrictions for nurses originating in the Philippines. The authors show that, in regions traditionally prone to send nurses abroad, expansions (restrictions) in emigration prospects boosted (decreased) enrollment in nursing education programs and resulted in an increase (decrease) in the stock of graduates in this field. Using evidence from university students in seven different countries, Kulka et al. (2023) find that there is a positive correlation between the level of international applicability of human capital and migration intentions. Based on a survey of secondary school students in Tonga, Gibson and McKenzie (2010) report that students considering going abroad were more eager to study science subjects and to improve their English language skills. We contribute to this strand of the brain drain literature by providing an analysis that involves a comprehensive set of study topics, which in turn allows to pin down the incentives related to skills in human capital investment. Indeed, our analysis is based on enrollment of students in a major university offering a comprehensive set of degrees, which we match with the economic rewards of corresponding professional occupations in the domestic and foreign markets. A second original point of our study, albeit less important, is that we provide evidence of an incentive effect of emigration prospects on human capital investment between developed countries. Almost all the contributions providing evidence of such an effect consider south-north emigration prospects. This is quite understandable since the incentive effect is driven by the magnitude of wage differentials. Nevertheless, we show that such an incentive effect might also occur within a context of neighboring regions of developed economies when prospects of improved employment of migrants are non negligible.

Our paper is also related to a second important strand of literature that focuses on the determinants of choice in terms of specific skill acquisition. In the human capital theory (Becker (1962)), beyond preferences for specific topics as well as other factors such as abilities to learn, students should act as rational forward-looking agents and tend to choose the topics that are more rewarded on the labor market (Chapman (1981), Cameron and Heckman (1998b), Cameron and Heckman (1998a), Gibbons and Vignoles (2012)). Azmat and Kaufmann (2024) show that German reunification led to an increase in college plans of East German through a change in perceived education returns and risk. In the signaling theory, degrees also act as signaling devices of future productivity, allowing workers to grab higher wages in the labor market (Spence (1978)). Investments in specific skills by students are also explained in sociology by the rational choice theory, which involves long-term benefits such as income or job prestige (Breen and Goldthorpe (1997)). Arcidiacono (2004) finds that the choice of education is driven by the intentions to enter in specific occupations. Furthermore, Arcidiacono et al. (2012) show that beyond abilities and preferences, choices of study fields are driven by expectations of earnings by students. Such an evidence is corroborated by papers showing that risk preferences of students affect specific major choices and their associated professional occupations. While this evidence shows that characteristics of professional occupations in the domestic labor market drive educational choices, to the best of our knowledge, no empirical contribution has looked at the specific role of the foreign labor market. Our contribution fills this gap by bringing some evidence that prospects of emigration play a role in this choice. In that sense, our paper is a bridge between the literature on brain drain and the literature devoted to the choice of skill investment in higher education.

Finally, our paper is also connected to the brain waste literature. If domestic students tend to invest more in skills that are rewarded abroad, and if industrial structures of the domestic and the foreign economies are different, the existence of an incentive effect can lead, at least in the short run, to suboptimal outcomes at origin, even with moderate brain drain rates.[3] In our context, this concern is relevant, since there are substantial differences between the industrial structures in the Lorraine region and Luxembourg. While Lorraine is characterized by a traditional industrial structure based on usual manufacturing sectors, Luxembourg is an economy dominated by a booming financial sector and related specialized services such as consulting, auditing, IT infrastructure and research (Statec (2023)). Most of the literature on the emigration of highly skilled workers has addressed the question of the brain waste from the perspective of the receiving countries. Brain waste results in an under-utilization of human capital, at least assessed from the nominal education degrees. In some professional occupations such as medical ones, this phenomenon is related to the lack of recognition of credentials between countries. Nevertheless, the observed mismatch between jobs and education can also be explained by the difference in education quality among countries, especially in the case of south-north brain drain (Mattoo et al. (2008)). In contrast to this literature,

[3]Such a negative effect is nevertheless less obvious in the long run due to the existence of the skill-biased technological change. In the long term, specific investment in skills that were initially in short supply might induce the creation of specific activities with beneficial consequences for the economic development of the origin country.

the issue of the brain waste here applies directly to the sending country and results from a short-run mismatch of skills associated with the incentive effect of emigration.

The paper is organized as follows. Section 2 presents the model and its testable implications. Section 3 gives details about the context and presents our original data as well as the other data used in the econometric analysis. Section 4 presents the results, while Section 5 concludes.

2 Underlying model and testable implications

To understand the way in which the mechanism of the incentive effect of emigration works, we assume that prospective students of the University of Lorraine, at the start of their tertiary education cycle, tend to choose the educational program that is associated to the largest expected utility. In line with the Random Utility Maximisation (RUM) approach, each prospective student n maximizes her utility over all possible educational programs j ($j = 0, 1, ..., J$) offered at the University of Lorraine. Formally, the utility of individual n of choosing program j is expressed as U_{jn} and can be additively decomposed into a deterministic component V_{jn} and a stochastic component ε_{jn}:

$$U_{jn} = V_{jn} + \varepsilon_{jn}. \tag{1}$$

2.1 Expected returns of skills in the domestic and foreign labor markets

The deterministic part of the utility is given by the expected returns on the domestic and foreign labor markets. It takes the following form:

$$V_{jn} = \alpha(I_{in} \times \log[\mathbb{E}(w^*_{jn})])) + \beta \log[\mathbb{E}(w_{jn})] + \delta_j \tag{2}$$

where δ_j is a degree-specific constant capturing common factors across individuals influencing the level of attractiveness of skill j.

The two key components of the deterministic component of utility V_{jn} are the expected return on the domestic and foreign labor markets, denoted respectively by $\mathbb{E}(w_{jn})$ and $\mathbb{E}(w^*_{jn})$. The foreign labor market of interest is captured in its entirety by the characteristics of the Luxembourgish market, given that wages and employment in Luxembourg are, by far, much more attractive than those of any alternative location in the neighboring regions. The expected return on skill j in the French labor market is determined by the expected wage of skill j, captured by the expected wage in an occupation closely related to that skill (w_j), and the probability of employment associated with skill j (denoted by $\Pr(e_{nj} = 1)$). We can thus express it as:

$$\mathbb{E}(w_{jn}) = \Pr(e_{nj} = 1) \times w_j \tag{3}$$

Similarly, the expected return of skill j for graduated student n on the foreign market is given by the expected wage in Luxembourg for the occupation associated with this type of skill w^*_j, the associated probability of employment $\Pr(e^*_{nj} = 1)$ as well as the probability of migrating to Luxembourg $\Pr(mig_n = 1)$ for individual n:

$$\mathbb{E}(w^*_{jn}) = \Pr(mig_n = 1) \times \Pr(e^*_{nj} = 1) \times w^*_j \tag{4}$$

In Luxembourg, the expected wage for individual n graduating with skill j depends on $\Pr(mig_n = 1)$, the probability of being allowed to migrate and work in Luxembourg. This probability is equal to 1 for French and for other European Union nationals due to the free mobility agreements at the European level. For non-EU students, international mobility is subject to the restrictions of the Luxembourgish immigration policy. This might result in a lower expected wage compared with a native student.[4] Immigration policy in Luxembourg belongs to the category of employer-driven systems. The possibility of obtaining an immigration visa depends mainly on getting a firm job offer from a Luxembourgish employer, as well as on additional checks from the immigration authorities.[5] In short, the fact that the worker is from outside the European Union creates some additional uncertainty about the probability of crossing the border and exerts downward pressure on the expected wage abroad. This expected wage also depends on $\Pr(e^*_{nj})$, the probability of finding a job in an occupation related to skill j for worker n. We assume absence of discrimination. Since

[4]For instance, while foreign EU workers can become cross-border workers (i.e., work under a Luxembourgish labor contract while living outside the country), this possibility does not exist for non-EU workers. Given the relatively higher cost of living in Luxembourg, in particular the high housing costs, this mitigates the expected net gain of migration compared with EU foreign workers.

[5]For instance, this entails stating the fact that the position cannot be filled by a native worker. Depending on the type of visa, it also requires that the wage offered is above a minimum level.

choices regarding the type of skill to acquire are made before university enrollment, we assume that individuals have similar information about this probability. This probability therefore depends only on the magnitude of the labor demand for that skill j in Luxembourg. The other important component of the expected wage is the return for skill j in the foreign labor market, w^*_j.

Let us assume that individuals have accurate information about the attractiveness of each skill in the Luxembourgish labor market. The presence of the component of attractiveness in the foreign labor market of the underlying utility of skill j is directly related to the existence of the incentive effect of emigration prospects on human capital. This effect is likely to vary across individuals, depending on whether they paid attention to the foreign alternatives to the labor market. Intended stayers, i.e., individuals with a strong preference to stay in France after graduation, would pay little attention to the variation of $\mathbb{E}(w^*_{jn})$, in contrast with individuals looking at work conditions in Luxembourg. We account for such a heterogeneity by interacting $\mathbb{E}(w^*_{jn})$ with variable I_n capturing whether individual n paid attention to the foreign labor market in general, and to the Luxembourgish one in particular, at the time of university enrollment.

For the sake of simplicity, we first assume that $\Pr(mig_n = 1) = 1$ for all individuals, i.e., everyone is able to get a work permit in Luxembourg without any restrictions.[6] Combining equations (2), (3) and (4) and assuming $\Pr(mig_n = 1) = 1$ for all individuals, we obtain the following specification of the deterministic part of the utility:

$$V_{jn} = \beta[\log[\Pr(e_j)] + \log(w_j)] + \alpha[(I_n \times \log[\Pr(e^*_j)]) + (I_n \times \log(w^*_j))] + \delta_j \tag{5}$$

This specification might be too restrictive as it implies that individuals do not distinguish between the prospects of employability and wage conditions. In particular, especially at an early stage of the career and even more when indicating their choice of education, students might attach different weights to both components. To allow for some flexibility, we bring the following alternative specification to the data and estimate different β and α for both components:

$$V_{jn} = \beta_1 \log[\Pr(e_j)] + \beta_2 \log(w_j) + \alpha_1(I_n \times \log[\Pr(e^*_j)]) + \alpha_2(I_n \times \log(w^*_j)) + \delta_j \tag{6}$$

[6] In robustness checks (see Section 4.5.), we account for the origin of the students (native, foreign EU or non EU students) to assess the influence of such an assumption.

In this specification, the incentive effect associated with the foreign location (i.e., the attractiveness exerted by the Luxembourgish labor market) is associated with parameters α_1 and α_2. In particular, the existence of an incentive effect on the choice of study topics should be reflected by $\alpha_1 > 0$ and/or $\alpha_2 > 0$. In other terms, the greater attractiveness of skill j in the foreign market raises the probability of enrolling in the study field associated with that skill in the origin country.

2.2 The structure of the error term

We can then derive the choice probabilities for each skill j by specifying the stochastic component of equation (1). In the RUM approach, each student n is supposed to choose the skill that gives the maximum level of her (expected) utility. P_{jn}, the probability that individual n chooses skill j is given by:

$$P_{jn} = \Pr(U_{jn} > U_{kn}, \forall j \neq k), \tag{7}$$

which can be expressed as :

$$P_{jn} = \Pr(\varepsilon_{jn} - \varepsilon_{kn} < V_{jn} - V_{kn}, \forall j \neq k), \tag{8}$$

Equation (8) makes clear that in order to solve the maximization program, one has to assume a particular probability distribution $f(\varepsilon_{jn})$ for the stochastic component of the utilities. The assumption that ε_{jn} follows an extreme value distribution of type-1 imposes the IIA assumption, i.e., homogeneity in the substitutions between all the degrees. In this case, following McFadden (1973), the derived choice probability for alternative j takes the following form:

$$P_{jn} = \frac{e^{V_{jn}}}{\sum_{k=1}^{K} e^{V_{kn}}}. \tag{9}$$

Equation (9) corresponds to the solution of the multinomial logit model. Other specifications for $f(\varepsilon_{jn})$ lead to alternative models and more complex solutions for equation (8). In particular, the solution depends on the way we assume the stochastic component is correlated within a given subset of various study topics. This will be explored empirically in Section 4.2.

3 Context and data

3.1 Lorraine and Luxembourg within the Great Region

In this study, we use survey data from the University of Lorraine on students' enrollment. The University of Lorraine is located in the new French region "Grand Est" and in the departments of Moselle and Meurthe-et-Moselle, both part of the historical region of Lorraine up to the 2014 territorial reform. The region and the departments are neighbors of the Grand Duchy of Luxembourg (hereafter Luxembourg) and belong to the so-called Great Region, encompassing specific regions of Belgium, France, Germany, and Luxembourg. For a couple of decades, due to its attractiveness, Luxembourg has been a country of intense immigration, with a proportion of immigrants close to 50%. About 50,000 French nationals are immigrants in Luxembourg. Furthermore, Luxembourg has been the most common destination for cross-border commuters in the EU (in relative terms), with 212,000 incoming cross-border commuters on a daily basis. France is the main provider of cross-border workers, with about 112,000 individuals crossing the border every day. All in all, French nationals represent about a quarter of the total labor force of the country. Most of them commute from neighboring areas located in the Department of Lorraine across the Luxembourgish border. A significant share of these workers graduated from the University of Lorraine.

3.2 Enrollment and survey data

The key data that we use to explain the eliciting of educational choices by the students are based on an annual survey conducted by OVU (Observatoire de la Vie Universitaire), a central service of the University of Lorraine. According to the Shanghai Ranking of higher education institutions, the University of Lorraine is in the top 300 of universities worldwide. It is home to about 60,000 students each year, is one the most important comprehensive institutions in France and by far the most important one in the northeast part of France (*Région Grand Est*). The initial purpose of this survey is to get first-hand information about how successful the graduates of the University were in integrating into the labor market. For that purpose, the body in charge of this assessment, OVU, conducts a large survey of all the students freshly graduated from the University who have decided to enter the labor market. All students graduating from the university are systematically surveyed three times after their departure of the university. Other students that are not active on the labour market are therefore not considered in this survey. Students extending their studies, either at the University of Lorraine or elsewhere are not considered. The same applies for those who do not express a desire to be active in the labour market. This means that our population of interest is the universe of graduating students from the university of Lorraine that are active in the labour market. The reported response rate is 77% for the survey wave that we use in this paper.

3.2.1 Location and individual characteristics of graduates

Our population of interest therefore involves former graduates of the University who have completed their education process and joined the labor market. The survey includes graduates in both bachelor's and master's programs. In this paper, we use the 2019 wave. This means that the educational choices of these students were made between three and six years before the survey, i.e., between 2013 and 2016. The survey includes 3,038 graduates.

Figures 1 and 2 provide heat maps based on the initial origin of the native students.[7] Figure 1 gives the intensity of enrollment of native students with respect to their region of origin. While the overwhelming majority of the native students come from the Grand Est region that includes the Department of Lorraine, a substantial proportion of students come from regions outside the Grand Est. This is explained by the fact that University of Lorraine is a comprehensive university providing a very broad set of study topics. This feature is important for our empirical investigation since a sound discrete choice analysis of study topics requires a choice set as large as possible.

The survey data provides the details of the completed degree as well as information about the individual characteristics of the graduates. This includes individual characteristics such as gender, age, and some information about their background such as the type of secondary degree or the postal code of parental address. This last piece of information turns out to be useful to capture the student's location at the time of the choosing of study topics. The data also include some information about their current status such as current location, type of work, the job location, the type of contract and, if possible, wages.

[7]For the sake of exposition, foreign students and students from the overseas French territories (e.g., Guadeloupe, Martinique) are not represented here. Non-French students represent 14.3 % of the total enrollment (see Table 1).

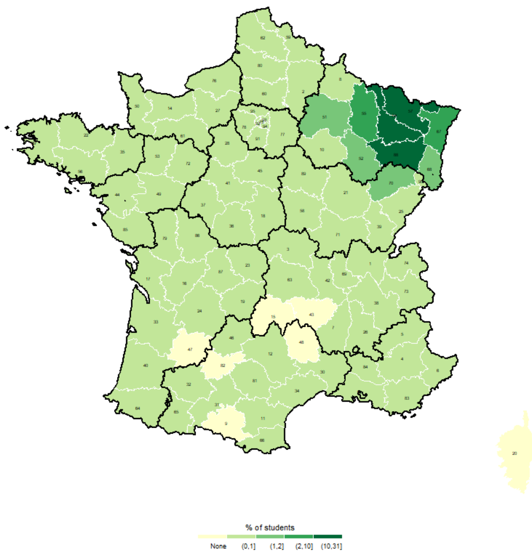


Figure 1: Origins of the graduates

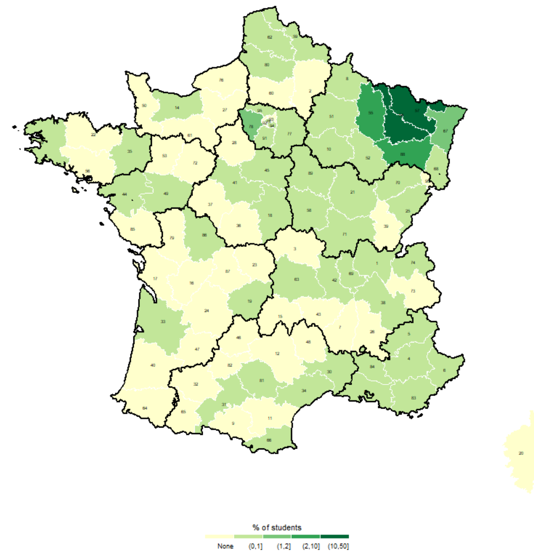


Figure 2: Share of graduates interested in Luxembourg, by origin of students

Table 1 provides some summary statistics of the individual characteristics of the graduates included in the survey. We have a balanced sample in terms of gender. The proportion of foreign students (14.3%) is in line with the share observed in the French system of higher education. About two-thirds of the graduates originate from the Grand Est region, and about half come from the Lorraine department. About a fifth of the students had a strong or very strong interest in Luxembourg at the time of enrollment; 10% of graduates work in Luxembourg. We have also a balanced sample in terms of level of education, with about three-fifths of the students graduating with a master's degree. The sample includes students from a broad set of disciplines. While the Faculty of Science hosts the highest number of students, there is a significant proportion studying social sciences and law.

At our request, the survey was supplemented by a couple of questions capturing the interest of the students in Luxembourg at the time of enrollment in the university. In particular, we wanted to capture their initial interest in the foreign labor market in general and the Luxembourgish one with the following questions. The first question asks: "At the start of your studies, did you consider a professional integration abroad?". Then, for those answering positively, we ask the following daughter question: "Was Luxembourg part of the countries of interest?". The answer to that question considers four levels of intensity, from "not at all" to "yes, absolutely". The variable based on

Table 1: Students' data summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Age	3,038	24.947	3.356	20	58
Female	3,038	0.492	0.500	0	1
Foreigner	3,038	0.143	0.350	0	1
Parents: Contiguity to LU	3,038	0.474	0.499	0	1
Parents: Distance to LU	3,038	481.3	1,257.9	0.00004	12,220
Origin: Grand Est	3,038	0.683	0.466	0	1
Origin: Lorraine	3,038	0.474	0.499	0	1
Interest in Grand Est	3,038	0.672	0.470	0	1
Interest in FR	3,038	0.444	0.497	0	1
Interest abroad	3,038	0.307	0.461	0	1
Interest in LU	3,038	0.204	0.403	0	1
LU as a deciding factor	3,038	0.055	0.229	0	1
Working in LU	2,759	0.104	0.305	0	1
Level: Master's	3,038	0.586	0.493	0	1
Faculty: Arts	3,038	0.063	0.243	0	1
Faculty: Law, Econ., Mgmt.	3,038	0.314	0.464	0	1
Faculty: Social Sciences	3,038	0.195	0.396	0	1
Faculty: Sciences	3,038	0.411	0.492	0	1
Faculty: Physical	3,038	0.017	0.128	0	1

Notes: Summary stats from raw data. The number of observations reflects the number of students answering that question. The interest questions are overlapping: Students could answer that they were interested in working in Grand Est, in France or abroad or any combination of the three. Those interested in working abroad are asked whether their interest was in Luxembourg. The proportion of students having an interest for Luxembourg is the share in the two highest modalities (strong and very strong).

that last question allows to capture the variation of variable I_n in equation (2).

Table 1 shows that about 30% of the students had an interest in working abroad after graduation. Among those students, about two-third express an interest in Luxembourg, confirming that the Grand Duchy is the main foreign alternative for graduates of the University of Lorraine. Figure 2 provides the intensity of the interest in Luxembourg, depending on the original location of native students, presenting the share of students for that region responding positively to the last question. The map makes clear that this interest is not random and is higher for native students having grown up close to Luxembourg.[8] The endogeneity of this variable and its potential impact of our results

[8]This variation is even more pronounced when including foreign students and French overseas students who are not accounted for in this map.

will be addressed in Section 4.3.

Our interest variable should reflect the attention paid to the Luxembourgish market at the time of enrollment and the willingness to consider foreign options after graduation. Our survey also includes some information about the place of work after graduation. About 10% of our students in the sample work in Luxembourg. In order to assess the informational content of the interest variable, we can compute the probabilities of working in Luxembourg, conditional on the interest paid at the time of enrollment. We find that the proportion of graduates is as follows: with a very strong interest, 56.6%, with an interest 13.9%, with little interest 6.85% and with no interest at all 5.49%. This suggests that the variable captures the propensity to internalize information about future work opportunities.

One potential concern is that our variable of interest is based on students' retrospective self-reports, which could introduce bias. This type of bias, known as recall bias, has been discussed in the broader social sciences literature and in economics specifically (Beckett et al. (2001), Dex (1995)). Therefore, it is important to assess the potential impact of retrospective self-reporting and the possible magnitude of such bias in our context. Two primary determinants of recall bias have been identified in the literature. The first relates to the time lag between the original event and the moment of recall (see de Nicola and Giné (2014) for instance). The longer this interval, the more susceptible the data becomes affected by the recall bias. In our case, the time lag is three years—a relatively short period—allowing students to reasonably remember their mindset at the time of enrollment. The second determinant is the tendency to reinterpret past opinions in a way that justifies one's current situation (Klayman (1995)). In our context, this would mean that students currently not working in Luxembourg may be more likely to underestimate their initial interest in the country, while those working in Luxembourg might overstate it. Since we have information on students' current employment status, we can test whether such a pattern is present. Table 2 presents the relationship between reported interest in Luxembourg and current employment location.[9] The data in Table 2 show a substantial number of students in the off-diagonal cells. This suggests that ex-post rationalization is not dominant: a significant share of students who initially expressed interest in Luxembourg are not currently employed there. This pattern aligns with the "beneficial brain

[9]Interest in Luxembourg is coded as 1 for high or very high interest, and 0 otherwise.

drain" hypothesis, whereby individuals who initially intend to emigrate at the time of educational investment ultimately decide to remain.

Table 2: Interest for Lux and Employment situation

	Not interested	Interested	Total
Not working	2356 (77.5%)	66 (2.1%)	2417
Working	396 (13.0%)	225 (7.4%)	621
Total	2752	286	3038

3.2.2 Educational Topics

One important piece of information concerns the educational choices of the students. The survey collects information about the level of the final degree (bachelor's or master's) as well as the specific topic chosen. The data gives quite detailed information about the completed educational programs. In our dataset, this amounts to 178 different programs, including general categories or majors (e.g., law, management, chemistry, engineering) but also more precise subcategories or minors (e.g., real estate law, management in entrepreneurship, ...).

Given the high degree of dimensionality of the choices, we consolidated the degrees into 58 different categories that contain all degrees that closely share the main topic (major) and that belong to the same educational level (bachelor or master).[10] Our criterion of consolidation is based on the share of common topics of each original degree. For example, in the database there are several commerce-related degrees (sharing the "commerce" major) that are differentiated only by their specialization (minor): "commerce and distribution", "commerce of alimentary goods" or "commerce of goods and services". These are grouped into a broader category labelled "commerce". Original-consolidated degrees correspondance table is available under request.

3.3 Degree-specific labor market indicators

To be able to identify the effect that both the local and foreign labor markets might have on the educational choice of students at the University of Lorraine, we need to compute the wages associated to each degree. The same holds true for their employability prospects, which are captured

[10] Beyond the computational constraints associated to choice sets with a large number of alternatives, the need to consolidate is due to the fact that two very close degrees will be hardly distinguishable by any determinant. Very often, two degrees just differ by a few elective courses.

by the labor demand indicators. The association between degrees on the one hand and wages or employability on the other hand involves several steps.

The first step is to link degrees with skills and jobs. Skills are identified by ROME codes.[11] In order to associate each degree with its corresponding ROME codes, we use the *France Compétences* online tool from the French Education Authority (Autorité nationale de financement et de régulation de la formation professionnelle et de l'apprentissage), which contains information on the skills acquired in each degree and the accessible jobs after graduation (and their corresponding ROME codes).[12] As an illustration, the degree in Economics has two associated ROME codes: 'Banking/finance customer relations' and 'Socio-economic studies and forecasts'. This means that training in economics provides graduates with the skills and knowledge required to work in those jobs. One degree can be associated to one or several ROME codes.[13] From now on, we refer to this correspondence as the 'ROME-degrees' correspondence.

The second step is to link jobs identified by ROME code to "professional categories" (PCS) as well as the broader "professional families" (FAP). The identification of professional categories is needed since wage data are available at the professional level. We use a correspondence table compiled by the French Ministry of Labor.[14] This correspondence identifies for each professional family (FAP) the occupations (PCS) are considered to be part of that family and which jobs (ROME) are related to those occupations. We provide an example of this "FAP-PCS-ROME" correspondence table in Table 3. As an illustration, the professional family of secondary school teachers (FAP W0Z90) is composed by teachers (PCS 341a) and general teachers (PCS 422a), with their respective job categories of general secondary education (ROME K2107) and technical and vocational education (K2109).

Finally, we also need to establish a correspondence between ROME codes and ISCO codes to harmonize data across countries. This table is provided by the French Employment Agency.[15] We

[11] ROME stands for Répertoire Opérationnel des Métiers et des Emplois.

[12] The tool can be found under https://www.francecompetences.fr/recherche_certificationprofessionnelle/

[13] The number of ROME codes for a given degree ranges from 1 to 7.

[14] DARES – La nomenclature des familles professionnelles (Version 2009). Table de correspondance FAP/PCS/ROME.

[15] https://www.francetravail.org/files/live/sites/peorg/files/documents/Statistiques-et-analyses/Open-data/ROME/Correspondance_ROME_ISCO08.xlsx

Table 3: FAP-PCS-ROME correspondence

Professional family (FAP)	Occupation (PCS)	Job (ROME)
Secondary school teachers (W0Z90)	Secondary school teachers (341a)	General secondary education (K2107)
Secondary school teachers (W0Z90)	General secondary school teachers (422a)	Technical and vocational education (K2109)

Note: In parentheses, the corresponding FAP, PCS or ROME code to each of the categories.

refer to this as the "ISCO-ROME" correspondence.

With these correspondences, we can relate jobs and occupations to each degree and thus build indicators of wage and employability that gather the information of these occupations for each degree and country.

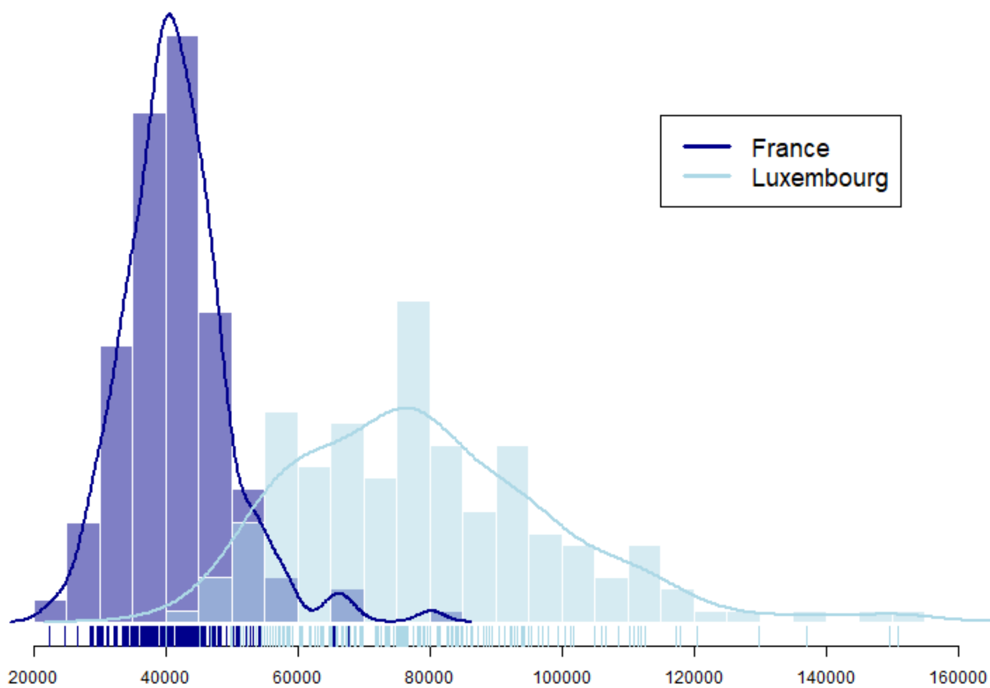
3.3.1 Domestic and foreign skill prices

For France, wages are available for each occupation. For that purpose, we use the ECMOSS database "Coût de la main d'œuvre et structure des salaires" provided by the National Statistical Agency (INSEE), which gives the salary by professional categories (PCS). This dataset is based on a survey that gathers salary data for each occupation. We first calculate the average salary for each occupation. We then use the PCS-ROME correspondence explained above and calculate a ROME-specific salary as a weighted average of all the occupations related to it, weighted by the number of times we observe each PCS in the ECMOSS database. We then rely on the ROME-degrees correspondence to calculate a simple average wage per degree from the ROME-specific salaries we just calculated.

For Luxembourg, we use data from the 'Structure of Earnings Survey' carried out by National Staistical Agency (STATEC). This survey includes a sample of companies in Luxembourg and covers all economic activities (except the agriculture sector). The survey includes individual salaries based on employee profiles, the characteristics of the occupations and the profiles of their employers. We compute the average salary by job (at ISCO-4 level), translate the data to ROME codes using the ISCO-ROME correspondence, which then allows us to finally calculate the average salary by degree.

Figure 3 reports the distribution of wages for both countries.[16] The comparison of both densities illustrates the wage premium of working in Luxembourg rather than in France. The average annual premium after taxes amounts to about 38,000€, i.e. a 47% top-up for French workers in Luxembourg. The distribution of (gross) wages in Luxembourg also exhibits a higher variance.

Figure 3: Distribution of wages in France and Luxembourg



Note: The average (gross) wage for France is of 41.554€/year, with a standard deviation of 7.991. For Luxembourg, (gross) wages have an average of 79.338€/year and a standard deviation of 19.613.

3.3.2 Labour demand indicators

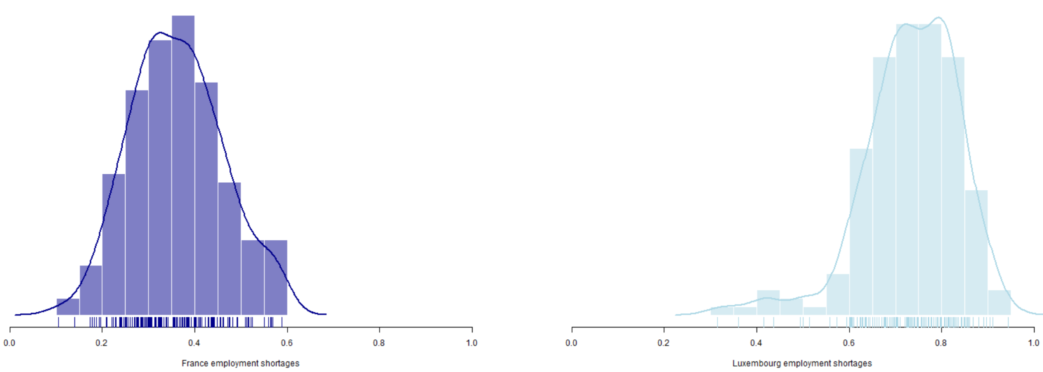
Our measure of employability of graduates is based on indicators of labor market tightness in both countries. The indicator of tightness of the French labor market comes from the BMO survey (Besoins en Main-d'Œuvre). It measures hiring intentions, which reflect the labour needs of firms and opportunities for job seekers. They are also conditioned by recruitment difficulties, as assessed

[16] The density smoothing is calculated using a Gaussian kernel with Silverman's rule-of-thumb. The final smoothing parameter is 6000.

by employers. This database contains a percentage indicator of difficulties in recruiting workers for each occupation. Using the FAP-PCS-ROME correspondence, we assign a measure of market tightness to each job.[17] Finally, similar to what we did for wages, we take a simple average over all ROME codes, using the ROME-degrees table to assign a final figure to each of the degrees.

The data for Luxembourg comes from the Agence pour le développement de l'emploi (ADEM), which is the public employment service in Luxembourg. These data relate to job offers without assignment, namely the percentage of vacancies that did not find suitable candidates after six months. These unassigned offers are broken down by ROME code, which can therefore be associated with each degree in a similar fashion to what we did above using the ROME-degree table and taking averages.

Figure 4: Distribution of labour shortages in France and Luxembourg



Note: The market shortage indicator in France has an average value of 36.2%, with a standard deviation of 9.9%. For Luxembourg, the average value is 73.4% and the standard deviation is 10.4%. Measures are not comparable across countries.

Figure 4 reports the density plots for both countries.[18] Note that, since the definition of both measures is not the same, comparisons should be made with caution. Nevertheless, it seems apparent that in Luxembourg there is a much higher need of workers across most occupations, such that finding a job in that market is easier than in France.

[17]In the case of missing information in the correspondence for some ROME codes, we use the BMO average at the 3- or 2-digit ROME level.

[18]The density smoothing is calculated using a Gaussian kernel with Silverman's rule-of-thumb. The final smoothing parameter is 3000.

4 Modeling educational choices and incentive effects

Our estimations rely on a discrete choice model based on the RUM model (equations 1 and 2) of educational choices. In the benchmark estimations, we will report results based on a multinomial logit (MNL) specification that assumes an extreme value distribution of type-1 for ε_{jn}. The flexibility of this model explains its overwhelming popularity in social sciences in general and in the education and migration literatures in particular. Nevertheless, this flexibility comes at the cost of oversimplifying assumptions that can be questioned in our context. Therefore, the remaining sections explore therefore the robustness of the benchmark results compared with other approaches lifting some of the underlying assumptions of the MNL model.

4.1 Benchmark results

Table 4 provides the estimations of equation (1-5) using the multinomial logit model. This model is based on the choice of an Extreme Value Distribution of type-1 for ε_{jn}. This distribution assumes that the independence from irrelevant alternatives (IIA) holds, whose validity might be questioned in this context. However, due to their flexibility, the multinomial logit estimations provide a first assessment of the existence of the incentive effect of emigration prospects in terms of educational choices. In this specification, beyond the economic factors of attractiveness in terms of employability and wages on the domestic and foreign markets, we account for a set of dummies. We include a master's dummy that captures the relative attractiveness of a master's degree compared with a bachelor's one. We also include faculty dummies that account for the relative attractiveness of broad categories of topics such as sciences or arts. Note also that in discrete choice models the utilities V_{jn} are unitless. Therefore, for comparison purposes across models, it is interesting to report normalized coefficients, i.e., coefficients expressed as a ratio of another one. Thus, we also report the scaled coefficients of the incentive effects related to wage and employability in Luxembourg, as a ratio of the impact of employability in France.

Column (2) of Table 4 includes the estimation results of the full model. The comparison with the more parsimonious specifications (columns 1, 3 and 4 of Table 4) suggests that the inclusion of all economic factors and all types of dummies is relevant. We find clear support for an incentive effect of the prospects of working in Luxembourg, since topics associated with a higher level of employability in Luxembourg tend to be chosen more often by students beyond the attractiveness exerted by the domestic market alone. While employability on the domestic market remains the most important factor, estimations of columns (1-3) suggest that employability in Luxembourg plays a significant role. Regarding the wage level in Luxembourg, there is less overwhelming evidence of its importance in students' decisions, although all estimated coefficients are positive with a subset of these being significant.

While these estimations are supportive of an incentive effect, they rely on a set of assumptions and therefore need to be checked for robustness. This is discussed in the following sections.

4.2 Accounting for heterogenous substitution patterns

The multinomial logit model that yields the estimations in Table 4 rests on an important assumption, namely the hypothesis of Independence from Irrelevant Alternatives (IIA). In our context, the IIA hypothesis implies that the substitution rate between study fields is the same. As an illustration, under this hypothesis, an increase in the economic attractiveness of, say, mathematics, will have the same (negative) impact on the probability of enrollment in French literature, computer ccience or biomedicine. In the real world, for a set of different reasons, we might be concerned that this assumption is violated. First, students have specific preferences for categories of topics. For instance, students might be interested in topics related to the understanding of societies such as sociology, economics or management. In this case, we might expect that substitutions among these topics would be higher compared with topics belonging to a different category. A second reason is the background of students. Some topics might require some specific background. This is, for instance, the case in quantitative fields, such as mathematics. It might be expected that substitution among topics belonging to these categories will be higher. Or, to put it differently, students with little background in mathematics will exhibit a low substitution rate from, say, French literature, to physics even in the presence of an increase in the attractiveness of the latter topic.

We analyze the robustness of our results with respect to the incentive effect of prospective emigration by estimating alternative models that allow for a deviation from the IIA assumption. In the discrete choice literature, the way to deal with this is to specify a different distribution for ε_{jn} in equation (1). We consider two alternative models, the (multinomial) nested logit model (NL)

Table 4: Incentive effect of Luxembourg: Benchmark results

	Dependent var: Prob. of enrollment in topics			
	(1)	(2)	(3)	(4)
Empl France	3.67^{***}	4.83^{***}	4.74^{***}	–
	(0.192)	(0.27)	(0.273)	
IntLux × Empl Lux (α_1)	1.61^{***}	2.09^{***}	2.530^{***}	–
	(0.466)	(0.51)	(0.478)	
Wage France	0.062	0.549^{***}	–	0.187
	(0.138)	(0.139)		(0.145)
IntLux × Wage Lux (α_2)	0.330^{*}	0.282	–	0.610^{***}
	(0.191)	(0.207)		(0.195)
Master's	0.264^{***}	0.187^{***}	0.258^{***}	0.248^{***}
	(0.045)	(0.044)	(0.039)	(0.044)
Arts	–	0.195	0.278^{*}	0.188
		(0.160)	(0.158)	(0.160)
Law, Econ and Magmt.	–	0.231	0.408^{***}	0.460^{***}
		(0.151)	(0.145)	(0.151)
Human and Soc Sc.	–	1.010^{***}	1.008^{***}	0.888^{***}
		(0.149)	(0.146)	(0.150)
Sciences	–	0.249	0.370^{**}	0.845^{***}
		(0.152)	(0.148)	(0.147)
scaled α_1	0.438^{***}	0.432^{***}	0.533^{***}	–
scaled α_2	0.089^{*}	0.058	–	–
Obs	3038	3038	3038	3038
Nber of topics	58	58	58	58
Log-Lik.	-12147.82	-12046.24	-12054.41	-12209.73
LRT (p-val)	0.0000	–	0.0003	0.0000

Notes: Multinomial Logit estimation. Dependent variable: Probability of enrollment in topics. Master's dummy captures topics leading to a master's degree (reference level: Bachelor). Arts, LEM, HSS and Sciences dummies capture topics belonging to faculties (reference level : Faculty of Physical Education). IntLux is a dummy identifying students with a very strong or strong interest in Luxembourg at time of enrollment (reference level: Weak or no interest). LRT provides p-value of a Likelihood ratio test of model against model of column (2). Scaled coefficients α_1 and α_2 are normalized estimates of incentive effects as a ratio of the coefficient of employability in France. Standard errors in parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

and the cross-nested model (CNL). We discuss here in a non-technical way, the main features of the two alternative models as well as their specific contribution in terms of implied substitution patterns. Appendix Aprovides the technical details about these models for the interested reader.

The NL model specifies the categories of alternatives that are expected to exhibit similarities in the stochastic component of utilities (ε_{jn}). Topics included in each category are supposed to be more similar compared with topics outside the category. Categories are reflected by nests in the model and are chosen ex-ante, based on theoretical arguments. However, since the MNL model is nested in the NL model, likelihood ratio tests can be used to validate the choice of the nests. We use two alternative dimensions to define the nest structure. In the first NL model, we consider nests based on topics with, and without, a significant quantitative dimension. Topics such as chemistry, physics, and economics belong to the quantitative nest, while law or literature belong to the non-quantitative nest. In the second NL model, we make a distinction between topics addressing societal issues and topics without this dimension. Topics such as sociology or economics belong to the first category, while literature, mathematics and medicine belong to the second one. Appendix Aprovides a classification of each field along both dimensions.

The second model is an extension of the NL model. Instead of partitioning the set of topics using one dimension, the cross-nested logit Model (CNL) combines the various dimensions to define overlapping nests. In our context, each topic belongs to one of the four possible nests that combine quantitative and societal criteria. For instance, economics belongs to a nest including quantitative and societal topics; mathematics belongs to a quantitative- non-societal nest; sociology to a non-quantitative- societal nest, and so on. This approach allows for a more flexible way of capturing complex substitution patterns among topics. Once again, substitution is supposed to be higher between topics within the same nests than across the nests.

Table 5 provides the estimations for the various models. The specification follows the MNL model of column (2) from Table 4 that is best supported by the data. This specification includes both economic factors of attractiveness in both markets as well as the full set of degree and faculty dummies. Columns (2) and (3) of Table 5 provide the NL estimates with each partitioning criterion. Columns (4) and (5) provide the CNL estimations combining both criteria. Since these models are highly non-linear, it is desirable to constraint some coefficients such as the similarity parameters. This is done in the estimations of column 5 for the μ parameters of the non-quantitative nest. The bottom line is that the results support the relevance of each underlying criterion.[19] This suggests that the IIA hypothesis and the homogeneity of substitution patterns between topics are rejected

[19]In statistical terms, all null hypotheses $H_0 : \mu = 1$ are rejected in favour of $H_A : \mu > 1$.

by the data.

The estimation results of Table 5 once again support the existence of the incentive effect of emigration prospects. Most of the estimations support an incentive effect associated with employability in Luxembourg. Nevertheless, there is also moderate support for an incentive effect in terms of wage conditions, for instance from the estimations of the best CNL model (column 5). Overall, these results show that the evidence of an incentive effect drawn from the MNL estimations in Table 4 holds when we account for potential deviations from the IIA hypothesis.

4.3 Endogeneity of interest variable

A final concern about our benchmark results regarding the incentive effect is the potential endogeneity of our interest variable. This variable interacts with the variables related to the attractiveness of the Luxembourgish labor market, namely employment and the wage level. In fact, one could argue that this variable is endogenous, as it could be correlated with unobserved factors that also affect the choice of study field. While this issue might concern only a small subset of individuals, the following example can be used to clarify its nature. Suppose that an individual has a strong preference for matters related to the ocean. This individual will, at the same time express none or very little interest for Luxembourg since it is landlocked, but also a strong preference for topics such as maritime law or naval engineering. This joint influence could, in principle, bias the estimation of the parameters associated with the idea of an incentive effect.

Endogeneity issues in discrete choice models such as ours have been addressed in the literature. See Guevara and Ben-Akiva (2010) for a review of the methods dealing with endogeneity in discrete choice models. The typical approach relies on a control function (CF) approach in the estimation of model (5). We provide the technical details of this approach in Appendix B.

The CF approach is the equivalent of an instrumental variable (IV) estimation for non-linear models such as the discrete choice models (See Wooldridge (2015) for a general description of the CF approach). In a nutshell, it requires, in a first stage, the use of an instrument that is used to predict the endogenous variable. The residuals of this first-stage regression are then included in the estimation of the choice model. The inclusion of this additional term allows for the correction of the potential endogeneity bias. Furthermore, the coefficient of this residual variable is indicative of the

Table 5: Incentive effect of Luxembourg: Heterogenous substitution patterns

	Dependent var: Probability of enrollment in topics				
	(1)	(2)	(3)	(4)	(5)
Empl France	4.83***	1.030***	4.87***	1.37***	2.38***
	(0.27)	(0.145)	(0.225)	(0.149)	(0.152)
IntLux × Empl Lux	2.09***	0.222***	1.920***	0.263	0.41*
	(0.510)	(0.090)	(0.451)	(0.188)	(0.235)
Wage France	0.062	-0.013	-0.211*	0.134**	-0.129*
	(0.138)	(0.021)	(0.125)	(0.052)	(0.066)
IntLux × Wage Lux	0.282	0.061**	0.386**	0.095***	0.334***
	(0.207)	(0.028)	(0.170)	(0.024)	(0.068)
Master's	0.187***	0.061***	0.261***	0.049***	0.154***
	(0.044)	(0.009)	(0.037)	(0.018)	(0.019)
Arts	0.195	0.027**	0.249**	0.034	0.109**
	(0.160)	(0.014)	(0.120)	(0.050)	(0.055)
Law, Econ and Mgmt.	0.231	-0.080***	0.133	-0.118**	-0.179***
	(0.151)	(0.151)	(0.114)	(0.049)	(0.056)
Human and Soc Sc.	1.010***	0.083***	0.834***	0.082*	0.204***
	(0.149)	(0.149)	(0.110)	(0.046)	(0.048)
Sciences	0.249	-0.215***	-0.586***	-0.356***	-0.544***
	(0.152)	(0.152)	(0.120)	(0.057)	(0.068)
scaled α_1	0.432***	0.215***	0.394***	0.192	0.172*
scaled α_2	0.058	0.059**	0.079**	0.069***	0.140***
μ_{quant}	–	3.82***	–	3.21***	1.60***
		(0.355)		(0.530)	(0.085)
μ_{noquant}	–	13.40***	–	99.2***	20***
		(2.020)		(11.1)	(1.18)
μ_{soc}	–	–	1.35***	3.21***	2.36***
			(0.027)	(0.231)	(0.107)
μ_{nosoc}	–	–	1	2.36***	2.23***
				(0.157)	(0.146)
Obs	3038	3038	3038	3038	3038
Nber of topics	58	58	58	58	58
Log-Lik.	-12046.24	-11729.18	-11936.97	-11468.53	-11451.3
LRT (p-val)	–	0.00	0.00	0.00	0.00

Notes: Col (1) MNL. Cols (2), (3) Nested Logit. In col(2), nest dimensions: quantitative and non-quantitative topics. In col(3), nest dimensions: social and non-societal topics. Cols (4), (5): CNL. Participation parameters set to 0.5. In col(3), μ_{nosoc} constrained to 1. In col (4) unconstrained estimation. In col (5) constrained estimations with bound set to 20 for μ parameters. Tests based on null hypothesis $\mu = 1$. Master's dummy captures topics leading to a master's degree (ref. level: Bachelor). Arts, LEM, HSS and Sciences dummies capture topics belonging to faculties (ref. level: Faculty of Physical Education). IntLux is a dummy identifying students with a very strong or strong interest in Luxembourg at time of enrollment (reference level: Weak or no interest). LRT provides p-value of a Likelihood ratio test of model against MNL model of col (1). Scaled coefficients α_1 and α_2 are normalized estimates of incentive effects as a ratio of the coefficient of employability in France. Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01

size and magnitude of this bias.

There are nevertheless two complications to the usual CF approach in our context. The first one is that our endogenous variable is interacted with rather than included autonomously in equation (5). The solution to this is to use the product of the instrument and the variable as the instrument in the CF estimation. More specifically, if Z_n is the instrument of the variable capturing the degree of interest in Luxembourg expressed by individual n, we use $Z_n \times EmplLux$ as the instrument for $IntLux_n \times EmplLux$. The same applies to the wage in Luxembourg. The second complication is that, due to the specification of model (5), we end up with two endogenous variables instead of one. The estimation of multiple endogenous variables in empirical work is often not advised. Therefore, we favour successive CF estimations, considering either $interest_n \times EmplLux$ or $interest_n \times wageLux$ as the endogenous variable alone. We nevertheless provide an estimation with the two endogenous variables instrumented simultaneously for information purposes but these results should be taken with some caution.

The implementation of the CF requires the choice of an instrument. This instrument should predict the interest in Luxembourg while not being correlated with some preferences with respect to the field of study. In our approach, we rely on the location of the student's parents at the time of enrollment. The idea is that the location of the parents and, therefore, the initial living place of the student is the result of the location choice of the parents, a choice that can be considered exogenous to any preference of the students regarding study fields. We then use distance between this location and Luxembourg as well as whether the initial student's location is in a French "département" contiguous to Luxembourg as predictors of the interest in Luxembourg variable. As a preliminary piece of evidence, Table 6 shows that distance-related variables predict the probability as well the magnitude of the interest expressed with respect to Luxembourg.[20] The results suggest that students who have lived in a French department contiguous to Luxembourg tend to express a higher interest for the country. Also, the greater the distance to Luxembourg, the lower this interest becomes. These preliminary findings suggest that contiguity and, to a lesser extent, distance can be used to generate instruments in the control function approach.[21]

[20]Distance is computed from the postal codes of the parents' location for native students (including students from overseas French departments). For foreign students, since postal codes are unavailable, we use the nationality of the students and compute the distance between the capital of the country and the Luxembourguish border.

[21]Note that while we have information of the department of origin for all students, exact location through the ZIP

Table 6: Distance, contiguity and interest in Luxembourg

	Dependent Var: Interest in Luxembourg					
	All students			With Interest for abroad		
	(1)	(2)	(3)	(4)	(5)	(6)
Contiguity	0.185***	0.349***	–	0.258***	0.603***	–
	(0.047)	(0.038)		(0.098)	(0.075)	
Log distance	-0.111***	–	-0.145***	-0.194***	–	-0.239***
	(0.022)		(0.019)	(0.034)		(0.03)
Female	-0.183***	-0.168***	-0.190***	-0.227***	-0.199***	-0.231***
	(0.037)	(0.037)	(0.037)	(0.068)	(0.070)	(0.068)
Foreign	0.508***	0.295***	0.510***	0.587***	0.242**	0.573***
	(0.075)	(0.058)	(0.080)	(0.193)	(0.010)	(0.134)
Constant	2.015***	1.439***	2.265***	3.589***	2.266***	3.936***
	(0.119)	(0.033)	(0.095)	(0.193)	(0.069)	(0.133)
Nber obs.	3036	3036	3036	931	931	931
R^2	0.050	0.034	0.044	0.119	0.072	0.111

Notes: Dependent variable: Interest in Luxembourg expressed at the time of enrollment. Scale: 1-4, with 1 being no interest and 4 indicating strong interest. Distance is minimal distance from home at time of enrollment to closest point on the Luxembourgish border. Contiguity = 1 if lived in a department contiguous to Luxembourg. Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01

There is nevertheless one potential threat to identification in using the initial location of the students. It could be argued that for some students, their parents or their neighbours are likely to work as cross-border workers in Luxembourg. This will be more likely the closer the initial location is to the border. Cross-border workers can convey some additional information on specific occupations of the Luxembourguish labor market and, in turn, shape the preferences of the students regarding some specific skills. This raises a concern regarding the full validity of the exclusion restriction of the distance-related instruments. To address such a concern, we conduct two alternative estimations. First, we run some CF estimations excluding students originating from localities with a relatively high share of cross-border workers.[22] Second, we also leverage information on how students got their job, dropping those who joined the Luxembourguish labor market through

code of the parents is missing for a subset of students.

[22]For that purpose, we use data from the social security records in Luxembourg providing the location of workers in Luxembourg (residents and cross-border workers). The aggregate data at the locality level are available for Luxembourg, Belgium, France and Germany. See www.data.public.lu/emploi-total-par-commune-de-residence-au-luxembourg-et-dans-les-pays-frontaliers/.

acquaintances since this might mean them having extra inside information that might have shaped their degree choice.

Table 7 presents the CF estimates of equation (5). We rely on the multinomial logit specification and use contiguity or distance to the border as alternative instruments. We provide seven different estimations depending on the instrumented variable(s) and the choice of the instruments (contiguity, distance or contiguity and distance in the two-endogenous variable case). The first stage estimates corresponding to the CF estimations are provided in Table 18 in Appendix B. The results suggest that the incentive effect documented before is robust to the endogeneity issue. Comparing the results with those of Table 4, we find that the prospects of employability in Luxembourg indeed influence the choice of topic for students. This is true when instrumenting employability (col 1) or wage (col 2). It holds also when excluding students that are likely to come from localities with a significant proportion of cross-border workers (cols 3, 4 and 6) or those getting their job in Luxembourg through acquaintances (cols 5 and 6). The results are also robust when instrumenting both endogeneous variables (col 7). In general, there is little evidence of a significant endogeneity effect since the residuals $\hat{v_{1,jn}}$ and $\hat{v_{2,jn}}$ in the CF are not found significant. Overall, these estimations show that the main bottom line is confirmed, namely that there is support for an incentive effect driven by prospects of employability in Luxembourg.

4.4 Placebos and alternative specification

We run a set of placebo tests to test the existence of a potential incentive effect of the Luxembourgish labor market among students with no interest in Luxembourg. Since they claim not to have an interest in the Luxembourgish labour market, this would suggest that the variations in attractiveness of various topics associated to this market should not affect their choice. To that aim, we adopt the following specification (10):

$$V_{jn}^{(pl)} = V_{jn} + \gamma_1[(1-I_n)\times \Pr(e_j^*)] + \gamma_2[(1-I_n)\times \log(w_j^*)] \tag{10}$$

and test whether the γ coefficients are significant and consistent with the theory. Columns (1), (2) and (4) of Table 8 report the results for these estimations. Column (2) and (4) report the results of specification 10. In column (2), we use the multinomial logit model, while in column (4), we

Table 7: Incentive effect of Luxembourg: Endogeneity of interest

	Dependent var: Probability of enrollment in topics						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Empl France	5.04***	4.75***	5.00***	4.95***	5.00***	4.95***	4.97***
	(0.33)	(0.314)	(0.338)	(0.382)	(0.335)	(0.344)	(0.371)
IntLux × Empl Lux (α_1)	6.25**	2.08***	6.36*	8.94*	6.18**	6.07*	6.13**
	(3.07)	(0.509)	(3.33)	(4.64)	(3.27)	(3.57)	(3.07)
Wage France	0.478***	0.430	0.445**	0.377**	0.395**	0.382**	0.381
	(0.153)	(0.27)	(0.155)	(0.165)	(0.154)	(0.156)	(0.275)
IntLux × Wage Lux (α_2)	0.299	0.740	0.314	0.234	0.352*	0.386*	0.676
	(0.208)	(0.907)	(0.214)	(0.236)	(0.214)	(0.220)	(0.907)
$\hat{v_{1,jn}}$	-4.4	-0.439	-4.68	-7.13	-4.56	-4.55	-4.29
	(3.15)	(0.846)	(3.41)	(4.7)	(3.36)	(3.65)	(3.16)
$\hat{v_{2,jn}}$	-	-	-	-	-	-	-0.362
							(0.846)
Master's	0.178***	0.196***	0.195***	0.255***	0.192***	0.211***	0.185***
	(0.044)	(0.047)	(0.044)	(0.046)	(0.044)	(0.045)	(0.048)
Arts	0.183	0.207	0.197	0.213	0.178	0.172	0.193
	(0.161)	(0.163)	(0.162)	(0.171)	(0.161)	(0.163)	(0.163)
Law, Econ and Mgmt.	0.223	0.237	0.23	0.251	0.222	0.23	0.228
	(0.151)	(0.152)	(0.153)	(0.161)	(0.151)	(0.153)	(0.153)
Human and Soc Sc.	1.03***	1.00***	1.03***	1.09***	1.03***	1.03***	1.02***
	(0.151)	(0.149)	(0.152)	(0.161)	(0.151)	(0.153)	(0.151)
Sciences	0.197	0.256*	0.21	0.269	0.20	0.219	0.203
	(0.158)	(0.153)	(0.16)	(0.172)	(0.158)	(0.160)	(0.159)
scaled α_1	1.24**	0.44***	1.27*	1.81*	1.24**	1.23*	1.23**
scaled α_2	0.06	0.16	0.06	0.05	0.07*	0.08*	0.14
Nber Obs	3038	3038	2977	2776	2994	2940	3038
Nber of topics	58	58	58	58	58	58	58
Log-Lik.	-12045.6	-12046.14	-11803.75	-11807.5	-11873.48	-11639.68	-12045.54
Endog. var. 1	Int×Empl	Int×Wage	Int×Emp	Int×Emp	Int×Emp	Int×Emp	Int×Empl
Endog. var. 2	-	-	-	-	-	-	Int×Wage
Instrument 1	Contig.	Dist.	Contig.	Contig.	Contig.	Contig.	Contig.
Instrument 2	-	-	-	-	-	-	Dist
Municipality drop	None	None	>20%	>10%	None	>20%	None
Job obtention drop	None	None	None	None	Contacts	Contacts	None

Notes: Dependent variable: probability of enrolment in topic. Bootstrapped standard errors in parenthesis. Multinomial logit estimations. $\hat{v_{p,jn}}$ is the residual of a first-stage estimation regressing the endogeneous variable(s) on instrument p indicated below. First-stage estimations are reported in Table 10 in Appendix B.Instruments are contiguity and/or distance between initial location of the students at the time of enrollment and Luxembourg. Scaled coefficients α_1 and α_2 are normalized estimates of incentive effects as a ratio of the coefficient of employability in France. Municipality drop: Dropping those students coming from a municipality with 10% or 20% cross border workers. Job obtention: Drop students who got their job in Luxembourg through personal contacts. Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01

rely on the CNL. In Column (1), we include terms that are specific to students having an interest for Luxembourg. we find that γ_1 is insignificant in column (1) and (2) and negative in column

(4), which suggests that variations in employability have no positive impact on the enrollment of students with no interest for Luxembourg. γ_2 coefficients exhibit a negative sign that is theoretically counterintuitive. This holds irrespectively of the inclusion or exclusion of the coefficient for students showing interest in Luxembourg at enrollment. All in all, these results support the fact that, in contrast to those paying attention to Luxembourg, other students not interested in moving abroad were not subject to the incentive effect associated with foreign opportunities.

We also adopt an alternative specification to the benchmark one (equation 6). Indeed, the underlying assumption in equation (6) is that employability and wage condition prospects in France and in Luxembourg are complementary. One could nevertheless argue that students paying more attention to the Luxembourguish labour market will pay less attention to the French one. In order to consider this, we estimate the following alternative specification:

$$V_{jn} = \beta_1(1-I_n) \times \log[\Pr(e_j)] + \beta_2(1-I_n) \times \log(w_j) + \\ \alpha_1(I_n \times \log[\Pr(e_j^*)]) + \alpha_2(I_n \times \log(w_j^*)) + \delta_j \quad (11)$$

Column (3) of Table 8 includes the results. The results confirm the existence of an incentive effect. This specification even supports the case for such an effect driven both by employability and by wage conditions in Luxembourg.

4.5 Additional checks and extensions

Finally, we look at various variants of our benchmark set-up to assess the robustness of our estimates of the incentive effect. We also run sample specific regressions to check that the incentive effect varies with the expected change compared with the full sample, which brings further support for the validity of our estimates.

4.5.1 Native students and EU students only

The incentive effect might vary across the origins of the students. In particular, for specific reasons, it can be different between native students on the one hand and foreign students on the other one. It can also be different between EU and non EU students for other reasons. Given the nature of the

Table 8: Incentive effect of Luxembourg: Placebos

	Dep. var: Probability of enrollment in topics			
	(1)	(2)	(3)	(4)
	MNL	MNL	MNL	CNL
Empl France	4.86***	4.79***	–	2.49***
	(0.192)	(0.27)		(0.151)
(1-IntLux) × Empl France	–	–	3.86***	–
			(0.264)	
IntLux × Empl Lux	1.83***	–	1.67***	–
	(0.516)		(0.462)	
(1-IntLux) × Empl Lux	-0.127	-0.22	–	-0.376***
	(0.307)	(0.30)		(0.113)
Wage France	0.997***	1.03***	–	-0.003
	(0.163)	(0.151)		(0.068)
(1-IntLux) × Wage France	–	–	-0.121	–
			(0.149)	
IntLux × Wage Lux	-0.238	–	0.548***	–
	(0.218)		(0.213)	
(1-IntLux) × Wage Lux	-0.841***	-0.852***	–	-0.132**
	(0.136)	(0.13)		(0.057)
Master's	0.307***	0.321***	0.262***	0.200***
	(0.051)	(0.048)	(0.044)	(0.023)
Arts	0.178	0.185	0.27*	0.123**
	(0.160)	(0.160)	(0.16)	(0.057)
Law, Econ and Mgmt.	0.372**	0.360**	0.452***	-0.166***
	(0.154)	(0.153)	(0.15)	(0.066)
Human and Soc Sc.	1.100***	1.090***	1.02***	0.230***
	(0.151)	(0.121)	(0.15)	(0.051)
Sciences	0.343**	0.363**	0.551***	-0.531***
	(0.154)	(0.153)	(0.151)	(0.071)
μ_{quant}	–	–	–	1.56***
				(0.088)
μ_{noquant}	–	–	–	20***
				(1.090)
μ_{soc}	–	–	–	2.32***
				(0.106)
μ_{nosoc}	–	–	–	2.21***
				(0.135)
Obs	3038	3038	3038	3038
Nber of topics	58	58	58	58
Log-Lik.	-12034.44	-12039.01	-12113.3	-11453.43

Notes: Cols (1)-(3): Multinomial Logit estimation. Col (4) CNL with 4 nests. μ_{noquant} constrained to 20. Dependent variable: Probability of enrollment in topics. Master's dummy captures topics leading to a master's degree (reference level: Bachelor). Arts, LEM, HSS and Sciences dummies capture topics belonging to faculties (reference level: Faculty of Physical Education). IntLux is a dummy identifying students with a very strong or strong interest in Luxembourg at time of enrollment (reference level: Weak or no interest). Standard errors in parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

incentive effect, we can expect that native students will be more subject to the incentive effect than foreign students. One of the reasons for this is that foreign students also contemplate an additional location alternative, i.e., their origin country. It is well documented that return rates of foreign students are quite high, even in attractive destinations, which has been flagged for a long time as an issue for the hosting country that supports a substantial part of the cost of education (Chaloff and Lemaître (2009)). The reason is that, beyond economic incentives, individuals have strong preferences for living in their own country. Therefore, the incentive effect exerted by Luxembourg might be mitigated by the existence of this important alternative location. We explore this by running the MNL model of equations (1-2), excluding foreign students. Foreign students represent about 14% of students in our sample. Column (1) of Table 9 provides the new estimates. We find that the incentive effect associated with employability in Luxembourg is stronger in the sample of native students compared to the full sample.

We also consider a sample of just EU students since we might expect that the incentive effect will be higher compared with non-EU students. The reason is that, for non-EU students, due to visa restrictions and other regulations governing, for instance, the residence of cross-border workers in Luxembourg, $\Pr(mig = 1)$, the probability of working in Luxembourg will be lower than 1. This in turn should lower the expected foreign wage and the foreign wage premium, making the incentive effect less important. Column (2) of Table 9 provides the new estimates obtained from a sample of just EU students. We find that the results are very similar to the sample excluding EU students as well, most likely because they account for a very low percentage of the total student sample.

4.5.2 Alternative measures of the interest for Luxembourg

In the benchmark estimations, we have used an interest variable in Luxembourg based on the two higher levels of this variable (strong and very strong interest). This variable is important as it captures the possible efforts of collecting information about the Luxembourgish labor market at the time of enrollment. In a variant of the benchmark results, we use only the highest modality of that variable, looking specifically at the students who stated a very strong interest for Luxembourg. We might expect the incentive effect to be higher for these ones. Column (3) of Table 9 provides the estimates and confirms this expectation.

Table 9: Additional checks and extensions

	Dependent Var: Probability of enrollment in topics				
	(1)	(2)	(3)	(4)	(5)
Empl France	5.46***	5.48***	4.82***	4.81***	5.43***
	(0.313)	(0.31)	(0.27)	(0.269)	(0.312)
IntLux × Empl Lux (α_1)	3.34***	3.36***	2.98***	4.38***	6.1***
	(0.592)	(0.581)	(0.723)	(0.938)	(1.07)
Wage France	0.413***	0.375**	0.575***	0.597***	0.474***
	(0.155)	(0.154)	(0.138)	(0.137)	(0.154)
IntLux × Wage Lux (α_2)	0.206	0.224	0.335	0.179	0.12
	(0.231)	(0.226)	(0.26)	(0.342)	(0.378)
Master's	0.0163	-0.00986	0.195***	0.202***	0.00466
	(0.046)	(0.0456)	(0.0432)	(0.0432)	(0.0458)
Arts	0.119	0.157	0.197	0.198	0.126
	(0.165)	(0.163)	(0.16)	(0.16)	(0.165)
Law, Econ and Mgmt.	0.217	0.228***	0.234***	0.238	0.22
	(0.154)	(0.153)	(0.151)	(0.151)	(0.154)
Human and Soc Sc.	1.08***	1.08***	1.01***	1.01***	1.08***
	(0.152)	(0.151)	(0.149)	(0.149)	(0.152)
Sciences	-0.0526	-0.0571	2.265***	0.257*	-0.0319
	(0.157)	(0.155)	(0.095)	(0.152)	(0.156)
scaled α_1	0.612***	0.613***	0.618***	0.911***	1.123***
scaled α_2	0.048	0.041	0.070	0.037	0.022
Obs	2605	2659	3038	3038	2605
Nber of topics	58	58	58	58	58
Log-Lik.	-10325.56	-10541.75	-12045.87	-12046.26	-10327.74

Notes: All columns are multinomial logit estimations. Col (1) excludes all foreigners from the sample; Col (2) excludes only non-EU graduates. Col (3) redefines IntLux as dummy identifying students with only a **very strong** interest in Luxembourg. Col (4) uses the alternative question of whether Luxembourg was a deciding factor in the study choice. Col (5) uses the same definition as column (4) but only for natives. Dependent variable: Probability of enrollment in topics. Master's dummy captures topics leading to a master degree (reference level: Bachelor). Arts, LEM, HSS and Sciences dummies capture topics belonging to faculties (reference level : Faculty of Physical Education). Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01

In our survey, we have also another variable capturing the interest in Luxembourg. We ask more specifically whether Luxembourg was a deciding factor in making for educational choices at the time of enrollment (as opposed to a significant one for the other question). Note that only 5.5% of the students replied positively, which means that we are considering here a very specific part of the population of interest. Once again, we might expect the incentive effect to be much higher for these ones. Column (4) of Table 9 provides the estimates and confirms this expectation, with an estimated incentive effect of employability prospects in Luxembourg similar with the one exerted by the French labor market.

Finally, in column (5), we combine the use of this last variable restricting the sample to native graduates only. We find that the incentive effect associated with employability in Luxembourg further increases with respect to the previous estimates.

5 Conclusion

In this paper, we assess a new kind of incentive effect of emigration prospects in terms of human capital accumulation. The existing literature has mostly looked at whether attractive emigration prospects induced individuals to invest more into education in their origin country. Evidence of such an incentive effect has been provided in terms of the general level of human capital level, but much less in terms of the specific type of human capital. Furthermore, the incentive effect has been explored mostly in the context of south-north migration prospects, i.e., emigration from developing to developed countries. No evidence has been provided in the context of human mobility between two developed countries.

To shed some light of such an incentive effect, we take advantage of a survey conducted with graduates of the University of Lorraine, located in the northeast of France. The region of Lorraine is located near the country of Luxembourg, which enjoys a booming economy based on the development of financial activities and high-tech services to firms. The Luxembourgish labour market offers very attractive opportunities for workers of the Lorraine region, with minimal costs in terms of mobility, cultural and linguistic adjustment as well as administrative procedures. We leverage data on individual enrollment and graduation in a large set of study subjects and test the existence of the incentive effect of migration prospects. We find evidence that students tend to invest more in human capital associated with occupations that offer high attractive returns in Luxembourg. The appeal of the Luxembourgish labour market is captured by two dimensions: employability (i.e., probability of employment) and wage conditions. We find more evidence in favor of the first dimension, even though some results support certain evidence of an effect associated with wage conditions.

Our results are specific to students who stated that they paid attention to the foreign labour market at the time of enrollment, providing some evidence that the incentive effect depends on the student's acquiring some information about foreign opportunities. Students who did not consider the foreign labor market in general, or Luxembourg in particular, do not seem to be affected by the appeal of the foreign labor market when making educational choices. The results are robust to a set of considerations that could affect the validity of the results. First, the initial interest in Luxembourg might be endogenous, which could bias the estimation of the incentive effect. We tackle this by taking advantage of the initial location of the students before enrollment and show that students living close to Luxembourg are more likely to pay attention to the foreign labor market. The incentive effect is still found when this source of endogeneity is considered in the estimations. Second, we account for the heterogeneous substitution patterns between study topics by estimating a more advanced discrete choice model. Partitioning the choice set of topics along two dimensions (societal and quantitative topics), we find robust evidence of the incentive effect of emigration prospects.

The existence of such an incentive effect is much more than an intellectual curiosity and entails potential significant implications for the economic development of regions and countries. To the extent that there are differences in the industrial structures, the existence of such an incentive effect might lead to an underinvestment in skills that are needed in the region of origin of the students. Therefore, at least in the short-run, this incentive effect might worsen the issue of skill mismatch and skill shortages observed in many regions of developed countries. Interestingly, our context provides a good example of such a case. While Luxembourg is an economy dominated by the development of financial and high-tech services, the Lorraine region is characterized by a more traditional industrial structure based on manufacturing activities. Like many regions in Western Europe, the Lorraine economy is shaped by skill shortages in many important sectors. Pôle Emploi, the public organization in charge of the monitoring of the labor market in France, has often claimed that these skill shortages are amplified by the brain drain to Luxembourg. Nevertheless, the brain drain is only one face of the coin. Brain drain implies a depletion of human capital at origin in favour of foreign regions or countries *after* the acquisition of skills. What our documented incentive effect suggests is that, regardless of the intensity of the brain drain, there is an effect of emigration prospects in terms of the *composition* of skills that can also be detrimental to the region of origin, at least in the short-run. In that sense, the brain drain aggravates the shortage of specific skills induced by the incentive effect.

However, these negative consequences might be offset in the long run. Acquisition of new skills by individuals could induce a skill-biased technological change that may well be beneficial for the region of origin over time . This will be the case, if the magnitude of the brain drain is moderate. In that sense, the incentive effect of emigration prospects in terms of specific skills might lead to the same phenomenon of a long-run beneficial brain-drain identified in the previous literature (Beine et al. (2008); Mountford (1997); Docquier and Rapoport (2012)). Therefore, the implications of the incentive effect in terms of skills might be very different depending on the time horizons. We leave this investigation for further research.

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Appendix A: Accounting for unobserved heterogeneity in substitution

This section details how we account for the potential heterogenous substitutions across studied topics. The literature has extended the logit model and generated more complex models that take into account the fact that substitution across a subset of alternatives (here topics) can be higher or lower than with the rest of these alternatives. This issue is related to the well-known violation of the Independence of Irrelevant Alternatives (IIA) assumption that underlies the use of the logit (MNL) specification in equation 1:

$$U_{jn} = V_{jn} + \varepsilon_{jn}. \tag{12}$$

The relevance of the MNL specification relies on the validity of the IIA hypothesis. In our context, IIA implies that any pair of topics exhibit the same substitution among the whole choice set of study fields. Statistically speaking, the validity of the IIA hypothesis implies that ε_{jn} follows an extreme value distribution of type 1, which in turn implies no correlation of ε_{jn} across any pair of j alternatives. The logit model implies very restrictive substitution patterns that can be visualized by computing the cross-elasticity, i.e., the change in the probability of choosing a particular topic (conditional on the choice set C) linked to a change in the value of an attribute z_{jn} (e.g. wage or employability) specific to another topic (Train (2009)):

$$\frac{\partial P_n(j|C)}{\partial z_{kn}} = -\gamma_z P_n(j|C) P_n(k|C). \tag{13}$$

The corresponding elasticity is given by the following equation:

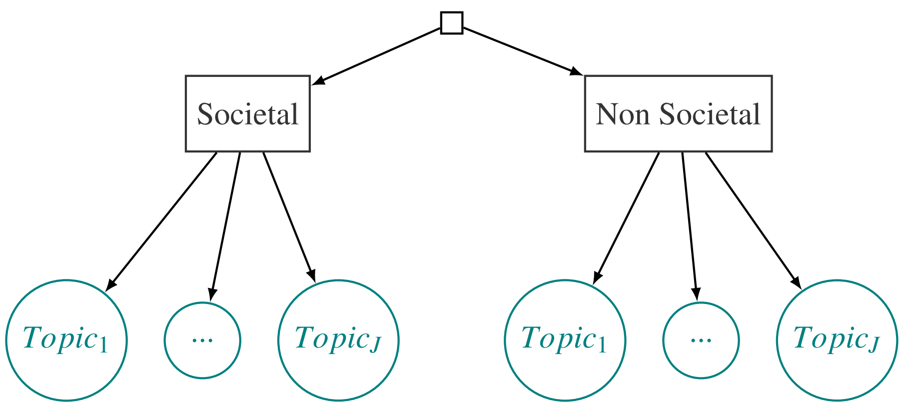
$$E_{j,z_{kn}} = -\gamma_z z_{kn} P_n(k|C), \tag{14}$$

where γ_z is the estimated effect of topic z. The cross-elasticity for destination j implied by the logit model is the same across all other topics (i.e., it does not depend on the specificity of topic j).

The nested logit model (NL) breaks down the hypothesis of uncorrelated ε_{jn} by creating nests of topics within which the substitution is supposed to be higher than with other topics outside the nest. This is done by assuming a new distribution for ε_{jn}, i.e. a specific version of the multivaratiate extreme value distribution (for more details, see Bierlaire (2006)). Under this distribution, each topic is assigned to a category of topics in which the unobserved similarity is supposed to be higher, i.e., the substitution is greater than with topics outside the category. In our estimation, we consider two types of categories. In the first approach, we suppose that students make a distinction between quantitative and non-quantitative topics. In the second approach, we suppose that students make a distinction between topics related to the analysis of the society (societal) and other topics (non-societal). Figure 5 graphically represents how the nested logit model partitions the choice set of topics in the case of the societal/ non-societal partitioning criterion.

Figure 5 provides a graphical representation of the partitioning of the choice set of topics, distinguishing quantitative topics from non-quantitative ones.

Figure 5: Graphical representation of nested logit for study fields



The cross-nested Model (CNL) also breaks down the hypothesis of uncorrelated ε_{jn} but combines the above chosen categories of topics by creating overlapping nests. In our context, each topic might belong to four nests: societal-quantitative, non societal-quantitative, societal-non-quantitative, non-societal-non-quantitative. Statistically, the CNL relies on the Generalized Multivariate Extreme Value Distribution with the following probability function $P_n(j|C)$:

$$P_n(j|C) = \sum_{m=1}^{M} \frac{\left(\sum_{k\in\mathscr{C}_n} \alpha_{km}^{\mu_m/\mu} e^{\mu_m V_{kn}}\right)^{\frac{\mu}{\mu_m}}}{\sum_{p=1}^{M}\left(\sum_{k\in\mathscr{C}_n} \alpha_{kp}^{\mu_p/\mu} e^{\mu_p V_{kn}}\right)^{\frac{\mu}{\mu_p}}} \frac{\alpha_{im}^{\mu_m/\mu} e^{\mu_m V_{in}}}{\sum_{j\in\mathscr{C}_n} \alpha_{km}^{\mu_m/\mu} e^{\mu_m V_{jn}}}, \tag{15}$$

which can nicely be interpreted as

$$P_n(j) = \sum_{m=1}^{M} P_n(m|\mathscr{C}_n) P_n(j|m), \tag{16}$$

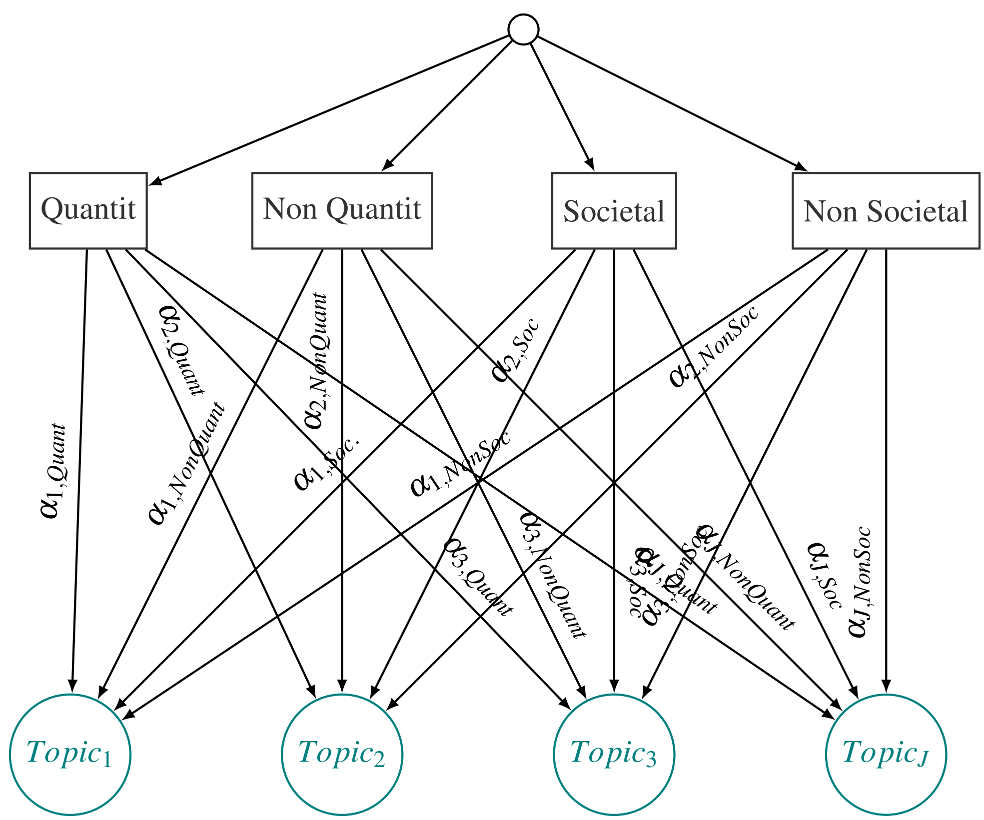
where

$$P_n(j|m) = \frac{\alpha_{jm}^{\mu_m/\mu} e^{\mu_m V_{jn}}}{\sum_{k \in \mathscr{C}_n} \alpha_{km}^{\mu_m/\mu} e^{\mu_m V_{kn}}}, \tag{17}$$

In this model, the parameters μ_ms capture the similarity between the ε_{jn}s within nest m. The α_{jm} parameters are participation parameters, capturing the extent to which topic j belongs to nest m. In the CNL, μ_m and α_{jm} jointly capture the correlation between the topics.[23] This specification generalizes the NL model, in which each topic is assigned to a single nest (i.e., $\alpha_{jm} = 1$ for one m, and 0 for the others). In the CNL specification, this restriction is relaxed. The CNL imposes the normalization constraint that $\sum_{m=1}^{M} \alpha_{jm} = 1 \; \forall j$. Therefore, the NL model might be seen as a linear restriction of the CNL model. In turn, the logit model can be obtained as a particular case of the NL with $\frac{\mu}{\mu_m} = 1$ for each m.

The partition of the choice set by the CNL can be represented by figure 6.

Figure 6: Graphical representation of the cross-nested logit for study fields



[23] See Bierlaire (2006) for a discussion of the conditions to define a GEV function and its properties. In particular this function has properties of non negativity and homogeneity, and complies with some limit properties and the sign of its derivatives.

Each α_{jm} takes a value of 0 (non inclusion of j in nest m) or 0.5 (inclusion of j in nest m) in order to comply with the normalization constraint $\sum_{m=1}^{M} \alpha_{jm} = 1. \; \forall j$. The table listing all the topics with their respective assignment to each nest is available upon request.

Appendix B: Endogeneity and the control function approach

Several methods can be used for the treatment of endogeneity in discrete choice models. See Guevara and Ben-Akiva (2010) for a review. The control function (CF) approach is one of the main approaches to estimate discrete choice models in which a variable of interest is endogenous. Control function approaches are typically used in non-linear models, as reviewed by Wooldridge (2015). They can be seen as the counterpart of the instrumental variable approach for non-linear models. Control function estimation and instrumental variable estimation converge in linear models.

To estimate equations (1) and (6), we first need to instrument the interaction terms involving the endogenous variable, namely, the interest in Luxembourg variable I_n. We proceed to run several CF estimations depending on which variable(s) is considered endogenous. To illustrate, if we consider $I_n \times \Pr(e_j^*)$ as endogenous and if we use contiguity as the instrument of I_n, we proceed to two successive estimations. First, we estimate the following equation:

$$I_n \times \Pr(e_j^*) = \gamma_1 contig_n + \gamma_2 \Pr(e_j) + \gamma_3 \log(w_j) + \delta_j + \nu_{jn} \tag{18}$$

In this regression, the estimate of γ_1 is informative of the strength of the instrument used in the CF estimation. In particular, failure to reject $H_0 : \gamma_1 = 0$ reflects a weak instrument problem. After estimating equation 18, we get the residuals ν_{jn} that will be inserted as an additional covariate in the deterministic component of our multinomial logit model:

$$V_{jn} = \beta_1 \Pr(e_j) + \beta_2 \log(w_j) + \alpha_1 (I_n \times \Pr(e_j^*)) + \alpha_2 (I_n \times \log(w_j^*)) + \lambda \nu_{jn} + \delta_j \tag{19}$$

where $\hat{\nu_{jn}}$ is the residual of the first-stage equation (18). One appealing feature of the CF approach is that the estimate of λ in equation (19) is informative of the strength of the endogeneity problem as well as the direction of the bias associated with this endogeneity issue. In fact, testing for the hypothesis $H_0 : \lambda = 0$ provides a counterpart of the Hansen endogeneity test for non-linear models (Once again, see Wooldridge (2015) on this).

Table 10 provides the first stage estimations (equation 18) for the three different cases that we consider, both for the full sample and for the reduced samples that exclude those students whose initial location was a municipality with a non-small share of cross-border commuters. We instrument employability using contiguitiy to Luxembourg and log wages using distance.

Table 10 provides the estimation results of the first stage regressions used in the CF approach.

Table 10: First stage results

	Dependent variable:					
	IntLux × Empl					IntLux × Wage
	(full)	(20%)	(10%)	(full - work)	(20% - work)	(full)
	(1)	(2)	(3)	(4)	(5)	(6)
Contig. × Empl Lux	0.109***	0.102***	0.077***	0.103***	0.096***	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Dist. × Wage Lux						-0.031***
						(0.001)
Empl France	-0.043***	-0.042***	-0.042***	-0.041***	-0.041***	0.183
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.154)
Wage France	0.011***	0.010***	0.010***	0.010***	0.010***	0.346***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.008)
Master's	0.016***	0.018***	0.023***	0.017***	0.021***	0.312***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.022)
Arts	0.002	0.002	0.002	0.002	0.002	-0.030
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.068)
Law, Econ and Mgmt.	0.002	0.002	0.002	0.002	0.002	0.012
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.062)
Human and Soc Sc.	-0.004	-0.003	-0.003	-0.003	-0.003	0.033
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.065)
Sciences	0.010**	0.010**	0.010**	0.010**	0.009**	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.063)
Municipality drop	None	>20%	>10%	None	>20%	None
Job obtention drop	None	None	None	Contacts	Contacts	None
Observations	176,204	172,666	161,008	173,652	170,520	176,204
R^2	0.217	0.210	0.189	0.209	0.202	0.216
Adjusted R^2	0.217	0.210	0.189	0.209	0.202	0.216

Notes: OLS estimation. Dependent variable: Endogenous variable in main model. Contig. is a dummy variable indicating whether the original region of the student shares a border with Luxembourg. Dist. is the log distance from parents' residence to Luxembourg. Master dummy captures topics leading to a master's degree (reference level: Bachelor). Arts, LEM, HSS and Sciences dummies capture topics belonging to faculties (reference level: Faculty of Physical Education). IntLux is a dummy identifying students with a very strong or strong interest in Luxembourg at time of enrollment (reference level: Weak or no interest). Municipality drop: Dropping those students coming from a municipality with 10% or 20% cross border workers. Job obtention: Drop students who got their job in Luxembourg through personal contacts. Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01