The Geography of Higher Education and Spatial Inequalities*

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Job Market Paper - *Link to latest version*

Abstract

This paper shows that the within-country spatial distribution of colleges largely contributes to spatial inequalities. Using data on the universe of college applicants and programs in France, I document that higher education options are unevenly distributed across space while students' demand is highly sensitive to geographic proximity. This creates inequalities in access to higher education across space, feeding gaps in educational attainment and spatial skill sorting. To quantify these effects, I build a dynamic model linking equilibrium sorting on the higher education market and location choices of entry-level workers. I show that students' and programs' preferences can be identified and estimated from data on choices and equilibrium outcomes. One-third of regional gaps in educational attainment are explained by the interaction of the uneven distribution of colleges and mobility frictions. Eliminating the latter, however, generates a trade-off, as it benefits students from low-opportunity areas but accelerates their migration to higher education hubs, magnifying regional inequalities. Low-opportunity areas could halt this brain drain and outsource the education of their local labor force by tying mobility scholarships with incentives to return.

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1 Introduction

While human capital is a fundamental economic input, individuals' educational attainment widely differs across birthplaces. The gap in college graduation rates between commuting zones in the United States reaches up to 50 percentage points (Chetty et al., 2018). These disparities reveal the existence of local barriers to investment in human capital, in turn hindering growth (Hsieh et al., 2019). Spatial differences in educational attainment may also drive the observed concentration of skills across local labor markets, which impacts regional inequalities and efficiency (Diamond and Gaubert, 2022). Understanding the sources and welfare consequences of these spatial gaps is thus key.

Inequalities in economic opportunities across birthplaces and earnings differences across regions have been studied separately. A first strand of the literature documents the causal effect of individuals' childhood location on their lifetime outcomes (Chetty and Hendren, 2018; Chyn and Katz, 2021). Its underlying mechanisms, however, remain unclear. A distinct literature identifies worker sorting as a main cause of earnings disparities across local labor markets (Combes et al., 2008; Dauth et al., 2022; Card et al., 2023). While sorting is often understood as the result of individuals' migration decisions (Diamond, 2016), Combes et al. (2012) suggest that another important factor may have been overlooked: 'sorting at birth', whereby individuals attain different skill levels due to disparities in the fundamental characteristics of their home region. This paper bridges these two strands of the literature by identifying a key driver of inequalities across both birthplaces and local labor markets: the geography of the higher education market. It uses rich administrative data, quasi-experimental policy variations, and a dynamic structural model to show how the within-country distribution of higher education programs interacts with mobility frictions to generate spatial gaps in students' welfare and educational attainment, in turn contributing to spatial skill sorting and regional inequalities.

I investigate this link in four steps providing several empirical and methodological contributions. First, I use data on the universe of college applicants and programs in France to empirically document that (i) higher education options are highly unevenly distributed across space, while (ii) students' demand for programs is elastic to geographic proximity. Second, I leverage local policy variations to show that mitigating mobility frictions within the higher education market allows students from educational deserts to apply farther away from home

but could trigger a long-lasting brain drain toward higher education hubs. Third, I build a dynamic model combining a two-sided matching model of the higher education market with a model of location decisions at entry on the labor market. I show that students' and programs' preferences are identified from data on choices and equilibrium outcomes, without parametric assumptions on the deterministic part of their payoffs. Fourth, I take the model to the data and investigate the effects of eliminating mobility frictions — encompassing pecuniary and non-pecuniary costs of studying away from home — within the French higher education market, while holding constant the spatial distribution of programs. I find that spatial gaps in educational attainment would decrease by one-third. However, mitigating mobility frictions would generate a trade-off, as it would benefit students from low-opportunity areas but accelerate their migration to higher education hubs, increasing regional divergence. I show how policies tying mobility scholarships to incentives to return would allow low-opportunity areas to outsource the education of their local labor force to higher education hubs.

Specifically, I begin by using rich administrative data to empirically document two facts linking the geography of the higher education market, individuals' educational choices, and spatial inequalities. First, I show that higher education options are unevenly distributed across space. Out of the ninety-six provinces (*départements*) of metropolitan France, fifty gather less than 5% of the total supply of seats in academic programs, leading to a bachelor's degree. This does not reflect the spatial distribution of the population, as these areas concentrate 25% of high school students. In contrast, 50% of the academic seats supply is agglomerated in only twelve provinces.

Second, I provide evidence suggesting that students' demand for higher education programs is highly sensitive to proximity. More than 50% of students enroll in a program located less than 25 kilometers away from where they live. This pattern reveals students' preferences rather than colleges' admission decisions, as the median offer received by students is located twenty kilometers farther away than the accepted one. Overall, by estimating a gravity model, I find that the elasticity of students' enrollment flows to distance is -2.5, which is substantial and larger than that found for labor migration in France (Zerecero, 2021). College choices are thus highly sensitive to distance from home. As these mobility frictions interact with the uneven spatial distribution of colleges, I find that students' probability to enroll in an academic program increases with their proximity to such institutions. This may further impact local labor markets, as I document a positive relationship between the share of a

region's labor force with at least a three-year degree and the local availability of programs delivering such diplomas.

In this context, breaking the dependence of students' application decisions on the local supply of higher education options seems key to tackling spatial inequalities. I leverage local policy changes to explore the direct and distributional effects of mitigating mobility frictions. I first evaluate a program guaranteeing moving subsidies to low-income students conditional on enrolling out of their home region. I find that it allowed students to apply to programs farther away from their home location. To document the distributional effects of removing barriers to mobility, I then zoom in on the Greater Paris area and exploit a change in geographic priorities determining students' university admission. The removal of the priority of students from Paris to enroll in their local universities led to a 50% increase in the share of high-ability students from peripheral locations enrolled in programs in Paris. These students left their local universities and crowded out low-ability applicants from Paris. Survey data on education and work migration flows suggest that, if happening at the scale of the country, such a brain drain could be long-lasting. Indeed, more than half of the students graduating out of their home location do not come back at entry on the labor market.

I build a dynamic model encompassing these mechanisms. It flexibly accounts for differences in preferences and admission chances across students, and captures potential long-run distributional effects of students' spatial mobility. The framework combines a two-sided matching model of the higher education market, where students are forward-looking, with a model of optimal location choices at entry on the labor market. In the first period, students and programs meet on a centralized platform and express their preferences over one another. Each student's payoff from enrolling in a given program depends on its associated flow and continuation value and mobility frictions, capturing pecuniary and non-pecuniary costs associated with studying away from home. I assume that the resulting equilibrium is stable with respect to students' lifetime utility and programs' preferences, and that programs rank applicants truthfully. The second stage of the model takes place after graduation, when individuals choose the location in which to enter the labor market, taking into account migration costs, a potential home bias, and location-specific wages and amenities.

I describe how to identify the primitives of this model without imposing parametric assumptions on the deterministic part of agents' payoffs. I first show how to identify preferences over local labor markets from data collecting individuals' home, study, and work locations.

I then develop a novel procedure combining data on programs' ranking of applicants and on realized matches to identify programs' and students' preferences in a two-sided matching model. This strategy circumvents the need for exclusion restrictions in disentangling preferences of agents on both sides of the market highlighted in Agarwal and Somaini (2022) and He et al. (2023). I propose a tractable estimation procedure. I use a Maximum Likelihood strategy to estimate individuals' preferences over locations and programs' preferences over applicants, before estimating students' preferences over programs using a Simulated Method of Moments strategy with optimal instruments.

Parameter estimates show that students' demand is highly elastic to distance. The average student would need to receive a monthly scholarship of 1,102 euros to agree to enroll 100 kilometers away from her home location, which corresponds to 75% of the average entry-level wage. Mobility frictions, rather than programs' characteristics, are the main component of the value associated with a program for students from higher education deserts. Regarding local labor market decisions, I find that individuals display a large preference for their home location. Yet, the magnitude of moving costs for individuals graduating out of their home location on average outweighs their preference to return home. Overall, model predictions closely match both enrollment and work flows between education hubs and deserts.

I use the estimated model to quantify how mobility frictions interact with the geography of the higher education market to generate spatial inequalities. Holding constant the distribution of programs, I simulate individuals' education and labor market choices in a counterfactual scenario where mobility frictions are eliminated. This breaks the link between their demand and the local supply they face. On the higher education market, predicted sorting depends both on how students shift their demand, as well as on how programs select who to admit given the new pool of applicants. The dynamic nature of the model also enables to simulate counterfactual location choices at entry on the labor market. Overall, this allows us to quantify changes in educational attainment and welfare between students who grew up in different locations, as well as in skills and economic activity across regions.

I find that the uneven distribution of programs across space severely constrains students' human capital investments and welfare. One-third of the spatial gaps in the share of individuals graduating with at least a bachelor's degree is explained by mobility frictions within the higher education market. Eliminating these frictions, however, generates a trade-off. It would lead to a 38% decrease in welfare inequalities between students from higher education

hubs and deserts, but would magnify regional inequalities by 10%. This is driven by a brain drain, characterized by a 14% increase in the number of individuals from deserts working in hubs.

I perform additional quantification exercises. I show how modeling both programs' admission decisions and entry workers' location choices is key in highlighting this trade-off. Furthermore, I eliminate both mobility frictions within the higher education market and workers' moving costs between their study and home locations. As individuals can now return home at no cost, inequalities between both students and local labor markets decrease. Yet, students from low-opportunity areas accumulate less human capital as they anticipate that they will likely enter their home labor market, where returns to education are lower.

Finally, I explore the role of policies in circumventing the above trade-off. I show how low-opportunity areas can leverage regional trade in education services to invest in their local human capital. I design contracts tying a mobility scholarship to incentives to return home after graduation, whereby students failing to come back have to repay the full scholarship. For a cost equivalent to 6% of entry-level workers' total wages, such a policy would decrease inequalities across local labor markets and between students by 17% and 10%, respectively.

Related Literature This paper contributes to several strands of the literature. First, it relates to the literature studying the geography of opportunities (Chetty et al., 2014; Chetty et al., 2018) by underlining the role of differences in the local supply of higher education options. The existence of educational deserts has been documented in the United States (Hillman, 2016). Studies in Belgium (Kelchtermans and Verboven, 2010), England (Gibbons and Vignoles, 2012), and the United States (Fu et al., 2022; Ishimaru, 2020) show that students' demand for higher education programs is sensitive to proximity. Fu et al. (2022) study how the spatial distribution of four-year colleges impacts students' welfare, using survey data on applications and enrollment decisions. Ishimaru (2020) uses NSLY data to additionally model migration decisions on the labor market, and explore the mechanisms linking individuals' childhood location and economic outcomes. I contribute to this literature by linking inequalities in opportunities to spatial gaps in educational attainment and spatial skill sorting. I use data on the universe of students and programs to model the two-sided nature of the higher education market and account for potential equilibrium effects triggered by counterfactual policies.

Second, this paper contributes to our understanding of regional inequalities. Spatial skill sorting is a key driver of these disparities (Combes et al., 2008; Dauth et al., 2022; Card et al., 2023). The urban economics literature primarily focuses on studying sorting through workers' migration decisions (Diamond, 2016). This paper highlights the importance of an overlooked factor, 'sorting at birth' (Combes et al., 2012). In particular, it underlines that spatial inequalities in higher education opportunities are key in generating the latter.

Third, this paper relates to the literature evaluating place-based policies designed to mitigate inequalities across local labor markets. It typically investigates the role of firms' subsidies (Busso et al., 2013; Austin et al., 2018; Ku et al., 2020) and local infrastructure investments (Kline and Moretti, 2014). As human capital is portable, it remains unclear whether regions would benefit from investing directly in the production of local skills (Bound et al., 2004). The construction of higher education institutions is associated with increases in education and local economic development (Nimier-David, 2022; Howard et al., 2022). In contrast, Hsiao (2023) uses a spatial equilibrium model to show that a school construction program in Indonesia increased inequalities across urban and rural regions. In this paper, I instead take the spatial distribution of education options as fixed, given that the construction of colleges is limited in practice and could lead to inefficiencies due to potential agglomeration and peer effects, and study the potential for moving subsidies to increase local human capital. Kennan (2015) similarly takes as given this distribution to evaluate how tuition reductions would affect the supply of college graduates across states in the United States by extending the migration model of Kennan and Walker (2011). In this paper, as I find that mobility frictions are a key driver of students' human capital investments, I quantify the effects of subsidizing students' moving while taking into account the local supply they face at a very granular level. I show that mobility subsidies would increase regional trade in tertiary education services. When tied to incentives to return home, this would enable low-opportunity areas to outsource the education of their local labor force to higher education hubs.

Finally, I contribute to the literature on empirical models of two-sided matching. A couple of recent papers show that exclusion restrictions are necessary to identify preferences of agents on both sides of the market from data on realized matches only (Agarwal and Somaini, 2022; He et al., 2023). I show how to avoid such assumptions by exploiting additional data on programs' rankings of applicants and provide a tractable estimation procedure.

Overview The rest of the paper is organized as follows. Section 2 introduces the context and data. Section 3 describes the geography of the higher education market and explores the effects of mitigating barriers to students' mobility. Section 4 presents the model. Section 5 discusses the identification and estimation of agents' preferences. Estimation results and model fit are presented in Section 6. Section 7 describes counterfactual results. Finally, Section 8 concludes.

2 Context and Data

This section provides an overview of the French higher education market, before detailing the college admission procedure. Finally, it describes the data sources used throughout the paper.

2.1 The French Higher Education Market

Education in France is organized in a centralized manner, with the higher education system being managed by the Ministry of Higher Education and Research. It is administrated through thirty catchment areas (Figure A.1), implementing the directives of the Ministry within their area.

To access the higher education system, students have to take a national exam in their last year of high school.[1] After this exam, and conditional on receiving a passing grade, students can choose to pursue their education by enrolling in a higher education program. There are six main types of programs available, half of them targeting students willing to acquire a master's degree — they are the equivalent of four-year colleges in the United States. First, students can apply to three-year university programs, with the aim of obtaining a bachelor's degree — after three years — and a master's degree, after five years of education. Second, they can apply to two-year elite programs. These programs are highly selective and prepare students to take competitive exams for admission to the most prestigious public and private higher education institutions. Once enrolled in these elite schools, students will then typically continue their education and earn a master's degree. Third, there are also programs offered by engineering and business schools.

[1] Appendix B.1 provides more details about the high school system in France.

Additionally, there are three main types of short-term programs, providing more technical and vocational training. First, students can enroll in technology-oriented programs tailored to train mid-level technical professionals. Second, there are two-year vocational programs, with a stronger emphasis on internships. Finally, students can also apply to programs offered by social work and nursing schools, which train workers in two to three years. Details can be found in Appendix B.2.

2.2 College Admission Procedure

Since 2009, the higher education admission procedure is centralized and operates on an online platform.[2] Every year, students in their final year of high school register on this platform. An online search engine is available: students can specifically search for programs in a given major or location. A map allows students to locate each institution offering a certain major they may be interested in. A general presentation of each program can be found on the platform, as well as a description of the admission criteria and information regarding the number of seats and the number of applicants in the year before. Figures A.2 to A.7 present this interface, as well as the type of information students have access to.

After searching for programs, students submit their applications on the online platform. Programs consist of an institution-type-major combination. For instance, a student wishing to be considered for admission to a university program in either economics or mathematics at the Sorbonne University needs to submit two separate applications. In theory, the number of applications is limited to ten. However, the effective number of applications allowed is substantially larger in practice as, in many cases, several applications are processed as a single one. For example, listing up to ten different institutions offering a two-year elite program in physics would only count as one application. In the selected sample, which I define below, the mean number of applications is 10.6, and 25% of students submit 13 applications or more (Table A.3).

Once applications are submitted, each program observes its set of applicants and has to rank them. Applicants are ranked based on the information they and their high school submit on the platform. In particular, programs can access students' high school grades. They can also require students to submit a resume or a cover letter on the platform. Programs do not have to disclose how the different characteristics they observe are weighted to determine their

[2]See Appendix B.3 for a history of the admission system.

ranking: programs' preferences are thus unobserved. Interviews of members of admission committees, however, reveal that programs typically first choose the weights to assign to each observed characteristic.[3] These weights are then fed into an algorithm generating the ranking of applicants. The use of cover letters and resumes seems less common.

The ranking provided by programs is then modified to take into account some equity-based admission policies chosen by policymakers ex-ante. In particular, a minimum share of low-income students — defined by their scholarship eligibility — is targeted for each program. There are also place-based quotas for university programs, which specify the maximum share of out-of-catchment area students who can be admitted.

Once programs have finalized their ranking of applicants, the admission stage starts. Offers are released to students at the top of the programs' ranked-ordered list, up to the number of seats available. Students can thus receive several offers. When this is the case, they can accept one offer and decline the others. Rejected offers are sent dynamically to applicants remaining unmatched, following the initial ranking of each program. Students can also decide to delay their decision by holding on to their current offers, waiting for an offer from a program they prefer. Students observe both their rank on the waitlist and the rank of the last admitted student the year before, helping them predict whether they will receive an offer.

2.3 Data

I assemble a unique dataset, gathering the actions of the universe of applicants and programs on the college admission platform in France and tracking students until they exit the higher education system. I complement this information with a survey of individuals at entry on the labor market to understand individuals' location decisions. This section describes these different datasets.

College Admission System: First, I use administrative data from the college admission platform in France. It gathers information on the universe of college applicants each year. It includes a very rich set of students' characteristics, including their gender, the socio-economic status of their parents, their scholarship status, as well as their test scores. Importantly, I

[3]See 'Parcoursup : enquête dans les coulisses des commissions d'examen des vœux', Le Monde, Séverin Graveleau, Soazig Le Nevé et Eric Nunès. Published on May 23^{rd}, 2023. Last accessed: August 18^{th}, 2023.

also observe the precise location of residence of each student, at the ZIP code level — there are 37,901 ZIP codes in France. Table A.1 presents the average characteristics of the main sample of students considered throughout the paper. I focus on students living in metropolitan France and who are in high school at the time they apply. This represents a sample of 505,069 students in 2019.

This administrative dataset also gathers the universe of programs available on the platform. I observe the characteristics of each program, including its type, major, the number of available seats, and its GPS coordinates such that the distance between each program and student on the platform can be computed. I restrict attention to the 10,917 programs located in metropolitan France, excluding online programs. Table A.2 describes the average characteristics of this sample of programs.

Finally, this dataset covers in detail the application and admission steps. It gathers all applications submitted by each student. It also records the ranking of applicants by programs. It tracks the offers sent, students' acceptance and rejection decisions, and their final program of enrollment. Tables A.3-A.4 describe applications, offers and enrollment patterns.

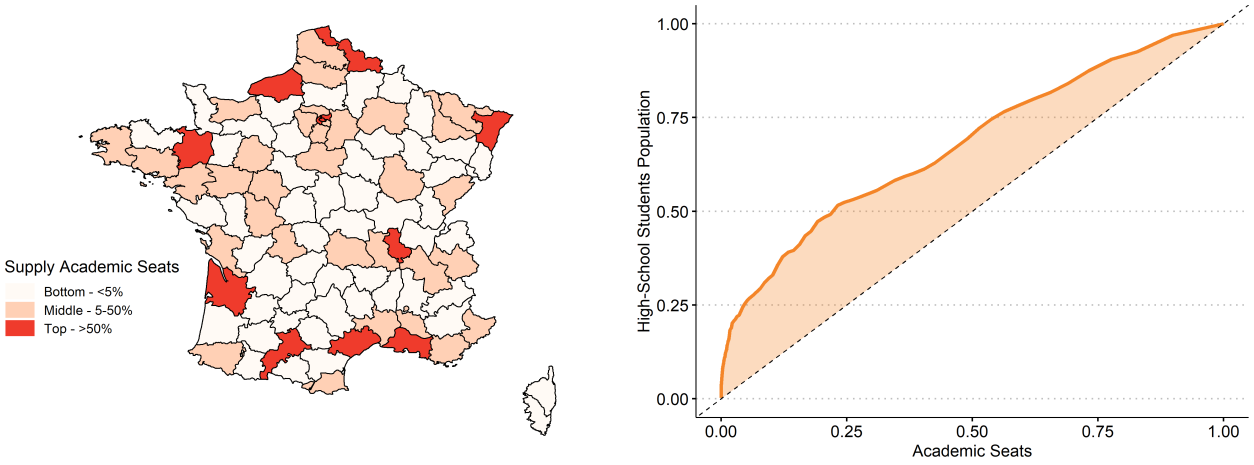
Higher Education Census: Second, I use an administrative dataset recording the path of each student enrolled in the French higher education system until their exit. As this dataset can be merged with the one described above, I can track students' path from their entry in the higher education system to the time they graduate or drop out. I observe whether students switch programs, the highest degree they obtain, and their province of graduation.

Location Choices and Earnings: I complement these datasets with a survey of individuals, following students after they exit the French education system. I restrict attention to students who graduated from high school. This dataset records the home, graduation, and work locations of each individual, such that their migration decisions are observed. The survey also reports individuals' wages within the three years after they left the education system. Table A.5 describes the work flows, study flows, and earnings of these individuals.

3 Descriptive Evidence and Policy Evaluation

In this section, I first provide descriptive evidence linking the geography of the higher education market to spatial inequalities in educational attainment and spatial skill sorting.

Figure 1: Distribution of the Supply of Academic Seats and High School Student Population



a) Spatial Distribution of Academic Seats **b) Student-Seat Mismatch**

NOTES. Panel a) presents a map of the distribution of academic seats in metropolitan France. Provinces are ranked according to their position in the distribution of academic seats. Provinces in white are at the bottom of the academic seats supply distribution: they jointly account for less than 5% of the total supply. In contrast, provinces in red are at the top of this distribution: half of the academic seats supply is concentrated there. Panel b) plots the relationship between the spatial distributions of academic seats and of high school students. It depicts the cumulative distribution of the supply of academic seats across provinces on the x-axis, and the corresponding cumulative distribution of the high school student population on the y-axis. Provinces are ranked according to the share of academic seats they offer. For example, provinces gathering 25% of the total supply of academic seats concentrate 50% of the population of high school students.

Second, I use local policies mitigating mobility frictions to explore their impact on students' demand, as well as their distributional effects.

3.1 Spatial Distribution of Colleges and Inequalities

I first document that the distribution of programs across space is uneven, and does not match the spatial distribution of the population of students. Second, I show that — consistently with the presence of (monetary and non-monetary) mobility costs — students' demand for higher education programs is elastic to geographic proximity. Overall, these patterns correlate with observed spatial gaps in enrollment choices and skill sorting.

3.1.1 Fact 1: Higher Education Programs are Unevenly Spatially Distributed

The spatial distribution of higher education programs is highly uneven. I focus on academic programs, combining university and two-year elite programs, which are the main paths to a bachelor's degree. Panel a) of Figure 1 maps the spatial distribution of first-year academic

Table 1: Number of Programs Around Students' Home Location

	Quantile			
	10^{th}	25^{th}	50^{th}	75^{th}
	(1)	(2)	(3)	(4)
Panel A: 10 kilometer-radius				
Three-Year University Program	0	0	0	29
Two-Year Elite Program	0	0	0	10
Engineering & Business Schools	0	0	0	6
Two-year Technical Programs	0	0	1	10
Two-year Vocational Programs	0	2	17	63
Nursing Schools	0	0	1	8
Panel B: 40 kilometer-radius				
Three-Year University Program	0	7	35	115
Two-Year Elite Program	0	3	11	34
Engineering & Business Schools	0	2	7	25
Two-year Technical Programs	2	6	13	29
Two-year Vocational Programs	30	53	93	268
Nursing Schools	1	4	9	24

NOTES. Number of programs, by program types, located within a given radius around students' home location. Panel A considers a ten-kilometer radius, while Panel B presents results for a forty-kilometer radius. I consider 40 kilometers as the threshold defining students' commuting zone, to the extent that 96% of the daily commuting trips in France are 40 kilometers or less. This table shows that 10% of the students have no three-year university programs located within a forty-kilometer radius around their home location.

seats at the province level. Of the 96 provinces of metropolitan France, ten do not offer a single academic seat.[4] Overall, half of the provinces jointly account for less than 5% of the total supply of academic seats. I refer to these areas as higher education deserts. In contrast, 50% of the total supply is agglomerated in only 12 provinces. Overall, the supply of academic seats is thus highly concentrated.

This geography of academic seats could, however, merely reflect the population distribution of students over space. Yet, Panel b) of Figure 1 illustrates that the spatial distribution of academic programs is far from mirroring that of high school students. Provinces concentrating less than 5% of the total supply of academic seats gather 25% of the high school student population. In contrast, only 28% of students live in one of the twelve provinces accounting for more than 50% of the total supply. There is thus an imbalance between the spatial distributions of academic seats and students.[5]

[4]In total, 17 provinces offer no university programs, while 18 provinces do not have any two-year elite programs.

[5]This imbalance contrasts greatly with the number of seats in two-year technological and vocational

As a result, a substantial share of students face very a low supply of academic programs close to their home location. Table 1 presents the distribution of the number of programs, by type, located within a 10- and 40-kilometer radius around students' home. I consider 40 kilometers as the threshold defining students' commuting zone, to the extent that 96% of the daily commuting trips in France are 40 kilometers or less.[6] I find that 50% of students do not have a single university, two-year elite, engineering or business program within ten kilometers from their home. Enlarging the radius to include any programs located within commuting distance, we observe that more than 10% of applicants cannot find any university or two-year elite programs within this boundary. A quarter of the students find at most seven university programs within commuting distance.[7] As each program corresponds to a specific major, this implies that these students have very few different majors available close to their home location, as illustrated by Table A.6. For example, 10% of the students have to travel at least 92 kilometers to reach a medicine program.

3.1.2 Fact 2: Students' Demand is Elastic to Geographic Proximity

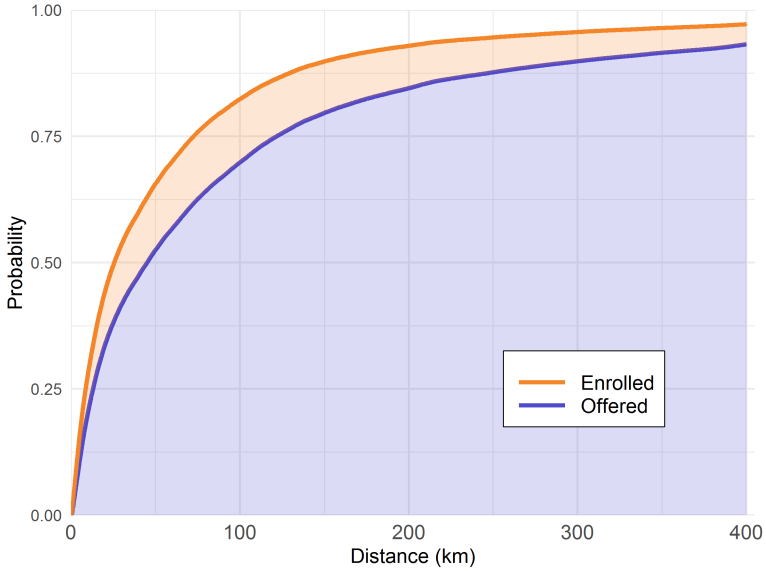
The concentration of academic programs across space would have no consequences on students' college choices unless they face some monetary or non-monetary moving costs. Such costs could include expenses for traveling to the study location, rent, as well as the emotional toll of being far away from family and friends. Students' enrollment patterns suggest that such costs are present and play a significant role in their higher education choices. As shown in Figure 2, 25% of students enroll less than 8.5 kilometers away from their home. The median distance of enrollment is only 25 kilometers. This pattern is not generated by the fact that students only receive admission offers from programs located very close to their home location. On the contrary, the distribution of the distance to the offers received (purple line) first-order stochastically dominates that of the distance to accepted offers (orange line). The median offer is located 20 kilometers farther away than the accepted one. This gap increases

programs, which is considerably more evenly distributed across space (Figure A.9) and thus better matches the spatial distribution of high school students (Figure A.10).

[6] According to the same study, in France, the average individual only makes 6.3 trips at more than 80 kilometers from their home each year. Source: SDES, Insee – Enquête Mobilité des Personnes 2018-2019. Data: 'La mobilité locale et longue distance des Français - Enquête nationale sur la mobilité des personnes en 2019', accessed at statistiques.developpement-durable.gouv.fr. Last accessed: October 9^{th}, 2023.

[7] Figure A.8 provides a map of the mean number of academic programs located within commuting distance of students' home location at the province level. The mean number of academic programs located within a 40-kilometer radius around students' home location is less than ten in 24 provinces.

Figure 2: Cumulative Distribution - Distance of Enrollment & Offers



NOTES. This figure shows the cumulative distribution function of the distance (in kilometers) between students and the program where they enroll (orange) and between students and the programs for which they receive offers (purple).

to 50 kilometers at the third quartile of the distribution.

This suggests that students favor programs closer to their home location, consistently with the existence of mobility frictions. To measure the elasticity to distance of students' enrollment patterns, I borrow from the migration and trade literature and estimate a gravity model. I regress the flow of students from a given province enrolling in programs located in each destination province, controlling for the distance between the centroids of the two locations and including origin and destination fixed effects, capturing differences across locations, such as local college supply.[8] I find an elasticity of enrollment to distance equal to -2.5 (Table A.7), which suggests that college choices are highly sensitive to distance from home.[9]

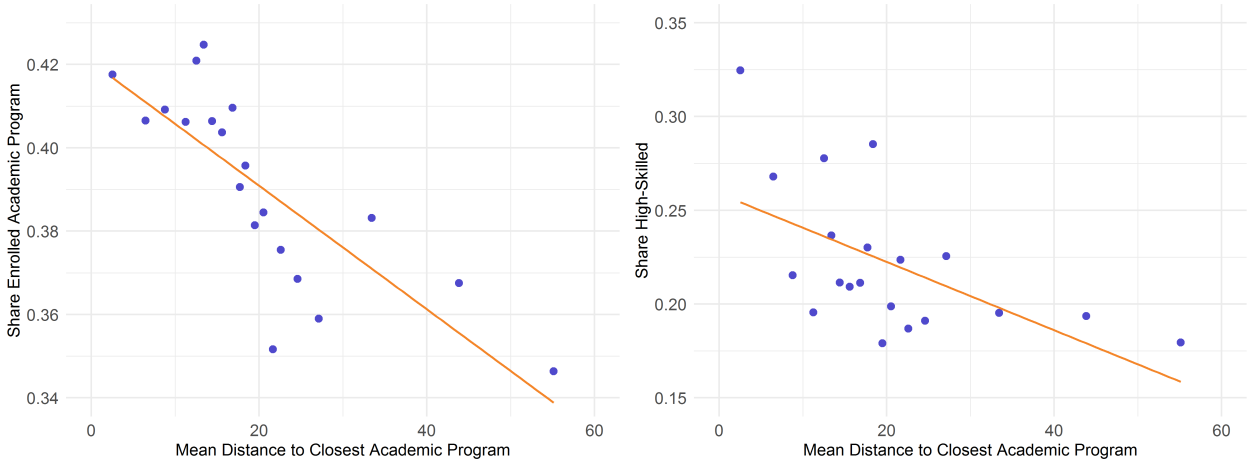
3.1.3 Implications: Spatial Inequalities

Overall, the interaction of mobility frictions with the uneven distribution of higher education programs is likely to generate important inequalities between students from higher education hubs and deserts. Panel a) of Figure 3 highlights the existence of a correlation between the share of students from a given province enrolled in an academic program and the local

[8] I estimate this model using a Pseudo-Poisson Maximum-Likelihood Estimation strategy. See Silva and Tenreyro (2006) on the advantages of using this approach to estimate gravity models.

[9] This elasticity is about 30% larger than that found for labor migration in France (Zerecero, 2021).

Figure 3: Higher Education Market Geography and Spatial Inequalities



a) Spatial Gaps in Academic Enrollment **b) Spatial Skill Sorting**

NOTES. Panel a) is a binned scatter plot, at the province level, of the relationship between the share of students from a province enrolled in an academic program and the mean distance (in kilometers) to the closest academic program for the average student of the province. Figure A.11 shows that a similar relationship holds for specific majors, such as medicine programs. Panel b) is a binned scatter plot, at the province level, of the relationship between the share of the total labor force of a province holding a three-year degree or more (share high-skilled) and the mean distance (in kilometers) to the closest academic program for the average student of the province.

availability of such programs.

Additionally, as individuals often choose to work in their home region — given moving costs and home bias (Kennan and Walker, 2011) — the previous correlation is likely to contribute to the skill sorting observed across local labor markets. We indeed observe a similar relationship between the share of a province's labor force with at least a three-year degree and the local availability of academic programs (Panel b) of Figure 3).

Both these correlations could be driven by other factors than mobility frictions — such as differences in students' pre-college human capital, preferences or returns to education across provinces. In Section 4, I build a model accounting for these other potential channels, allowing us to isolate how mobility frictions interact with the geography of the higher education market to generate spatial inequalities between students and across local labor markets.

3.2 Mitigating Mobility Frictions: Changes in Demand and Distributional Consequences

The above patterns suggest that mobility frictions within the higher education market generate spatial inequalities. To mitigate the latter, it would be key to break the dependence

between students' application decisions and their local supply of programs. In this section, I first show that moving subsidies allow students to apply farther away from their home location. Second, I explore the distributional effects of alleviating barriers to mobility, both within the higher education market and across local labor markets.

3.2.1 Mobility Scholarship and Changes in Students' Demand

Studying away from home entails direct expenses — such as travel costs and rents — which are likely to be an important component of mobility frictions. Could moving subsidies allow students to apply farther away from their home location? To answer this question, I evaluate a moving scholarship introduced in 2019, guaranteeing 500 euros to low-income students conditional on enrolling in a program located outside their catchment area. This amount covers a fraction of the costs associated with such a move, corresponding to approximately 9% of the annual budget of the average student.[10]

This program is only available to recipients of a means-based scholarship in high school, as a way to target low-income students. Using applications data from 2015 to 2019, I can thus compare the change in the application distance of eligible and non-eligible students, before and after the implementation of the policy. As several reforms of the admission system have been implemented over the years, potentially affecting differently the application behavior of students with different eligibility status, I use an additional comparison group. In particular, I compare the change in outcomes, before and after the introduction of the policy, of eligible (E) and non-eligible (NE) students living in provinces with low (L) and high (H) supply of higher education programs.[11] As they face many options close to their home location, the latter group is unlikely to be impacted by the reform. I estimate the following model:

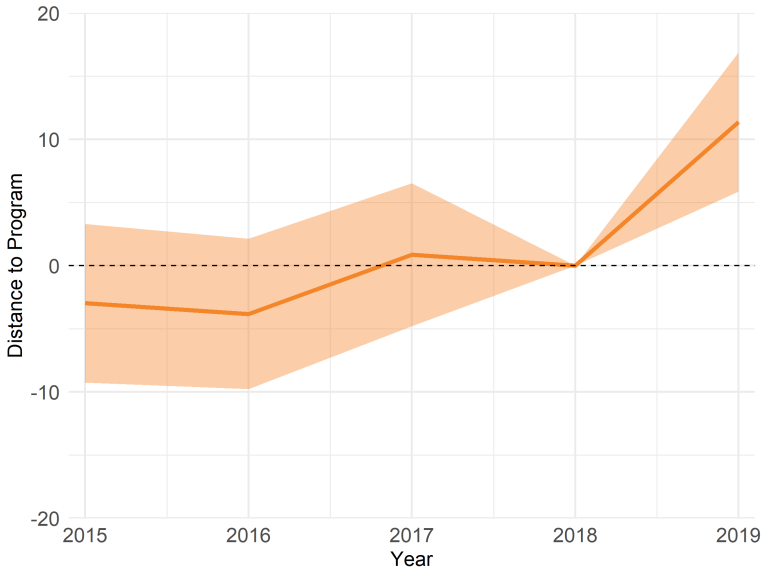
$$d_{i,e,s,t} = \alpha_{s,t} + \alpha_{e,t} + \alpha_{s,e} + \sum_{\tau=-3,\tau\neq 0}^{1} \beta_{2018+\tau} D_{e,s,2018+\tau} + \epsilon_{i,s,e,t} \tag{1}$$

where $d_{i,e,s,t}$ is the distance, in kilometers, between a student and the program to which she submits application i, in year t, while being of eligibility status $e \in \{E, NE\}$ and living in a province with supply level $s \in \{H, L\}$. $\alpha_{s,t}$ are supply level-year fixed effects controlling for the fact that changes in outcomes may have been different for students living in high-

[10] Source: Observatoire National de la Vie Etudiante.

[11] I define as high-supply areas the ten provinces at the top of the supply distribution. Low-supply areas are defined as the bottom five provinces of the supply distribution.

Figure 4: Effect of the Spatial Mobility Scholarship on Application Distance



NOTES. This figure presents parameter estimates of $\beta_{2018+\tau}$ from Equation (1). It shows the effect of the policy offering moving subsidies, implemented in 2019, on the mean application distance, in kilometers. 95% confidence intervals are shown, computed using robust standard errors. These estimates are displayed in Table A.8.

or low-supply areas, regardless of their eligibility status. $\alpha_{e,t}$ are eligibility status-year fixed effects. They control for differences in trends between eligible and non-eligible students that are common across areas. Finally, $\alpha_{s,e}$ capture application behaviors for students with a given eligibility-location status that are constant over time. $D_{e,s,2018+\tau}$ is a dummy equal to one for students eligible for the scholarship and living in a low-supply area in year $2018 + \tau$, for $\tau \in \{-3, 1\} \setminus \{0\}$. I let its associated parameter vary across years. $\beta_{2018+\tau}$ is thus a triple-difference estimator, as it estimates the relative treatment effects for eligible students in the low- versus high-supply areas.

The identifying assumption is that, in the absence of the treatment, the relative evolution of outcomes for eligible and non-eligible students would be the same in high- and low-supply areas (Olden and Møen, 2022). Details are provided in Appendix C.1. I test this common trends assumption through placebo tests involving years prior to the policy implementation.

Figure 4 and Table A.8 present estimates of $\beta_{2018+\tau}$ for different years before and after the implementation of the policy, in 2019. I find that the moving subsidy allowed eligible students from low-supply areas to apply to programs located farther away from their home location. The reform was associated with an 11-kilometer increase in the distance to programs to which students apply. I find no pre-trends in the years prior to the implementation of the reform. Table A.8 shows that the impact of the policy is driven by an increase in the share of out-of-

catchment area applications. However, this did not translate into a significant increase in the share of offers received from out-of-catchment area programs, such that enrollment patterns were not affected.

Overall, these results suggest that students are willing to apply farther away when mobility frictions are softened, for example through moving subsidies. While the latter may allow students to apply to programs they prefer, the policy evaluation above does not allow us to quantify this effect. Furthermore, applications may fail to translate into admissions, as the market is two-sided: programs choose which applicants to admit.

3.2.2 Distributional Effects of Alleviating Barriers to Mobility

Alleviating mobility frictions alters students' demand. Such changes may entail substantial distributional effects, especially given the two-sided nature of the market and capacity limits: students can only enroll in a program admitting them. In this section, I investigate these distributional effects. First, I use a local policy change to show that eliminating barriers to students' mobility generates a brain drain toward higher education hubs in the short run. I then use survey data to illustrate how, if happening at the scale of the country, such a brain drain could be long-lasting as there exists stickiness in location choices.

Distributional Effects — Higher Education Market I first focus on the short run and present evidence suggesting that removing barriers to mobility is associated with a brain drain of students toward regions concentrating high-quality programs. To show this, I zoom in on the Greater Paris area, which is composed of three catchment areas: Paris, Versailles and Créteil.[12] While several universities are present in the region, Paris concentrates high-quality institutions, attracting students from the entire area. Geographic priorities — akin to quotas used by public universities in the United States, capping the share of out-of-state admitted students — were, however, limiting the admission chances of students living outside of Paris, up to 2018.[13] Table A.10 shows how these priorities affected the final ranking of students: on average, a student from Versailles applying to a program in Paris was down-ranked by

[12]Figure A.13 presents a map of the area and Table A.9 shows summary statistics of programs located in the region.

[13]In the United States, in 2017, the University of California for example implemented an 18% cap on out-of-state enrollment. See 'A bold plan for UC: Cut share of out-of-state students by half amid huge California demand', Los Angeles Times. Published on May 25^{th}, 2021. Last accessed: October 10^{th}, 2023.

483 positions after their implementation, while the average rank of the last-admitted student was 1,000. In 2019, to equalize the playing field, these geographic priorities were removed.

I evaluate how this reform impacts student sorting within the higher education market. In particular, I consider the following model:

$$y_{j,\ell,t} = \alpha_j + \sum_{\ell} \beta_\ell D_{\ell,t} + \epsilon_{j,\ell,t} \tag{2}$$

where $y_{j,\ell,t} = \frac{n^H_{j,\ell,t}}{n_{j,\ell,t}}$ is the share of high-ability students admitted by program j from location $\ell \in \{\text{Paris}, \text{Versailles}, \text{Créteil}\}$ in year t, with $n_{j,\ell,t}$ ($n^H_{j,\ell,t}$, respectively) the number of students (high-ability students, respectively) admitted by j in period t. High-ability students are those graduating from high school with honors or with the highest honors. I also consider the share of high-ability applicants to program j to investigate direct changes in demand. α_j are program fixed effects, capturing constant differences in $y_{j,\ell,t}$ across programs. $D_{\ell,t}$ is a dummy variable equal to one for university programs in location ℓ and in $t = 2019$, i.e. after the reform. I allow the reform to impact differently programs according to their location.

Table 2 presents parameter estimates from Equation (2). I find that this reform generated a brain drain of students from peripheral regions toward programs located in Paris. In particular, the share of high-ability students from Versailles enrolling in programs in Paris increased by 50% after the reform (Column (1)). In contrast, the share of high-ability students from Versailles enrolling in their local universities decreased by 25%. These students thus enrolled in universities located in Paris instead of their local institutions, revealing a brain drain.[14]

As the number of seats is limited, this brain drain had further consequences for overall sorting. Indeed, students from the peripheral areas crowded out low-ability students from Paris from their local universities: their share decreased by 31%, from a baseline of 22% when they were receiving priority (Column (3)). In turn, the share of low-ability students from Paris enrolled in universities located in the peripheral areas significantly increased.

Table A.11 shows that these enrollment effects were largely driven by programs being able to express their preferences without being subject to geographic priorities anymore, rather than by changes in demand spurred by the reform. The change in the share of

[14]We do not observe such movements for students from Créteil. This is consistent with the presence of geographic variation in students' schooling achievement: the share of students classified as high-ability is 6.5 points larger in Versailles than in Créteil.

Table 2: Removing Barriers to Mobility: Sorting Effects

	Share High-Ability		Share Low-Ability
	from Versailles	from Créteil	from Paris
	(1)	(2)	(3)
β_{Paris}	0.025***	0.009	-0.069***
	(0.007)	(0.007)	(0.015)
$\beta_{\text{Versailles}}$	-0.029***	-0.000	0.022***
	(0.010)	(0.003)	(0.001)
$\beta_{\text{Créteil}}$	0.003	-0.006	0.024***
	(0.002)	(0.004)	(0.006)
Baseline Paris	0.049	0.048	0.220
Baseline Versailles	0.114	0.013	0.030
Baseline Créteil	0.009	0.053	0.047
Program FE	Yes	Yes	Yes
Observations	680	680	680

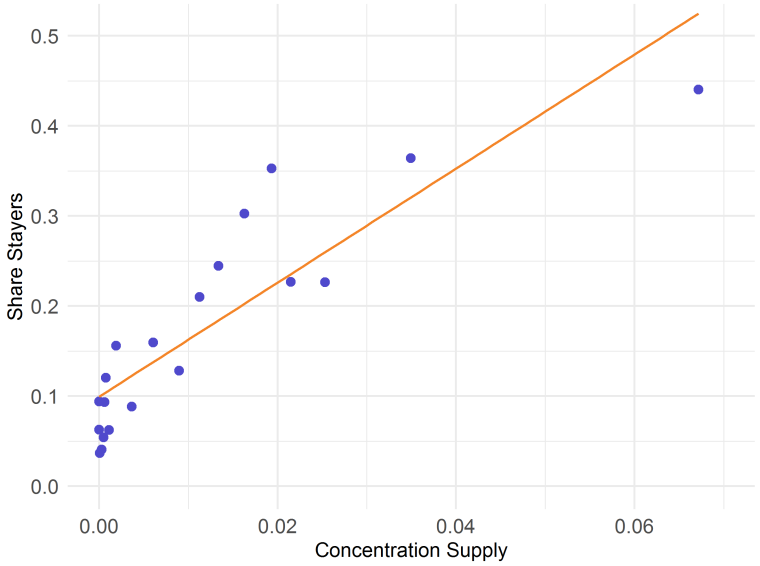
NOTES. This table presents estimates from Equation (2). I study the effect of removing barriers to mobility on the share of high-ability students from Versailles (Column (1)), the share of high-ability students from Créteil (Column (2)) and the share of low-ability students from Paris (Column (3)) enrolled in programs located in Paris, Versailles and Créteil. Standard errors clustered at the program level are shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

applications from high-ability students from Versailles to Paris is much smaller than the observed enrollment increase. This indicates that programs' admission decisions are key in shaping the equilibrium of the higher education market.

These results are robust to accounting for other factors that may have affected the higher education market at the same time (Tables A.12-A.13). In particular, I use non-university programs, which never faced geographical restrictions, as a control group (see Appendix C.2). This is akin to implementing a difference-in-differences where the groups compared share the same treatment status at endline, also known as reverse difference-in-differences (Kim and Lee, 2019). Fabre (2023) discusses the identification of treatment effects in such alternative difference-in-differences designs. Overall, these results suggest that alleviating mobility frictions may have important effects on students sorting within the higher education market.

Distributional Effects — Local Labor Markets If happening at the scale of the country, such a brain drain within the higher education market may, in turn, have long-lasting consequences for regional inequalities. Using data recording individuals' migration flows between their home, study and work locations, I indeed find that a substantial share of students

Figure 5: Contribution of the Student Population to the Non-Local Labor Force



NOTES. This binned scatter plot highlights the correlation between the concentration of the supply of academic programs and the capacity of provinces to retain students upon graduation. The x-axis measures the concentration of the supply in a given province through the share of academic seats located there. The y-axis displays the share of the non-local labor force of a province who graduated there.

graduating outside their location of origin enter the labor market elsewhere. Table A.5 shows that, among the 51% of students graduating outside their home location, more than half do not return at entry on the labor market. In contrast, only 18% of individuals studying in their home province enter the labor market in a different location.

Conditional on studying outside their home location, 17% of individuals enter the labor market in their study location. Location choices thus seem to display stickiness, with individuals having a high probability of contributing to the labor force of their study location. Higher education hubs benefit from this, as they can retain this population, as shown in Figure 5.

Overall, the extent to which mobility frictions generate inequalities across students living in different locations depends on two elements. First, it hinges upon students' preferences. The scholarship evaluated above hints at the fact that subsidizing moving costs could change students' applications, but does not allow us to pin down how students trade-off proximity and other programs' characteristics. Second, evidence shows that programs' admission decisions also matter. Initial spatial inequalities, such as differences in school quality and test scores, could then limit admission chances of students from low-opportunity areas, regardless of the

geography of the higher education market.

Regarding local labor markets, mobility frictions may act as a constraint on the human capital investment of the local population of higher education deserts. Yet, the above evidence suggests that such frictions could in fact limit the brain drain of workers from low- to high-opportunity areas, as students who leave to study do not necessarily return home upon graduation. This choice ultimately depends on preferences over locations' characteristics — such as wages and amenities — and moving costs.

In what follows, I build a framework flexibly incorporating the above channels. It includes a rich model of students' preferences over programs, accounting for mobility frictions. Importantly, students are forward-looking: they take into account how their enrollment choice may affect their location decision at entry on the labor market, through moving costs and location-specific amenities and returns to education. The higher education market is at equilibrium and takes into account programs' preferences over students. Overall, the model allows us to isolate how mobility frictions interact with the geography of the higher education market to generate spatial inequalities, both between students and across local labor markets.

4 Model

In this section, I build a dynamic model combining an equilibrium model of the higher education market, where students are forward-looking, with a model of location choices at entry on the labor market. I consider a two-stage framework, where the timing is as follows. In the first period, a set of high school students $\mathcal{I}$ and a set of higher education programs $\mathcal{J}$ meet on a centralized platform, where they can express their preferences over one another. A match between students and programs is formed on the platform. In the second stage, individuals exit the education system with a certain degree and choose the location in which to enter the labor market, from a set of locations $\mathcal{L}$.

In what follows, I first describe agents' preferences at each stage of the model. I then discuss how they map into choices and outcomes by detailing the equilibrium assumptions.

4.1 Preferences

I present the model backward, starting with payoffs from individuals' location decisions at entry on the labor market. I then describe students' and programs' payoffs within the higher

education market. Finally, I discuss the assumptions I impose on preferences.

4.1.1 Labor Market Location Decision: Payoffs

The second stage of the model takes place after graduation: individual $i \in \mathcal{I}$ chooses which local labor market $\ell \in \mathcal{L}$ to enter. The utility of individual i from choosing a given local labor market ℓ depends on the wage she would receive in this location, as well as other location attributes. This utility varies according to two types of individual's characteristics, h_i and y_i. The first vector collects variables determined before the individual enters the higher education system. The second object is a vector of state variables, which are influenced by the enrollment decisions of the student in the first stage, such as the degree obtained and the location at graduation. The utility from entering the labor market in location ℓ for individual i then writes:

$$\mathcal{W}_{i\ell} = w_{i\ell} + \omega(h_i, y_i, m_\ell) + \frac{1}{\theta}\nu_{i\ell} \tag{3}$$

where $w_{i\ell}$ is the expected monthly wage of individual i in location ℓ, and $\omega(h_i, y_i, m_\ell)$ is the value that an individual with characteristics (h_i, y_i) would receive from location ℓ's attributes, m_ℓ, such as its amenities. $\nu_{i\ell}$ is the idiosyncratic shock of individual i for location ℓ. θ controls the relative importance of the deterministic component of the utility relative to the shock.

4.1.2 Higher Education Market: Students' and Programs' Payoffs

The first stage of the framework is an equilibrium model of the higher education market, taking into account its two-sided nature. Indeed, students cannot simply choose in which program to enroll, as programs have capacity constraints. I consider a market where students and programs meet and express their preferences over one another on a centralized market. Before defining the equilibrium concept, I first formalize the payoffs derived by students when enrolling in a given program, and those of programs when admitting a given student.

Students' Preferences Over Programs On the platform, students observe program j's characteristics, $z_j, \forall j$. The payoff derived by student i when enrolling in program j is assumed to write as follows:

$$\mathcal{U}_{ij} = u(x_i, z_j) - c(x_i, d_{ij}) + \sigma\epsilon_{ij} + \bar{U}(x_i, h_i, z_j) \tag{4}$$

This payoff has two parts. First, students derive a flow utility from enrolling in a given program. $u(x_i, z_j)$ is the value from enrolling in program j, and is a function of student i's characteristics, x_i, and program j's characteristics, z_j. I detail in Section 5.1 how x_i and h_i may differ. $c(x_i, d_{ij})$ captures mobility frictions associated with enrolling to program j, as a function of student i's characteristics and the distance between i and j. I denote the outside option $0_{\mathcal{J}}$, and normalize to zero $u(x_i, z_{0_{\mathcal{J}}})$ and $c(x_i, d_{i0_{\mathcal{J}}})$.[15] ϵ_{ij} is an idiosyncratic preference shock. The parameter σ controls the scale of this shock.

Second, students are assumed to be forward-looking: they take into account that their choice on the higher education market will influence their outcomes in stage two, i.e. when they choose which local labor market to enter. This captures the fact that students anticipate that moving in the future may be costly, which makes labor market opportunities in their study location, as well as amenities, key when choosing where to enroll. Overall, $\bar{U}(x_i, h_i, z_j)$ captures the discounted expected value of choosing the optimal location in stage two for a student with characteristics (x_i, h_i), given the characteristics of program j. In particular:

$$\bar{U}(x_i, h_i, z_j) = \int \beta^{t(y_i)} \mathbb{E}\left[\max_{\ell \in \mathcal{L}} \left(w_{i\ell} + \omega(h_i, y_i, m_\ell) + \frac{1}{\theta}\nu_{i\ell}\right) | y_i\right] f\left(y_i | x_i, h_i, z_j\right) dy_i \quad (5)$$

where $f\left(y_i | x_i, h_i, z_j\right)$ captures the transition probability to graduate with state variables y_i, given student i's initial characteristics, (x_i, h_i), and the characteristics of program j, z_j. It will for example capture the probability that a student graduates with a certain type of degree, given both her characteristics and the characteristics of the chosen program. This is as in Kennan (2015), which also models graduation as the outcome of a stochastic process. Students thus know that each program is associated with a different probability of graduating with a given degree, depending on both x_i and z_j, as will be described below. β is the discount factor, and its exponent depends on the state variables of student i at graduation. It takes into account that individuals enter the labor market at different stages depending on the length of their studies. The scale of this continuation value is normalized by the relative importance of the deterministic part of the utility to the idiosyncratic shock in stage two.

As the scale of $\bar{U}(x_i, h_i, z_j)$ is fixed, due to the normalization of the wage parameter in $\mathcal{W}_{i\ell}$, I let the scale of the idiosyncratic part of the flow utility associated with program j,

[15] The outside option consists in not matching to any program available on the platform. As the latter gathers the quasi-universe of higher education programs in France, the outside option can be thought of as dropping out of the higher education system.

σ, free. Normalizing this scale to one, as is typically done in practice, would be a strong assumption in this model as it is a non-stationary framework. In particular, the choices made in the first and second stages are very different, while normalizing the scale of ϵ_{ij} to one would be equivalent to fixing the relative scale of utility in both stages one and two. I show how to identify this parameter thanks to an exclusion restriction in Section 5.1.

Supply Side: Program-Specific Score On the platform, programs observe applicants' characteristics, (x_i, h_i). While programs can express their preferences over applicants, they have to take into account some equity objectives imposed by the government. For example, scholarship-eligible applicants benefit from an affirmative action policy. Admission decisions are thus based on programs' preferences after they internalized the preferences of the government. These preferences can be captured by an applicant-program specific score, depending both on the student's and program's characteristics. The final score of applicant $i \in \mathcal{I}$ for program $j \in \mathcal{J}$ is defined as:

$$\mathcal{V}_{ji} = v(x_i, h_i, z_j) + \eta_{ji} \tag{6}$$

where $v(x_i, h_i, z_j)$ is the deterministic part of this score, depending on both students' and programs' characteristics. I normalize to zero the flow utility associated with programs' outside option, denoted $0_{\mathcal{I}}$, which captures that programs may decide to leave a seat empty. η_{ji} is an idiosyncratic preference shock.

4.1.3 Assumptions

I define here the regularity conditions and distributional assumptions I impose on agents' preferences. In particular:

Assumption 1

(i) The functions $\omega(.)$, $u(.)$, $c(.)$ and $v(.)$ are bounded.

(ii) $\nu_{i\ell}$, ϵ_{ij} and η_{ji} are independently distributed from a Type I Extreme Value distribution.

Assumption 1.(i) is satisfied in most settings. Assumption 1.(ii) is standard in the literature using dynamic discrete choice models, and stems from the fact that the distribution of unobserved shocks cannot be identified in these models (Magnac and Thesmar, 2002). It however

implies the independence of irrelevant alternatives property. In Section 5.2.5, I explore how to relax this assumption by adding unobserved heterogeneity.

4.2 Equilibrium

In this section, I characterize the equilibrium of the model. I start by describing individuals' optimal behavior when they enter the labor market. I then detail programs' optimal behavior on the platform, before defining the higher education market equilibrium.

4.2.1 Individuals' Location Decisions on the Labor Market

In the second stage of the model, taking place upon graduation, students choose in which local labor market to enter. In particular, they choose the location maximizing their second-stage payoff. Individual i will choose to enter location ℓ^* such that:

$$\ell^* = \arg\max_{\ell \in \mathcal{L}} \mathcal{W}_{i\ell}$$

When choosing which location to enter, individuals take into account the expected monthly wage they can receive in each local labor market ℓ, $w_{i\ell}$. In particular, I define $w_{i\ell} = E[w^*_{i\ell}|h_i, y_i]$ where $w^*_{i\ell}$ is a latent variable such that:

$$w^*_{i\ell} = w_\ell(h_i, y_i) + \tilde{\epsilon}_{i\ell}$$

where $\tilde{\epsilon}_{i\ell}$ is an idiosyncratic shock with zero-mean, independently distributed across i and ℓ, that the individual does not observe prior to choosing location ℓ, as in Kennan and Walker (2011). $w_\ell(h_i, y_i)$ is a function defined in Section 5.

This wage equation is very flexible, as it allows for differential returns to education across local labor markets through y_i, which includes the degree at graduation. This is thus consistent with a labor demand model allowing for degree-specific and location-specific exogenous productivity, as in Diamond (2016).[16] Note, however, that it does not allow for individuals' location choices to influence wages in equilibrium, which rules out the existence of within-location spillovers across workers and imperfect substitutability of workers with different

[16]The current wage equation is consistent with perfectly competitive local labor markets and a production function of the form $Y_\ell = \sum_s A_{\ell s} L_{\ell s}$, where Y_ℓ is the output in location ℓ, $A_{\ell s}$ is the location-specific productivity of workers of skill level s and $L_{\ell s}$ is the number of workers with skill level s in ℓ.

skills (Katz and Murphy, 1992). These effects are likely to be second-order in the short run, as I consider the location decisions of *entry-level workers* only, which represents a small fraction of the overall labor supply.[17]

4.2.2 Higher Education Market: Programs' Ranking of Applicants

On the platform, programs provide a ranking of applicants based on the student-program specific score defined in Equation (6), reflecting programs' preferences over applicants after having internalized the equity objectives of the government. This implies that the student ranked r^{th} by program j, denoted $i^*_{j,r}$, has the highest program j-specific score among applicants who have not been ranked higher, that is:

$$i^*_{j,r} = \underset{i \in \mathcal{A}_j \setminus \{i^*_{j,k}\}_{k=1}^{r-1}}{\arg\max} \mathcal{V}_{ji} \tag{7}$$

where $\mathcal{A}_j$ is the set of applicants to program j, including the outside option $0_{\mathcal{I}}$.

The above equation is implied by the assumption that rankings of applicants are a truthful reflection of programs' preferences, after taking into account policymakers' objectives. While programs do not have to disclose how their ranking decisions are made, this assumption is consistent with interviews of members of admission committees covering a broad range of programs, as discussed in Section 2. Admission officers state that they typically use an algorithm to rank students, where they first choose the weights they assign to each observed characteristic to reflect its importance in the admission decision. This behavior is made easier as the platform provides an online tool to generate a truthful ranking based on the program's chosen weights. This ranking is then modified to take into account the equity objectives of the government if not already met throughout the initial ranking provided.[18]

4.2.3 Higher Education Market: Equilibrium

Finally, I define the higher education market equilibrium. On this market, each student i is matched to a program $j \in \mathcal{J} \bigcup \{0_{\mathcal{J}}\}$. I assume that this final match is stable. A matching

[17] In future work, I plan to extend the model by including a location-specific labor demand allowing for spillovers across workers and imperfect substitutability across skill types, following Diamond (2016).

[18] For example, if most scholarship-eligible students have been ranked by the program at the bottom, the initial ranking would be modified to up-rank some of these students. These changes preserve 1) the initial ranking between scholarship-eligible students and 2) the initial ranking between non scholarship-eligible students.

between students and programs is stable if there exists no student-program pair that would like to break from their current match to re-match to each other (Gale and Shapley, 1962). Formally, this means that there is no (i, j)-pair, with $i \in \mathcal{I} \bigcup \{0_{\mathcal{I}}\}$ and $j \in \mathcal{J} \bigcup \{0_{\mathcal{J}}\}$, such that:

$$\mathcal{U}_{ij} > \mathcal{U}_{i\mu(i)} \text{ and } \mathcal{V}_{ji} > \mathcal{V}_{j\mu(j,\mathcal{R}_j)} \tag{8}$$

where $\mu(i)$ is the program to which student i is currently matched, $\mathcal{R}_j$ is the rank of the last-admitted student by program j and $\mu(j, \mathcal{R}_j)$ is the identity of this student. Such an equilibrium exists as long as there are no complementarities between admitted students. This assumption is met mechanically by the behavior of admission officers: they rank applicants individually, examining their characteristics separately, while admission offers are sent following this ranking. Regarding uniqueness, Azevedo and Leshno (2016) prove that a continuum model, where a finite number of programs are matched to a continuum of students, typically has a unique stable matching. They further prove that all of the stable matchings of a discrete economy converge to this unique stable matching of the continuum economy.[19] With its very large number of applicants, the French college admission system qualifies as a large discrete economy.

The definition of stability implies that, on the higher education market, each student is matched to the program they prefer among the set of programs willing to admit them. We can thus write this match as the solution of a discrete choice model with individual-specific choice sets (Fack et al., 2019):

$$\mu(i) = \underset{j \in \mathcal{F}_i \bigcup 0_{\mathcal{J}}}{\arg\max} \mathcal{U}_{ij}$$

where $\mathcal{F}_i$ is the set of programs which would admit student i, i.e. student i's *feasible set*. It is defined as the set of programs preferring to admit student i over their last-admitted applicant:

$$\mathcal{F}_i = \{j \in \mathcal{J} : \mathcal{V}_{ji} > \mathcal{V}_{j\mu(j,\mathcal{R}_j)}\} \tag{9}$$

Note that if a program leaves at least one seat empty, the identity of the last-admitted student will be the outside option, with associated utility $\mathcal{V}_{j0_{\mathcal{I}}}$. Such a situation can happen in two scenarios. First, a program may deem some applicants undesirable and prefer to keep some seats unfilled rather than admitting them. In other words, the program chooses the outside option over these applicants. Second, programs may receive fewer applications than seats.

[19] A discrete economy is an economy with a finite number of students.

In both cases, the program would then be feasible for a student i only if the latter is more desirable than the outside option.

Overall, assuming that the equilibrium is stable allows us to write the observed match as a function of the primitives of the model without having to take a stand on students' application behavior. Stability only requires that each student applies to their preferred feasible program. This is consistent with several plausible application strategies, making it a good approximation of what happens on the platform. For example, the equilibrium would be stable as long as students submit applications to the programs they prefer to the outside option and accept their favorite offer among the ones they receive.[20] While the number of applications is limited to ten in theory, which would make such behavior less plausible, the effective number of applications allowed is much larger in practice: applications to different institutions offering the same program type and major are typically processed as one. As a result, 25% of applicants submit more than 13 applications, while the maximum number of applications observed in the data is 162 (Table A.3).

A second plausible application behavior is that students are strategic: they submit applications maximizing their expected utility. In this case, a stable equilibrium is likely to arise when students are able to anticipate which programs are feasible. This is made easier by the fact that we are in the presence of a very large market, with many students and many seats per program. In such a setting, admission probabilities become close to degenerate, such that it is unlikely that students with rational expectations omit their favorite feasible program from their application portfolio (Fack et al., 2019). In particular, I find that the correlation between the rank of a program's last admitted student in 2018 and 2019 is 0.96, supporting the idea that applicants can anticipate whether a program is feasible or not.

5 Identification and Estimation

In this section, I first show how the primitives of the model can be identified from data on individuals' location decisions at entry on the labor market, programs' rankings of applicants, and realized matches on the higher education market. Importantly, identification does not

[20] Note that many studies of school-choice mechanisms assume that students are truthful (Abdulkadiroğlu et al., 2017; Abdulkadiroğlu et al., 2020): they rank programs following their preferences. The behavior described above can thus be thought of as a less stringent version of this assumption, as students do not have to rank programs on the French college admission platform.

rely on any functional form assumptions on the deterministic part of utility functions. I then present the estimation strategy.

5.1 Identification

I describe the identification argument, which works by backward induction. I first show that preferences over locations can be identified from data on location choices at entry on the labor market. I then turn to the first stage of the model and describe how to identify programs' preferences over students from observed rankings of applicants by programs. Finally, I show how to identify students' preferences over programs from data on realized matches. An exclusion restriction allows us to identify the scale of students' idiosyncratic preference shocks, avoiding fixing the relative scale of payoffs across stages of the model.

5.1.1 Individuals' Preferences over Locations

After graduation, students choose which local labor market to enter. At this stage, the model becomes a static discrete choice model. Let us denote $\boldsymbol{m}$ the vector collecting locations' characteristics and $\boldsymbol{w}_i$ the vector collecting individual i expected wages across locations. Assumption 1 allows us to directly map the share of individuals with characteristics (h_i, y_i) working in location ℓ, $\forall \ell \in \mathcal{L}$, denoted $\Pr(\ell^* = \ell | h_i, y_i, \boldsymbol{m}, \boldsymbol{w}_i)$, to the deterministic part of individuals' preferences over local labor markets:

$$\Pr(\ell^* = \ell | h_i, y_i, \boldsymbol{m}, \boldsymbol{w}_i) = \frac{\exp(\theta(w_{i\ell} + \omega(h_i, y_i, m_\ell)))}{\sum_{\kappa \in \mathcal{L}} \exp(\theta(w_{i\kappa} + \omega(h_i, y_i, m_\kappa)))} \tag{10}$$

The left-hand side of the above equation can be directly identified from data recording the location choices of individuals upon graduation. As this mapping can be inverted, we can thus recover θ and $\omega(h_i, y_i, m_\ell)$. Details of the proof can be found in Appendix C.3.

From this, the continuation value associated with a program with characteristics z_j chosen by a student with characteristics (x_i, h_i) can be identified. It writes:

$$\bar{U}(x_i, h_i, z_j) = \frac{1}{\theta} \int \beta^{t(y_i)} \left(\gamma + \log \left[\sum_{\ell \in \mathcal{L}} \exp(\theta(w_{i\ell} + \omega(h_i, y_i, m_\ell))) \right] \right) f\left(y_i | x_i, h_i, z_j\right) dy_i$$

where γ is the Euler constant and transition probabilities $f\left(y_i | x_i, h_i, z_j\right)$ can directly be identified from data recording each student's path within the higher education system. This

captures, in particular, the probability that a student with characteristics (x_i, h_i) enrolling in a program with characteristics z_j graduates with a certain degree.

5.1.2 Program-Specific Student's Score

Programs observe applicants and rank them based on the student's program-specific score defined in Equation (6). Let us denote $\boldsymbol{x}$ and $\boldsymbol{h}$ the vectors collecting x_i and h_i, respectively, for all i. Under Assumption 1, the probability that student i is ranked r^{th} by program j, denoted $\Pr(i^*_{j,r} = i|\boldsymbol{x}, \boldsymbol{h}, z_j)$, has a closed-form expression:

$$\Pr(i^*_{j,r} = i|\boldsymbol{x}, \boldsymbol{h}, z_j) = \frac{\exp(v(x_i, h_i, z_j))}{\sum_{a \in \mathcal{A}_j \setminus \{i^*_{j,k}\}_{k=1}^{r-1}} \exp(v(x_a, h_a, z_j))} \tag{11}$$

The left-hand side of this equation is directly identified from data on the final rankings of applicants by each program on the platform. Again, this mapping can be inverted, such that we can now recover $v(x_i, h_i, z_j)$. Details are provided in Appendix C.4.

5.1.3 Students' Preferences Over Programs

Finally, given the parameters identified above, I show that one can identify students' preferences from realized matches. Note that when programs' preferences over students, $\mathcal{V}_{ji}$, are perfectly observed, one can directly construct each student's feasible set. This is the case in many school choice systems, where the criteria and weights used to rank students are publicly available. In such settings, identification of students' preferences is direct as the match can be written as the solution of a discrete choice model with *observed* student-specific choice sets (Fack et al., 2019).

Yet, in the French higher education context, students' program-specific scores are not observed, which prevents constructing $\mathcal{F}_i$ directly. This is the case in most college admission processes, such as in the United States and the United Kingdom, where universities base their decisions on a discretionary combination of test scores, GPA, and extra-curricular information. Agarwal and Somaini (2022) and He et al. (2023) conclude that, in such settings, two different types of exclusion restrictions are necessary to identify students' preferences from realized matches: both a variable shifting only students' preferences and one shifting only feasible sets are needed, but may be difficult to find in practice.

I now show how additional data on programs' rankings of applicants allows us to circumvent the need for such exclusion restrictions. In particular, the share of students with observable characteristics (x_i, h_i) who are matched to program j writes:

$$\Pr(\mu(i) = j|x_i, h_i, \boldsymbol{z}) = \left[\sum_{\mathcal{F}\in\mathbf{F}} \Pr(\mathcal{F}_i = \mathcal{F}|x_i, h_i, \boldsymbol{z}) \Pr(\mathcal{U}_{ij} \geq \mathcal{U}_{ik}, \forall k \in \mathcal{F}|x_i, h_i, \boldsymbol{z})\right] \times \Pr(j \in \mathcal{F}_i|x_i, h_i, \boldsymbol{z}) \quad (12)$$

where $\mathbf{F}$ is the set of all potential feasible sets and $\boldsymbol{z}$ is a vector collecting programs' characteristics for all j. The first term of the right-hand side expression is the probability for student i to face feasible set $\mathcal{F}$. Feasible sets depend on programs' preferences, as defined in Equation (9). The second term is the probability that the utility associated with program j is greater or equal to the one derived from any programs in $\mathcal{F}$. Under Assumption 1, we can derive a closed-form expression for this second term:

$$\Pr(\mathcal{U}_{ij} \geq \mathcal{U}_{ik}, \forall k \in \mathcal{F}|x_i, h_i, \boldsymbol{z}) = \frac{\exp(\frac{1}{\sigma}(u(x_i, z_j) - c(x_i, d_{ij}) + \bar{U}(x_i, h_i, z_j)))}{\sum_{k\in\mathcal{F}\bigcup 0_{\mathcal{J}}} \exp(\frac{1}{\sigma}(u(x_i, z_k) - c(x_i, d_{ik}) + \bar{U}(x_i, h_i, z_k)))} \quad (13)$$

where $\bar{U}(x_i, h_i, z_j)$ has been identified in a first step.

Students' preferences over programs are identified in two steps. First, as $v(x_i, h_i, z_j)$ is identified from data on programs' rankings of applicants, one can construct $\mathcal{F}$ following Equation (9), given a draw of programs' preference shocks:

$$\mathcal{F}(x_i, h_i, \boldsymbol{z}, \boldsymbol{\eta}) = \{j \in \mathcal{J} : v(x_i, h_i, z_j) + \eta_{ji} > v(x_{\mu(j,\mathcal{R}_j)}, h_{\mu(j,\mathcal{R}_j)}, z_j) + \eta_{j\mu(j,\mathcal{R}_j)}\} \quad (14)$$

where $\boldsymbol{\eta}$ is the vector collecting η_{ji} for all programs and students.[21] We can then rewrite Equation (12) as an integral over $\boldsymbol{\eta}$:

$$\frac{\Pr(\mu(i) = j|x_i, h_i, \boldsymbol{z})}{\Pr(j \in \mathcal{F}(x_i, h_i, \boldsymbol{z}, \boldsymbol{\eta})|x_i, h_i, \boldsymbol{z})} = \int \Pr(\mathcal{U}_{ij} \geq \mathcal{U}_{ik}, \forall k \in \mathcal{F}(x_i, h_i, \boldsymbol{z}, \boldsymbol{\eta})|x_i, h_i, \boldsymbol{z}, \boldsymbol{\eta}) g(\boldsymbol{\eta}) d\boldsymbol{\eta}$$

where $g(.)$ is the probability distribution function of $\boldsymbol{\eta}$. The numerator of the left-hand side of this equation can be identified directly from data on realized matches. The denominator can be recovered using Equation (14) given that we identified programs' preferences in a previous

[21] As in Agarwal and Somaini (2022), equilibrium cutoffs can be taken as fixed as I consider a large economy (Azevedo and Leshno, 2016). Hence, feasible sets only depend on observable characteristics and $\boldsymbol{\eta}$.

step, while we observe the set of applicants to each program. The interior of the integral on the right-hand side has an analytical expression (Equation (13)) and the distribution of $\boldsymbol{\eta}$ is known.

Second, this mapping can be inverted to identify sequentially the scale of the shock, σ, $u(x_i, z_j)$, and $c(x_i, d_{ij})$.

Identification of σ: Note that we typically cannot identify the scale of the utility, such that we normalize the scale of the shock to one. In this model, it would however be a strong restriction because it would fix the relative scale of individuals' utility in stages one and two. I avoid this assumption, and now show how to identify σ.

The identification argument relies on an exclusion restriction: there is at least one variable belonging to the vector of student's characteristics entering in the second stage of the model, h_i, but excluded from the one entering in the flow utility associated with a higher education program, x_i. Under such an exclusion restriction, the data can be mapped into an expression where σ is the only unknown parameter.

Here, I assume that the excluded variable is the home province of the student. It can enter the flow utility associated with a given location, to allow for a potential home bias, but not the one from enrolling in program j. This exclusion restriction is fairly weak: it allows students' demand to depend on various forms of mobility frictions. In particular, the distance between student i and program j, d_{ij}, can be included in $c(x_i, d_{ij})$. The identification argument then relies on considering two students i and o with $x_i = x_o$ but different home locations, living at the same distance from a given program j to ensure that $u(x_i, z_j) - c(x_i, d_{ij}) = u(x_o, z_j) - c(x_o, d_{oj})$.[22] In contrast, the continuation value associated with a program depends on their home location and will thus differ across students i and o, allowing us to identify σ.

Proposition 1 *Suppose that $u(x_i, z_j) - c(x_i, d_{ij}) = u(x_o, z_j) - c(x_o, d_{oj})$ for $j \in \mathcal{J}$ with $x_i = x_o$ and $h_i \neq h_o$. If $\bar{U}(x_i, h_i, z_j) - \bar{U}(x_i, h_i, z_{0_\mathcal{J}}) \neq \bar{U}(x_o, h_o, z_j) - \bar{U}(x_o, h_o, z_{0_\mathcal{J}})$, then σ is identified.*

[22] Note that this would remain true even if we allow for the presence of a home bias in $c(.)$ as well. The identification argument would then rely on a program j located at the same distance from both students i and o, and outside of their respective home location. Similarly, the requirement of finding a program equidistant from both i and o can be relaxed: in fact, we can consider two programs, j' and j'', as long as $u(x_i, z_{j'}) - c(x_i, d_{ij'}) = u(x_o, z_{j''}) - c(x_o, d_{oj''})$, which requires the distance between i and j' and o and j'' to be equal.

The proof consists in taking a double difference in the logarithm of the probability to match to different programs across students i and o, in the spirit of a difference-in-differences. The within-student difference eliminates the denominator of the conditional choice probability, which is student-specific and depends on $\boldsymbol{\eta}$. The flow utility associated with program j, which is not identified at this stage, cancels out through the cross-student difference. Details can be found in Appendix C.5.

Identification of u(.) and c(.): Given the parameters related to students' preferences over locations and the scale parameter previously identified, one can then non-parametrically identify the functions $u(x_i, z_j)$ and $c(x_i, d_{ij})$. This does not rely on exclusion restrictions. The proof is again constructive and can be found in Appendix C.6.

5.2 Estimation

This section describes the estimation strategy. As the identification argument, the estimation proceeds backward, starting with the second stage of the model.

5.2.1 Estimation of Preferences over Local Labor Markets

Parametrization I parametrize the flow utility associated with entering the labor market in location ℓ for individual i as follows:

$$\begin{aligned}\omega(h_i, y_i, m_\ell) = &\mathbf{Degree}_i' \boldsymbol{\phi_1} \mathbb{1}\{\ell = \ell_i^G, \ell = \ell_i^H\} \\ &+ \mathbf{Degree}_i' \boldsymbol{\phi_2} \mathbb{1}\{\ell \neq \ell_i^G, \ell = \ell_i^H\} + \mathbf{Degree}_i' \boldsymbol{\phi_3} \mathbb{1}\{\ell = \ell_i^G, \ell \neq \ell_i^H\} + \delta_\ell\end{aligned} \tag{15}$$

where $\mathbf{Degree}_i$ is the set of dummies indicating the degree upon graduation of individual i. I consider three degree types: high school degree, two-year degree, and bachelor's degree and more. ℓ_i^G is the location of individual i at graduation, while ℓ_i^H is her home location. $\boldsymbol{\phi_1}$ thus captures individuals' taste for staying in their home location, conditional on having graduated there. $\boldsymbol{\phi_2}$ captures individuals' taste for returning to their home location when they did not graduate there. Both vectors reflect individuals' home bias, which may be stronger for those who also studied in their home location. These parameters are allowed to vary across degree types to take into account that the level of education may influence the strength of this home preference. $\boldsymbol{\phi_3}$ reflects individuals' taste for staying in their graduation location, when the

latter does not correspond to their home location. It captures the presence of stickiness in location choice at entry on the labor market, or moving costs, and is also allowed to vary by degree type. δ_ℓ are location fixed effects, capturing differences in amenities.

I define $w_\ell(y_i, h_i)$ as follows:

$$w_\ell(y_i, h_i) = \mathbf{Degree}_i' \boldsymbol{\kappa}_\ell + \boldsymbol{\kappa} h_i$$

where $\boldsymbol{\kappa}_\ell$ captures that returns to different degrees may differ across locations. h_i is a vector of individual i's characteristics including ability, measured by the individual's end-of-high school exam grades, gender, and scholarship status in high school.

Estimation The wage equation is estimated via an auxiliary linear regression. The primitive parameters capturing preferences over locations are estimated by Maximum Likelihood, using data on location choices of entry-level workers. I consider that individuals choose which province to enter in metropolitan France, i.e. $\mathcal{L}$ is the set including the 96 French provinces. The estimated parameters are those maximizing the following log-likelihood:

$$L^L(\mathbf{h}, \mathbf{y}, \mathbf{m}, \mathbf{w}; \boldsymbol{\Phi}) = \sum_{i \in \mathcal{I}} \sum_{\ell \in \mathcal{L}} \mathbb{1}\{\ell_i^* = \ell\} \log \left(\frac{\exp(\theta(w_{i\ell} + \omega(h_i, y_i, m_\ell)))}{\sum_{\kappa \in \mathcal{L}} \exp(\theta(w_{i\kappa} + \omega(h_i, y_i, m_\kappa)))} \right)$$

where $\mathbf{h}$, $\mathbf{y}$ and $\mathbf{m}$ gather the individuals' and locations' characteristics, respectively, $\mathbf{w}$ is the vector of individuals' expected wages across local labor markets and $\boldsymbol{\Phi} = \{\theta, \boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \boldsymbol{\phi}_3\}$.

5.2.2 Estimation of Programs' Preferences

Parametrization Program-j specific score of applicant i is a flexible function of the program's and student's characteristics. In particular, we have:

$$\mathcal{V}_{ji} = z_j' \boldsymbol{\Lambda} x_i^v + \eta_{ji}$$

where z_j is a vector of dummies corresponding to program j's type. I consider seven program types: three-year university programs, two-year elite programs, engineering and business schools, two-year technology-oriented programs, two-year vocational programs, nursing schools, and others. x_i^v is a vector of students' characteristics including the student's high school GPA, gender, high school track, socio-economic status, and scholarship status.

Estimation The vector of programs' preference parameters $\mathbf{\Lambda}$ can be estimated by Maximum Likelihood, as the ranking of applicants is observed. The log-likelihood writes:

$$L^P(\mathbf{x}, \mathbf{z}; \mathbf{\Lambda}) = \sum_{j \in \mathcal{J}} \sum_{i \in \mathcal{A}_j} \sum_{r=1}^{\bar{R}_j} \mathbb{1}\{i = i^*_{j,r}\} \log \left(\frac{\exp(z_j' \mathbf{\Lambda} x_i^v)}{\sum_{a \in \mathcal{A}_j \setminus \{i^*_{j,k}\}_{k=1}^{r-1}} \exp(z_j' \mathbf{\Lambda} x_a^v)} \right)$$

where $\bar{R}_j$ is the number of applicants ranked by j, and $\mathbf{x}$ and $\mathbf{z}$ gather the individuals' and programs' characteristics, respectively.

5.2.3 Estimation of Students' Preferences

Parametrization The value and mobility costs associated with enrolling in program j for student i are parametrized as follows:

$$u(x_i, z_j) = z_j' \boldsymbol{\delta} x_i^u \qquad\qquad c(x_i, d_{ij}) = d_{ij} \boldsymbol{\alpha}_1 x_i^d + d_{ij}^2 \boldsymbol{\alpha}_2 x_i^d$$

where $u(.)$ depends on the interaction of z_j with the vector of students' characteristics x_i^u including the student's gender, high school track, socio-economic status, honors at the end-of-high school exam, and scholarship status. $c(.)$ depends on the distance, in kilometers, between student i's home location — at the ZIP code level — and program j's GPS coordinates, denoted d_{ij}. The square of this distance is also included to allow for non-linearities in these costs. Through interactions with the vector of students' characteristics x_i^d, mobility frictions are allowed to vary across students with different socio-economic groups, scholarship eligibility, and gender.

Estimation As shown in the identification section, the conditional choice probability that a student with observable characteristics (x_i, h_i) is matched to j is an integral over $\boldsymbol{\eta}$, which does not have a closed-form expression. While preferences could be estimated by Simulated Maximum Likelihood (SMLE), the estimates would not be consistent when using a finite number of draws of $\boldsymbol{\eta}$. I avoid this issue by instead using a Simulated Method of Moments (SMM) procedure, which guarantees consistency with a finite number of draws (Gourieroux and Monfort, 1996), with optimal moments — the score of the likelihood. In particular, given the parameters estimated in a first step and for a given guess of students' parameters, I proceed as follows:

(i) Draw a vector of programs' shocks, $\boldsymbol{\eta}^b$.

(ii) Given programs' preference parameters and $\boldsymbol{\eta}^b$, compute $\mathcal{V}^b_{ji}$, $\forall i, j$ and construct $\mathcal{F}^b_i = \mathcal{F}^b(x_i, h_i, \boldsymbol{\eta}^b)$.

(iii) Construct the optimal moment associated with each variable entering in $\mathcal{U}_{ij}$. For example, the moment associated with d_{ij} writes:

$$\sum_i \sum_{j \in \mathcal{F}^b_i} \left[\mathbb{1}\{\mu(i) = j\} - \Pr(\mu(i) = j | \mathcal{F}^b_i, x_i, h_i, \boldsymbol{z}, j \in \mathcal{F}^b_i) \right] d_{ij}$$

where $\mathbb{1}\{\mu(i) = j\}$ is a dummy equal to one if student i matches to program j and $\Pr(\mu(i) = j | \mathcal{F}^b_i, x_i, h_i, \boldsymbol{z}, j \in \mathcal{F}^b_i)$ is the conditional choice probability that student faced with feasible set $\mathcal{F}^b_i$, given $(x_i, h_i, \boldsymbol{z})$, matches to j, defined in Equation (13).

For each vector of parameters guess, I repeat (i)-(iii) ten times and average moments across simulations. These averaged moments are then used to compute the Method of Moments objective function to be maximized.

Note that this method provides consistent estimates even for a fixed number of simulations (Gourieroux and Monfort, 1996; Train, 2009). This is an advantage with respect to using SMLE, which is not consistent with a fixed number of draws. Method of Moments is usually less efficient than Maximum Likelihood estimation. However, it is efficient when the optimal instruments, the score, are used. In this framework, the score has to be simulated, which introduces some noise. Simulation noise decreases as the number of draws increases. The estimation method presented here is thus a computationally tractable way to obtain consistent and efficient estimators of two-sided matching models.

5.2.4 Estimation of Transition Probabilities

Parametrization As in Kennan (2015), I let students' graduation outcome be the result of a stochastic process, depending on their characteristics and on the chosen program's characteristics. Students have thus different probabilities of graduating with a high school degree, a two-year degree or a three-year degree or more depending on their program of enrollment. I also let these characteristics influence the student's graduation location. I thus do not impose that a student entering a program in location ℓ also graduates in location ℓ.

Transition probabilities between the initial program and the location-degree at exit of the higher education system can be recovered directly from the data. In particular, I use the administrative dataset tracking the universe of students enrolled in the French higher education system. From this, I compute the joint probability that a student with characteristics x_i and h_i entering a program with characteristics z_j graduates with a given type of degree and in a given location, i.e. $y_i = (\mathbf{Degree}_i, \ell_i^G)$.

Although transition probabilities are identified non-parametrically, I estimate them parametrically, for tractability. I use a conditional logit model to capture the probability for an individual to be in a given location-degree bundle, across $|\mathcal{D}| \times |\mathcal{L}|$ possibilities, where $\mathcal{L}$ is the set of graduation locations, which is the same as the one of local labor markets. $\mathcal{D}$ is the set of degree types: high school degree, two-year degree, and bachelor's degree or more. I parametrize this joint probability as follows:

$$f(y_i|x_i,h_i,z_j) \equiv \Pr(\mathbf{Degree}_i, \ell_i^G|x_i,h_i,z_j) = \frac{\exp(\rho_1 \mathbb{1}\{\ell_i^G = \ell_j\} + \mathbf{Degree}_i'\boldsymbol{\rho}_2 z_j + \mathbf{Degree}_i'\boldsymbol{\rho}_3 x_i^u)}{\sum_{\ell^G,\mathbf{Degree}} \exp(\rho_1 \mathbb{1}\{\ell^G = \ell_j\} + \mathbf{Degree}'\boldsymbol{\rho}_2 z_j + \mathbf{Degree}'\boldsymbol{\rho}_3 x_i^u)}$$

where ℓ_j is the province where program j is located.

Estimation The set of parameters $\boldsymbol{\rho} = \{\rho_1, \boldsymbol{\rho}_2, \boldsymbol{\rho}_3\}$ is estimated by Maximum Likelihood. Details can be found in Appendix D.2.

5.2.5 Extension: Adding Unobserved Heterogeneity

The model can be extended to capture persistent unobserved preferences over locations. It may indeed be important to account for such unobserved preferences when modeling location choices, as they often display persistence. Allowing for unobserved heterogeneity would help disentangle the stickiness in location choices coming from unobserved preferences from state dependence (Heckman, 1981). We can rewrite the model in the second stage as follows:

$$\begin{aligned}\omega(h_i,\alpha_i,y_i,m_\ell) = \mathbf{Degree}_i'\boldsymbol{\phi_1}\mathbb{1}\{\ell = \ell_i^G, \ell = \ell_i^H\} + \mathbf{Degree}_i'\boldsymbol{\phi_2}\mathbb{1}\{\ell \neq \ell_i^G, \ell = \ell_i^H\} \\ + \mathbf{Degree}_i'\boldsymbol{\phi_3}\mathbb{1}\{\ell = \ell_i^G, \ell \neq \ell_i^H\} + \alpha_i a_\ell\end{aligned} \tag{16}$$

where a_ℓ is an amenity index and $\alpha_i \sim \mathcal{N}(0,\zeta)$. α_i is a persistent unobserved idiosyncratic taste for amenities.

Given the parameters of Equation (16) and a draw of $\alpha_i, \forall i$, one can compute the expected discounted continuation value associated with choosing the optimal location in the second stage. Further assuming full persistence of the taste for the amenity index, the utility from enrolling in program j writes:

$$\mathcal{U}_{ij} = u(x_i, z_j) - c(x_i, d_{ij}) + \alpha_i a_j + \sigma\epsilon_{ij} + \bar{U}(x_i, h_i, \alpha_i, z_j)$$

where a_j is the amenity index associated with the location of program j. The probability that student i matches with program j simply rewrites:

$$\Pr(\mu(i) = j | x_i, h_i, \boldsymbol{z}) = \int \Pr(\mu(i) = j | x_i, h_i, \alpha_i, z) f(\alpha_i | \zeta) d\alpha_i$$

Details are provided in Appendix D.3. Note that estimating preferences in this framework is more computationally costly as it requires to jointly estimate preferences.

6 Estimation Results and Model Fit

In this section, I first present parameter estimates, before discussing the fit of the model.

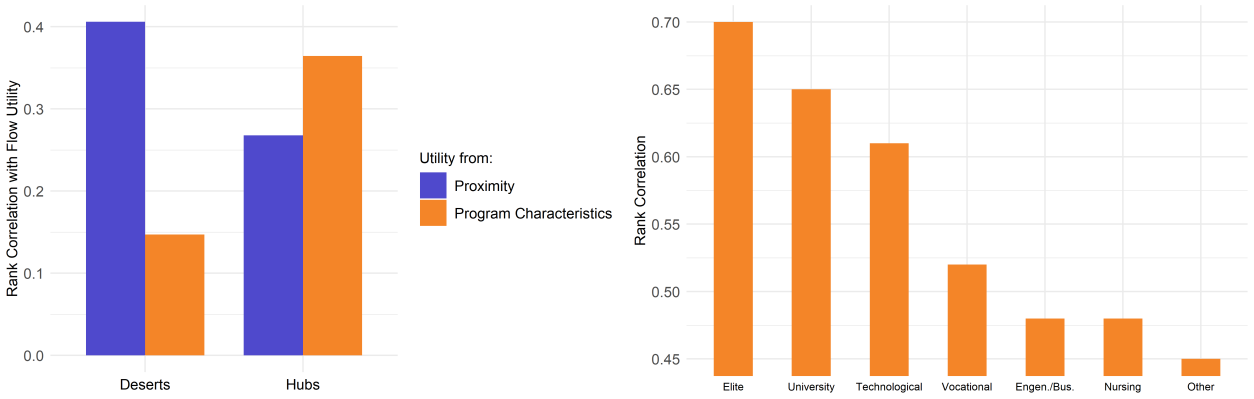
6.1 Estimation Results

Students' Preferences over Programs Estimates of students' preferences over programs highlight that students' demand is highly sensitive to distance (Tables A.14-A.16). The average student would need to receive a monthly scholarship of 1,102 euros to accept to enroll 100 kilometers away from her home location. There is also significant heterogeneity across socio-economic groups, as this amount reaches 1,317 euros/month for low SES students, which is 384 euros larger than for high SES students. While they take into account both pecuniary and non-pecuniary costs associated with studying away from home, these figures are in the range of the average monthly budget for students, estimated to be 635 euros.[23]

Panel a) of Figure 6 further illustrates the importance of mobility frictions in students' higher education choices. In particular, for each applicant, I rank programs according to their flow utility. I then compute the correlation between this rank and the rank of the

[23]This figure is provided by the *Observatoire National de la Vie Etudiante*, a research institute created by the Ministry of Education. It is based on a survey of 245,000 students in 2020.

Figure 6: Determinants of Students' and Programs' Preferences



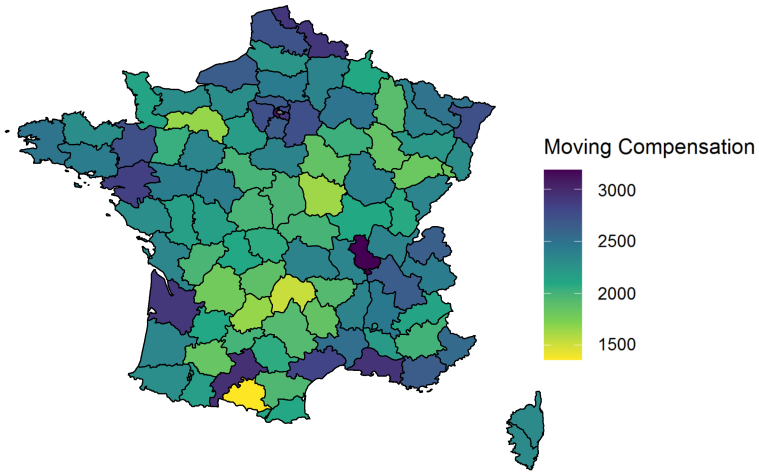
a) Students **b) Programs**

NOTES. Panel a) illustrates the determinants of the payoff students derive from enrolling in a given program. Using data at the student-program level, it plots, in purple, the rank correlation between the flow utility associated with a program and its proximity to the student's home location. It displays, in orange, the rank correlation between the flow utility associated with a program and the consumption value, $u(x_i, z_j)$, associated with the program's characteristics, z_j. It restricts attention to each student's top fifty programs. The figure shows these correlations separately for students from higher education deserts (the 50 provinces gathering less than 5% of the total supply of academic seats) and hubs (the ten provinces at the top of the seat supply distribution). Panel b) illustrates the importance of students' GPA in determining their ranking by different types of programs. Using data at the student-program level, it plots the rank correlation between the program-specific score associated with an applicant, $\mathcal{V}_{ji}$, and the GPA of the student. The figure shows these correlations separately by program type.

program according to its proximity to the student (in purple).[24] I do this separately for applicants from higher education deserts and hubs. I consider as educational deserts the fifty provinces gathering less than 5% of the supply of academic seats, while concentrating 25% of the students. Educational hubs are defined as the top ten provinces in the distribution of academic seats and similarly gather 25% of the student population. While this correlation is large for all students, it is about 60% higher for students from educational deserts. This is driven by the fact that these applicants have few higher education options around them, making distance a prevalent component of the payoff associated with a program. In contrast, with many more programs close to their home location, the ranking of students from higher education hubs is less sensitive to how distant programs are. As a result, their ranking is mostly determined by the utility they derive from the other characteristics of programs. The correlation between the utility rank associated with a program and its rank based only on the utility associated with its non-distance characteristics, $u(x_i, z_j)$, is twice as large for students from hubs (36%) as for students from low-opportunity areas (15%).

[24] A higher rank corresponds to a program closer to the student's home location. Given that distance is associated with a cost for students, ranking programs according to their proximity is the same as ranking them based on $-c(x_i, d_{ij})$.

Figure 7: Location Choices - Home Bias



NOTES. This map uses estimated preferences over local labor markets (Table A.18) to compute the compensation, in monthly euros, an individual from a given province would need to receive to be willing to move to Paris, conditional on having studied in their home location and having reached at least a bachelor's degree, abstracting from wage differences. Results can be found in Tables A.20-A.21, Column (1).

Program-Specific Score Table A.17 presents estimates of programs' preferences. Panel b) of Figure 6 shows how the ranking of students by programs correlates with students' GPA. This correlation is high for all programs, illustrating the importance of academic achievement in their admission decisions. This is particularly true for university and two-year elite programs, which are designed to lead students to graduate with at least a bachelor's degree. Final rankings are also determined by other applicants' characteristics. For example, the effect of being eligible for an income-based scholarship is equivalent to an increase in GPA of 0.27 standard deviations for admission to two-year elite programs, which may at least partly be driven by the equity objectives of the government.

Preferences over Local Labor Markets Table A.18 presents estimates of the parameters associated with the utility of entering the labor market in a given location. Results show that workers display a very large preference for their home location. In Figure 7 and corresponding Tables A.20-A.25, I use these estimates to compute the compensation an individual would demand to accept to enter the labor market in Paris rather than in her home location. I do this separately by level at graduation and keep wages fixed at their home location level. I first consider individuals graduating in their home location (Column (1)). For example, an individual from Creuse — one of the provinces at the bottom of the higher education

supply distribution — who graduated with at least a bachelor's degree in Creuse would need to receive 2,060 euros per month to agree to enter the labor market in Paris rather than in her home location. This reflects a strong home bias, as this amount is more than twice as large as the average wage difference between Paris and Creuse. This home bias is stronger for individuals who graduated with a high school degree: they would need to receive 3,015 euros/month to make such a move. Cross-province variation highlighted in Figure 7 reflects differences in amenities: workers from provinces with high amenity levels would need larger compensation to be willing to move out of their home location.

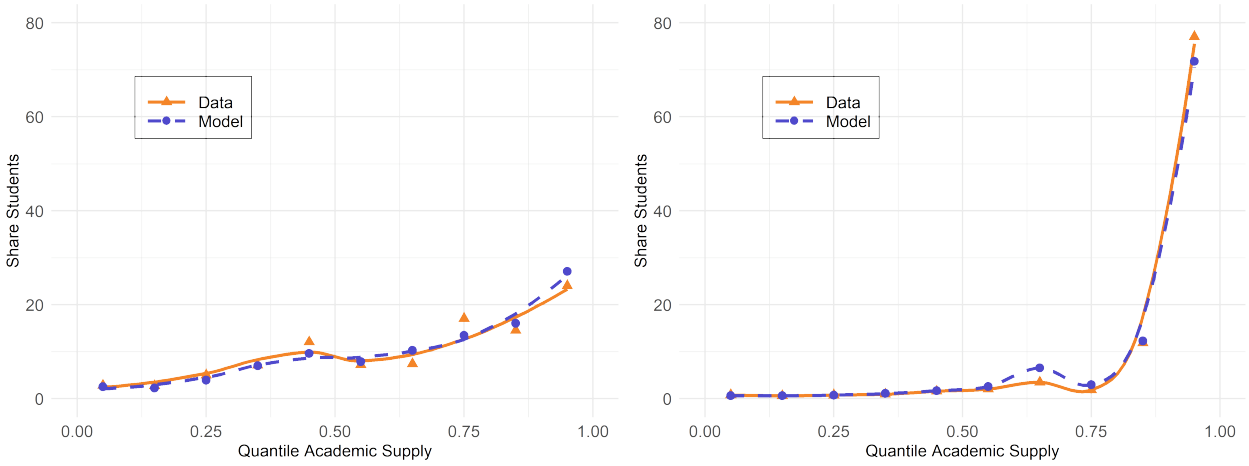
While the preference for home is a key determinant of individuals' location choice, they also face very high moving costs. This can be seen in Column (2) of Table A.20 and corresponding Figure A.14, where I compute the same object as above, but conditional on graduating in Paris instead of home. A student from Creuse who moved to Paris to study and graduated there with at least a bachelor's degree is now better off when entering the labor market in Paris, holding wages across labor markets equal. This individual would actually need a monthly tax rebate of 542 euros to agree to return home upon graduation. As the home bias is stronger for individuals with lower levels of education, an individual who moved to Paris to study but dropped out from higher education would only need to receive an additional 156 euros per month to return home. Overall, the magnitude of these moving costs is likely to allow higher education hubs to retain students graduating there, despite the existence of a large home bias.

6.2 Model Fit

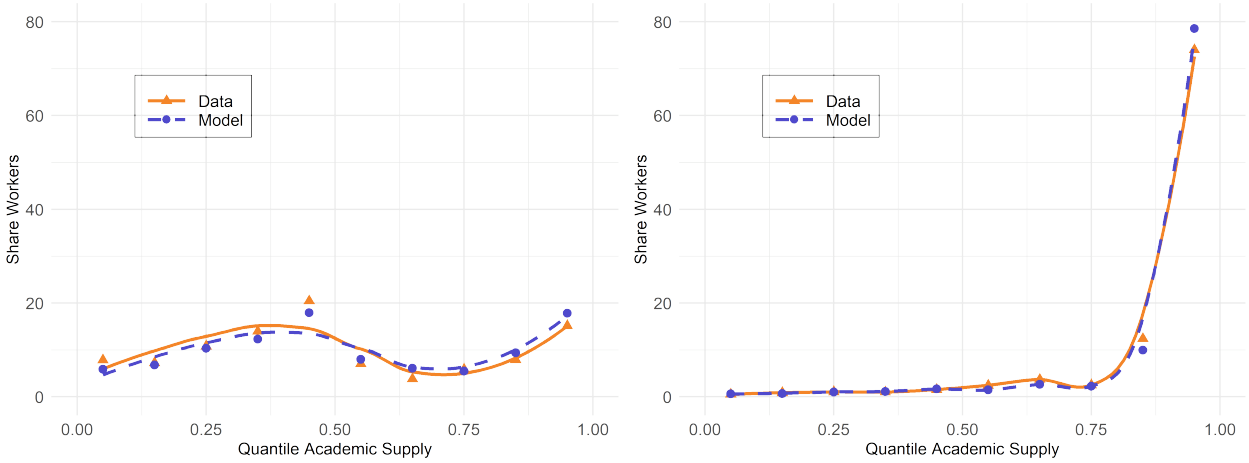
I simulate the higher education match and location decisions at entry on the labor market to evaluate the fit of the model.[25] Table A.26 compares these simulations to what is observed in the data. Panel A presents characteristics of the observed higher education match in Column (1) and of the simulated one in Column (2). Panel B shows patterns related to location choices. Overall, the simulated shares of students enrolling in different program types, distance to the matched program, and share of individuals entering the labor market in their home or study location closely match what is observed in the data.

[25] I use both students' (Tables A.14-A.15) and programs' (Table A.17) preference parameters to compute their utility. I then feed them into a Deferred Acceptance algorithm to simulate the stable match. I use individuals' preferences (Table A.18) over locations to simulate their choice of local labor market upon graduation.

Figure 8: Model Fit



a) Enrollment Flows - Students from Deserts **b) Enrollment Flows - Students from Hubs**



c) Work Flows - Workers from Deserts **d) Work Flows - Workers from Hubs**

NOTES. I rank provinces according to their supply of academic seats and group them into ten bins of equal size. Panel a) plots the share of students from higher education deserts enrolling in each of these bins. For example, about 25% of these students enroll in a program from a province in the top 10% of the academic seats supply distribution. Panel b) plots the same statistics, focusing on students from higher education hubs. Panel c) shows the share of workers from higher education deserts entering the labor market in each bin. For example, about 15% of them enter the labor market in a province belonging to the top 10% of the distribution of academic seats. Panel d) displays the same statistics for workers from higher education hubs. Each panel presents these flows in the data (orange triangles, plain line) and as predicted by the model (purple dots, dotted line).

I also evaluate the fit of the model using moments that are not directly targeted in the estimation. In particular, it is crucial for the model to be able to replicate migration flows both within the higher education market and across local labor markets. First, I simulate enrollment flows between provinces and contrast them with those observed in the data. I rank provinces according to their supply of academic seats and group them into ten bins. Panel a) of Figure 8 plots the share of students from higher education deserts enrolled in each of these bins. About 25% of students from higher education deserts enroll in an education hub, i.e. a province belonging to the top 10% of the academic seats supply distribution. This is in sharp contrast with enrollment flows of students from higher education hubs, as 75% stay in a hub to study (Panel b)). The model replicates these enrollment flows very closely, differently for students from hubs and deserts, while they were not targeted in the estimation.

I further use simulated enrollment flows at the province level to estimate the same gravity model as in Section 3, projecting them on origin and destination fixed effects, and on the distance between each location pair. Table A.27 presents results from the model fitted on enrollment flows observed in the estimation sample in Column (1) and on simulated flows in Column (2). The latter yields an elasticity of enrollment flows to distance of -2.27, which is very close to that found in the data (-2.50).

I then turn to flows of workers across local labor markets, which will be key objects in counterfactual predictions. Panel c) of Figure 8 plots the share of individuals from higher education deserts entering the labor market in provinces according to their decile in the distribution of the supply of academic programs. Only about 15% of them enter the labor market in a higher education hub. Again, this contrasts sharply with the decision of individuals from higher education hubs, who are 60 percentage points more likely to enter the labor market in a hub. While these moments were not targeted in the estimation, the model is able to closely match them.

Finally, an alternative way to evaluate the fit of the model is to use preference estimates to predict the effect of a 500 euro moving subsidy, as the one evaluated in Section 3.2.1. This scholarship corresponds to a monthly payment of 55.5 euros.[26] Preference estimates allow us to express the utility cost of enrolling one kilometer farther away from home, which is about 11 euros/month. According to these estimates, receiving 55.5 euros/month would thus cover the cost of traveling an additional five kilometers, a figure belonging to the 99% confidence

[26]The academic year usually lasts about nine months.

interval of the effect of the subsidy found in the data (Table A.8).

7 Counterfactuals

In this section, I first use the model to quantify how the uneven within-country distribution of higher education options interacts with mobility frictions to generate spatial inequalities, both between individuals and local labor markets. To do so, I eliminate mobility frictions within the higher education market, holding constant the distribution of programs. I then further remove moving costs at entry on the labor market as well. Second, I design and evaluate contracts allowing low-opportunity areas to outsource investments in their local human capital to higher education hubs, while providing students incentives to return home upon graduation.

7.1 The Geography of Higher Education and Spatial Inequalities

I first focus on spatial inequalities between students. Panel A of Table 3 presents several measures of these gaps at baseline (Column (1)). First, I compare individuals from higher education hubs and deserts. At baseline, we observe a 5 percentage point gap in the share of individuals graduating with at least a bachelor's degree in hubs (44.4%) and deserts (39.4%). The estimated model also allows us to quantify mean welfare differences, where welfare is computed based on Equation (4), for students across these regions, amounting to 991 euros/month. Second, I consider the variance of these different measures, across home locations, which captures the overall magnitude of regional inequalities.[27]

The model captures three key potential drivers of these gaps: differences in students' test scores entering programs' admission decisions, differences in students' preferences, and mobility frictions. It thus allows us to isolate how mobility frictions interact with the geography of the higher education market to generate the above spatial inequalities. To investigate this, I first break the link between the spatial distribution of programs and students' choices by eliminating mobility frictions. I simulate individuals' choices in this scenario and compare these counterfactual paths to the status quo. Details are provided in Appendix E.1.

Column (2) of Table 3 presents results from these simulations. I find that 76% of the gap in the share of individuals graduating with a bachelor's degree between educational

[27]Details on the computation of all measures considered in this section are presented in Appendix E.2.

Table 3: Mobility Frictions and Spatial Inequalities: Quantification

	Baseline	Counterfactual
	(1)	(2)
Panel A: Spatial inequalities between individuals		
Share High-Skilled:		
Gap Hubs-Deserts	4.97	1.16 **(-76%)**
Cross-Province Variance	26.98	18.19 **(-33%)**
Mean Welfare (€/month):		
Gap Hubs-Deserts	991	614 **(-38%)**
Cross-Province Variance	230,050	93,490 **(-59%)**
Panel B: Inequalities across local labor markets		
Share High-Skilled:		
Gap Hubs-Deserts	7.67	3.72 **(-51%)**
Cross-Province Variance	26.94	20.88 **(-22%)**
Sum Wages (M€):		
Gap Hubs-Deserts	2.1	2.3 **(+10%)**
Cross-Province Variance	97.6	115.2 **(+18%)**

NOTES. This table presents results from the main quantification exercise: removing mobility frictions within the higher education market. Panel A focuses on spatial inequalities between individuals, with respect to two variables: the share of individuals from a given province graduating with at least a bachelor's degree (share high-skilled, in percent) and welfare, based on Equation (4), expressed in monthly euros. Panel B focuses on spatial inequalities across local labor markets, measured by the share of their labor force with at least a bachelor's degree (in percent) and by the sum of entry-level workers' wages. Gaps in these variables are computed by comparing hubs and deserts — defined as the provinces respectively at the top and bottom of the academic seat distribution, both gathering 25% of the high school student population — and by measuring their variance across all provinces. Column (1) presents spatial inequalities in the status quo, while Column (2) shows their level and percentage change in the counterfactual. Appendix E.1 details how counterfactual simulations are performed. The computation of each outcome is formalized in Appendix E.2.

hubs and deserts can be attributed to mobility frictions within the higher education market. Overall, they account for one-third of the variance in educational attainment across home locations. Panel A of Table 3 also compares the average welfare of students from educational hubs and deserts in the status quo and after removing mobility frictions within the higher education market. While all students would benefit from removing such frictions, those from educational deserts would gain twice as much. As a result, the welfare gap between these two groups would decrease by 38%. The uneven distribution of higher education programs coupled with the existence of mobility frictions thus accounts for a substantial share of spatial inequalities in educational attainment and welfare across students.

Taking the point of view of local labor markets, however, leads to a very different conclusion (Panel B of Table 3). I find that inequalities across local labor markets, as measured by the variance of the sum of wages of entry-level workers in their labor force, increase by 18% in the counterfactual scenario (Column (2)). Such gaps between higher education hubs and

deserts similarly rise by 10% with respect to the status quo. This is driven by the fact that hubs are able to retain in their labor force a significant portion of the new students going there to study, at the expense of deserts. We indeed observe a 14% increase in the number of individuals from deserts entering the labor market in hubs (Table A.28). In particular, we observe an 11% increase in the share of entry-level workers in Paris (Column (2) of Table A.29). This results from the importance of mobility costs, as well as from location-specific returns to education. As some individuals still return home, educational deserts benefit from the fact that they received a better education. In particular, the gap in the share of workers entering the labor force with at least a bachelor's degree decreases by 51%, from a baseline of 7.5 points. Yet, the former effect dominates. Overall, this quantification exercise allows us to highlight the key trade-off generated by alleviating mobility frictions within the higher education market. It would decrease the welfare gap between individuals from high- and low-opportunity areas, at the cost of accelerating regional divergence.

The importance of this trade-off would be magnified if we were to omit programs' admission decisions. Column (1) of Table 4 shows results from a counterfactual where we eliminate mobility frictions and let each student enroll in their favorite program, regardless of capacity constraints and programs' preferences. As students from hubs would no longer be crowded out from their favorite programs, the decrease in spatial gaps in educational attainment is slightly reduced (-58%). However, inequalities across local labor markets increase much more than when the higher education market is at equilibrium. As any student can now be admitted to a program located in a hub, the outflow of workers from deserts to hubs is more pronounced (Table A.28). In particular, the share of workers choosing to enter the labor market in Paris would increase by 44% compared to the status quo (Column (3) of Table A.29). It is thus important to take into account the distributional effects of programs' admission decisions and capacity constraints.

Capturing the dynamic link between the higher education and labor markets is also crucial in documenting the above trade-off. Column (2) of Table 4 illustrates this by presenting results from simulations where mobility frictions are eliminated, as in the main counterfactual, but individuals' labor market location choice is fixed to be the same as in the status quo. It thus ignores the fact that changes within the higher education market may alter individuals' labor market location decision. This omission would lead to conclude that eliminating mobility frictions within the higher education market would decrease not only spatial

Table 4: Mobility Frictions and Spatial Inequalities: Quantification

	No Mobility Frictions within Higher Education Market			
	Only	& No Admission Restrictions	& Fixed Location Choice	& No Moving Costs
	(1)	(2)	(3)	(4)
Panel A: Spatial inequalities between individuals				
Share High-Skilled:				
Gap Hubs-Deserts	-76%	-58%	-76%	-33%
Mean Welfare (€/month):				
Gap Hubs-Deserts	-38%	-44%	-38%	-49%
Panel B: Inequalities across local labor markets				
Share High-Skilled:				
Gap Hubs-Deserts	-51%	-20%	-64%	-23%
Sum Wages (M€):				
Gap Hubs-Deserts	+10%	+32%	-1%	-11%

NOTES. This table presents results from a decomposition exercise. In all columns, mobility frictions within the higher education system are eliminated. Column (1) reports results from this change, corresponding to Column (2) of Table 3. Column (2) presents results from this counterfactual, when additionally ignoring programs' admission decisions: all students are admitted in their preferred program in stage 1. Column (3) presents results from a counterfactual where mobility frictions within the higher education market are removed, ignoring any effects from workforce re-allocation: location choices are fixed to be the same as under the status quo. Column (4) presents results from a counterfactual where both mobility frictions within the higher education as well as moving costs at the location choice stage are removed. Panel A focuses on spatial inequalities between individuals, with respect to two variables: the share of individuals from a given province graduating with at least a bachelor's degree (share high-skilled) and welfare, based on Equation (4), expressed in monthly euros. Panel B focuses on spatial inequalities across local labor markets, measured by the share of their labor force with at least a bachelor's degree and by the sum of entry-level workers' wages. Gaps in these variables are computed by comparing hubs and deserts — defined as the provinces respectively at the top and bottom of the academic seat distribution, both gathering 25% of the high school student population. Appendix E.1 details how counterfactual simulations are performed. The computation of each outcome is formalized in Appendix E.2.

inequalities in students' welfare but also inequalities between local labor markets as it does not allow for workers' out-migration from deserts.

Finally, I explore the role of moving costs in generating the highlighted trade-off. The latter originates from the fact that alleviating mobility frictions within the higher education market leads to a brain drain of students toward higher education hubs. While human capital is portable, this initial effect harms low-opportunity areas, as a significant share of students who leave to study fail to come back. Such patterns could be generated, through the model, by location-specific returns to education and moving costs. I quantify the role of the latter by simulating individuals' study and location decisions when removing moving costs between their graduation and home location, in addition to eliminating mobility frictions within the higher education market. Column (3) of Table 4 shows that this would lead to further reducing spatial gaps in welfare, as students can now come back to their home

location without incurring any moving costs. This would, however, reduce their incentives to obtain a bachelor's degree or more, given differences in returns to education across space. As a result, the decrease in educational attainment gaps across home locations would slow down compared to what is found in the main counterfactual. Yet, as more students would now come back, and with higher levels of education than in the status quo, inequalities across local labor markets would decrease. This hints at the fact that low-opportunity areas could benefit from outsourcing the education of their local labor force to higher education hubs, conditionally on incentivizing students to come back.

7.2 Outsourcing Education Through Contracts

Equalizing opportunities for students from different regions, and decreasing inequalities across local labor markets are two objectives often cited by policymakers. As one-third of the variation in educational attainment across provinces is explained by mobility frictions at the higher education stage, shutting down these barriers is key to reach the first goal. This could also allow low-opportunity areas to outsource the production of their local human capital to higher education hubs. The above simulations however reveal that many students would not come back, leading to a trade-off. Can policymakers circumvent this trade-off, and at what cost?

To go beyond this trade-off, higher education deserts need to decouple the educational investment of their local students from the local supply of programs, while incentivizing individuals to come back upon graduation. I explore the role of a policy instrument satisfying these two conditions. In particular, I design contracts offering a distance-based subsidy to students from higher education deserts. As a counterpart, they either have to enter the labor market in their home region or repay the scholarship. This is akin to scholarship programs already existing in Chile (Banco Central de Chile), Columbia (Banco de Republica), or Singapore, where students receive a scholarship to study abroad while agreeing to return to their home country upon graduation or repay.[28] The policy I evaluate thus corresponds to a within-country implementation of these programs.[29]

To evaluate such a policy, I simulate the counterfactual match by replacing the utility

[28] In Singapore, beneficiaries agree to pursue a career in public administration within the Singapore Public Service.

[29] Anecdotal evidence shows that some rural French communes implement such a scheme, for example to guarantee the presence of a general practitioner in their area.

Table 5: Policy - Change in Spatial Inequalities

	Change in Inequalities between:			
	Individuals (Mean Welfare)	Local Labor Markets (Sum Wages)	Share Repaying	Cost (% of Total Wages)
	(1)	(2)	(3)	(4)
$\tau = 0.25$	-10%	-17%	44%	6%
$\tau = 0.33$	-17%	-29%	39%	8%
$\tau = 0.50$	-33%	-52%	28%	15%

NOTES. This table evaluates a policy offering contracts to students from higher education deserts, conditional on entering their home labor market upon graduation, or having to repay. Such contracts offer them a distance-based subsidy covering τ% of the mobility frictions they face. Column (1) shows the effect of the policy on welfare inequalities across students from deserts and hubs. Column (2) presents its impact on gaps between hubs and deserts, as measured by the sum of the wages of entry-level workers in their labor force. Column (3) documents the share of individuals repaying the scholarship to avoid coming back home. This is also presented in Figure A.15. Column (4) quantifies the cost of these subsidies, expressed as a share of the cohort of entry-level workers' total wages. Appendix E.3 presents results from an additional policy counterfactual, where students commit to coming back if they participate in the program.

associated with a given program j, $\mathcal{U}_{ij}$, with the following object:

$$\begin{aligned} & u(x_i, z_j) - (1-\tau)c(x_i, d_{ij}) + \sigma\epsilon_{ij} \\ & + \frac{1}{\theta}\int \beta^{t(y_i)}(\gamma + \log(\exp(\sum_{\ell \in \mathcal{L}} \left[\theta(w_{i\ell} + \omega(x_i, y_i, m_\ell)) + \mathbb{1}\{\ell \neq \ell^H\}\tau c(x_i, d_{ij})\right))\right] f(y_i|x_i, h_i, z_j)dy_i \end{aligned} \tag{17}$$

In particular, the subsidy compensates for a fraction τ of mobility frictions associated with traveling distance d_{ij}, $c(x_i, d_{ij})$. The continuation value is also updated as students take into account that they will have to repay the subsidy if entering the labor market in a location that is not their home location, ℓ^H. I simulate individuals' paths when their utility is replaced by Equation (17).

Table 5 shows the effects of this policy on inequalities, both across individuals and local labor markets. I consider different degrees of generosity of the subsidy, with τ varying from 25% to 50%. When the subsidy covers 25% of the mobility frictions associated with distance, welfare inequalities across students from hubs and deserts decrease by 10%. As the contract incentivizes students to enter their home labor market upon graduation, by making them repay the policy otherwise, it leads to a 17% decrease in inequalities across places. As 44% of individuals prefer to repay the subsidy, its cost stays reasonable: it only represents 6% of the cohort's total wages. Overall, policies tying mobility scholarships to incentives to return would allow low-opportunity areas to leverage regional trade in education services to invest in their local human capital.

8 Conclusion

To what extent does the geography of the higher education market contribute to spatial inequalities, both between students and across local labor markets? This paper documents that, in France, higher education options are unevenly distributed across space, such that students with different home locations face very different college opportunities. This impacts their educational choices, as I show that their demand is sensitive to proximity. The local supply of colleges also correlates with the level of skills in each region's labor force. Breaking the dependence between educational choices and the local supply of higher education programs seems key to mitigating spatial inequalities. I, however, document that removing barriers to mobility within the higher education market has substantial distributional effects, and could lead to a long-lasting brain drain of students toward higher education hubs.

To quantify the role of the geography of the higher education market in generating spatial inequalities, I build and estimate a dynamic model, linking the higher education market at equilibrium to a location decision model at entry on the labor market. I find that students' demand for programs is highly sensitive to proximity and that there exist significant moving costs, generating stickiness in location choices. Quantification exercises highlight that the geography of the higher market, given the existence of mobility frictions, accounts for one-third of the gaps in educational attainment across space. However, eliminating such frictions would lead to an increase in the number of individuals from higher education deserts entering the labor market in hubs, increasing inequalities across regions. Policies tying mobility scholarships and incentives to return would allow low-opportunity areas to outsource the education of their local labor force, hence circumventing this trade-off.

The framework presented in this paper could be adapted to an international context to investigate the role of students' global migration in cross-country brain drain. Importantly, the administrative data used in this study record the college applications and educational paths of foreign students applying to French colleges. Future work should also investigate how local governments compete with each over through admission policies to attract and retain students in their labor force. Finally, endogenizing the production of human capital, to incorporate potential increasing returns and peer effects, would be key to studying the efficient distribution of higher education programs across space.

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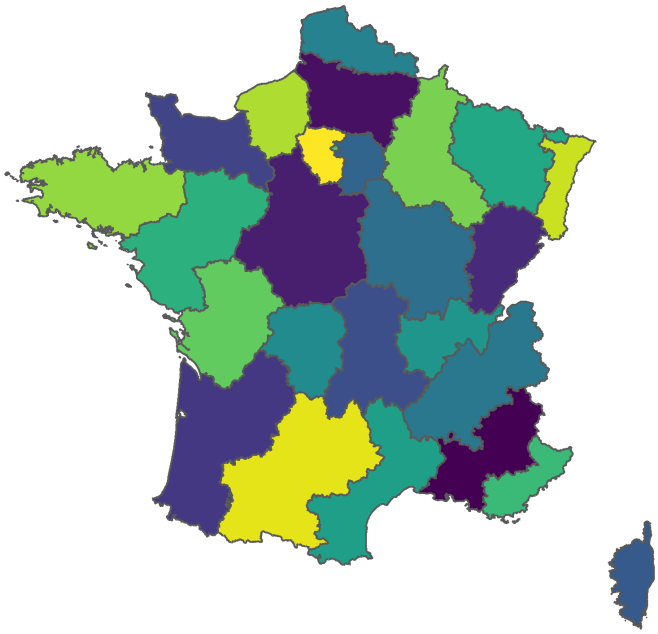
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A Additional Figures and Tables

Figure A.1: Catchment Areas



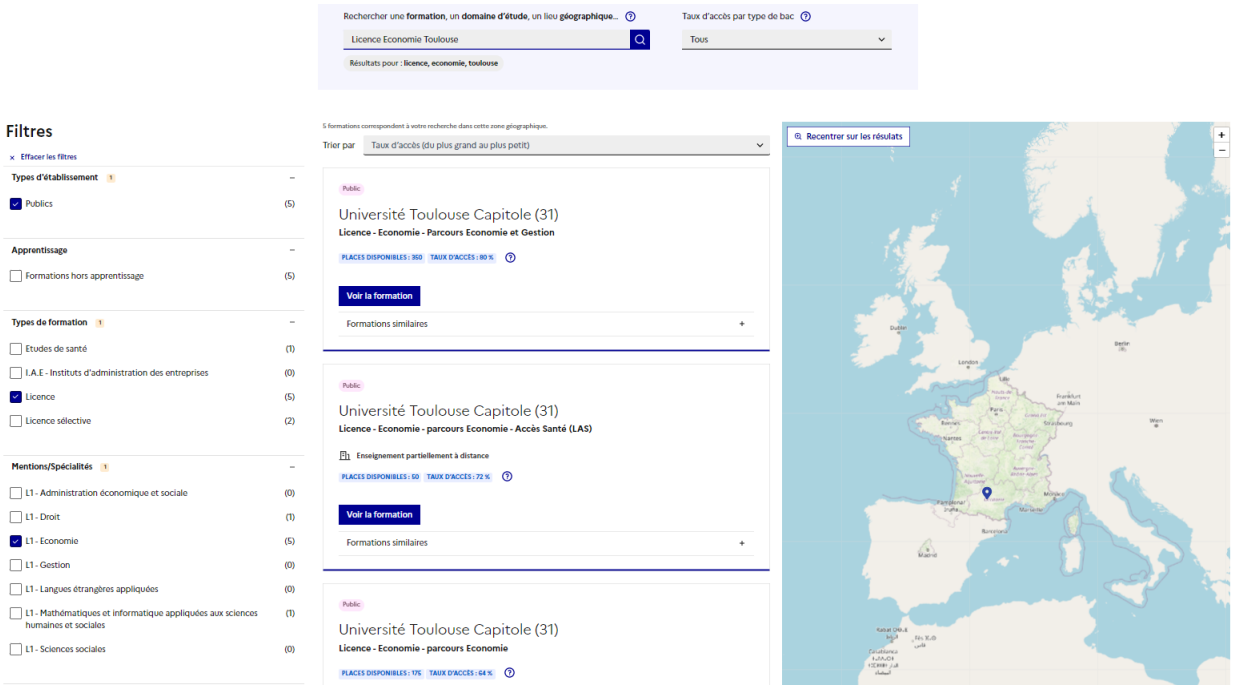
NOTES. This maps shows the geographic boundaries of the catchment areas in metropolitan France. Catchment areas outside metropolitan France are not shown.

Figure A.2: Search Engine



NOTES. Screenshot from the Parcoursup website. It depicts the search engine allowing students to look for programs available.

Figure A.3: Search Engine



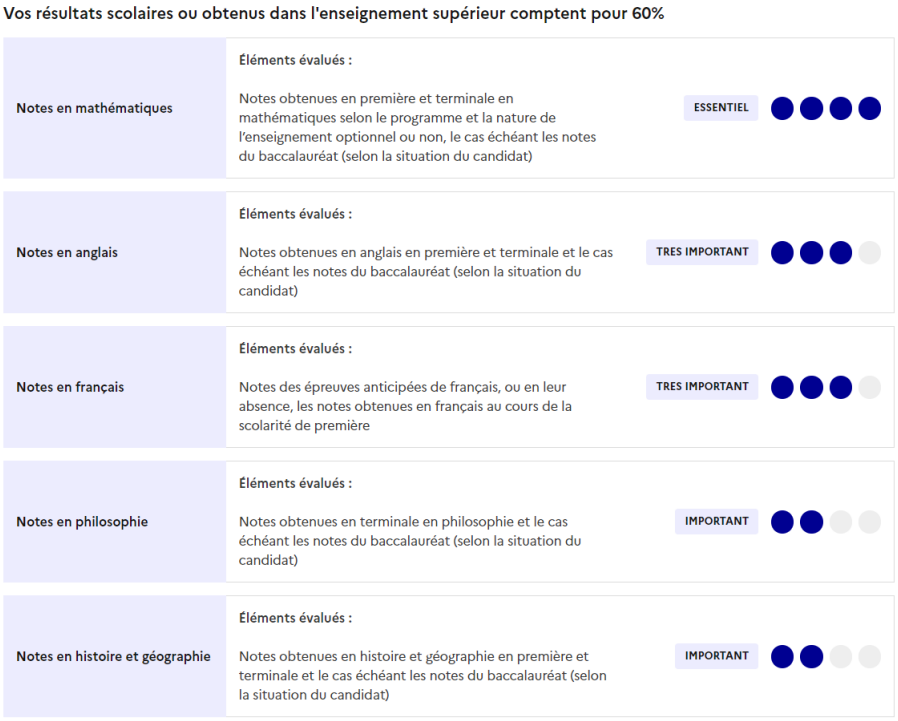
NOTES. Screenshot from the Parcoursup website. It depicts the result from a search for economics programs in universities located in Toulouse.

Figure A.4: Search Engine



Notes. Screenshot from the Parcoursup website. It depicts the type of information available to students when clicking on a specific program.

Figure A.5: Search Engine



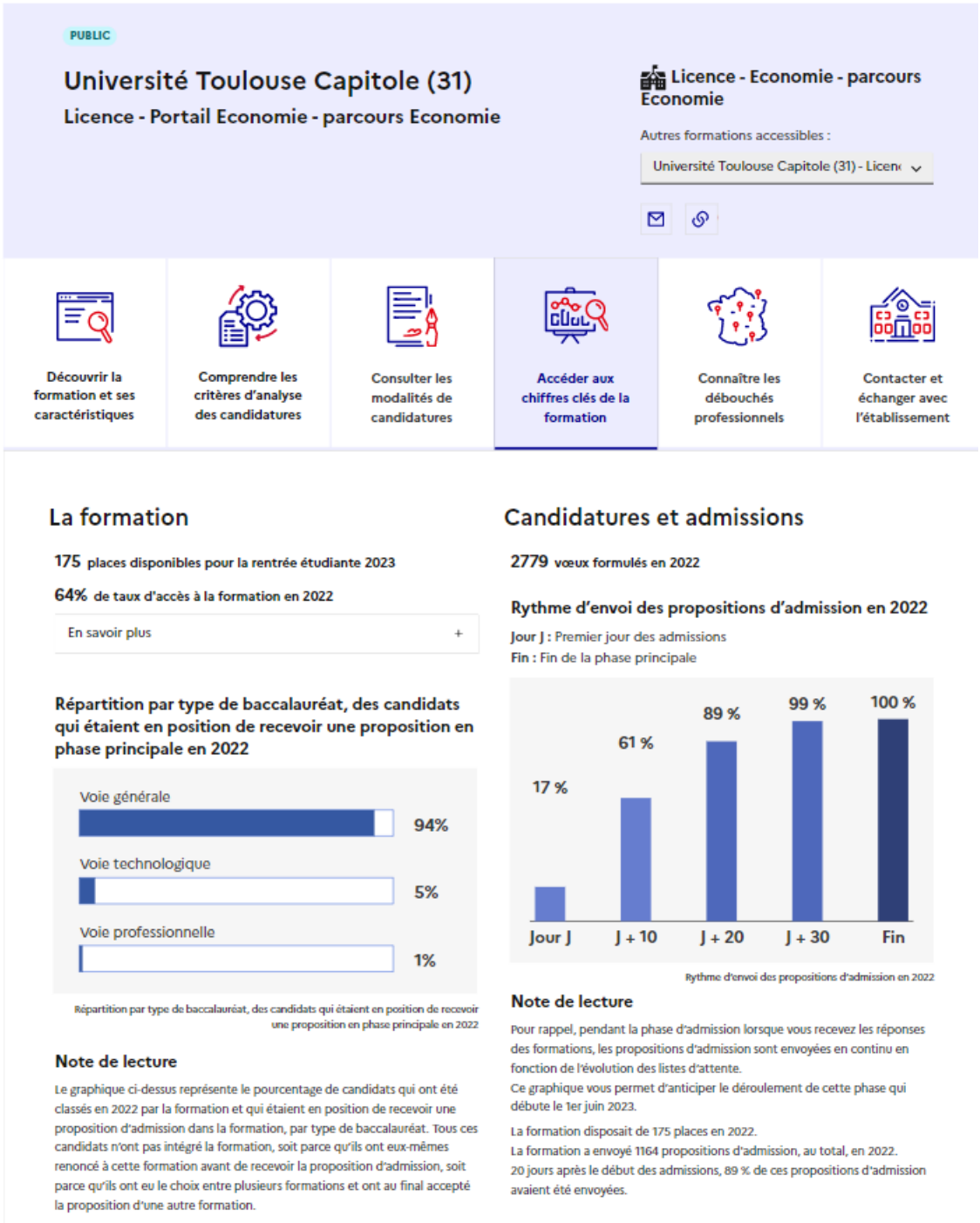
NOTES. Screenshot from the Parcoursup website. It depicts the type of information regarding admission criteria available to students when clicking on a specific program.

Figure A.6: Search Engine



NOTES. Screenshot from the Parcoursup website. It depicts the type of information regarding admission criteria available to students when clicking on a specific program.

Figure A.7: Search Engine



NOTES. Screenshot from the Parcoursup website. It depicts the type of information regarding admission criteria available to students when clicking on a specific program.

Table A.1: Summary Statistics: Students

	Mean	St. Dev.
	(1)	(2)
Female	0.5396	0.4984
Socio-Economic Characteristics		
With Scholarship	0.1939	0.3954
High SES	0.3139	0.4641
Medium High SES	0.1566	0.3634
Medium Low SES	0.3119	0.4633
Low SES	0.2177	0.4127
End-of-High School Exam		
With Highest Honors	0.0946	0.2927
With High Honors	0.1744	0.3794
With Honors	0.2963	0.4566
Pass	0.4347	0.4957
High School Track		
General HS Track	0.6257	0.4840
Technological HS Track	0.2222	0.4157
Vocational HS Track	0.1521	0.3591
Observations	505,069	

NOTES. This table presents summary statistics of college applicants in 2019. I restrict attention to high school students, living in metropolitan France.

Table A.2: Summary Statistics: Programs

	Mean	St. Dev.
	(1)	(2)
Panel A: Program Type and Major		
Three-Year University	0.2235	0.4166
Humanities	0.4152	0.4929
Economics - Law	0.1639	0.3703
Social Sciences	0.1939	0.3954
STEM	0.2270	0.4190
Two-Year Elite	0.0743	0.2623
STEM	0.5253	0.4997
Economics - Law	0.3144	0.4646
Humanities	0.1603	0.3671
Engineering/Business	0.0716	0.2579
Engineering	0.5166	0.5000
Business	0.0601	0.2378
Arts & Architecture	0.4233	0.4944
Two-Year Technical	0.0712	0.2571
Production	0.5997	0.4903
Services	0.4003	0.4903
Two-Year Vocational	0.4405	0.4965
Production	0.3498	0.4769
Services	0.5492	0.4976
Agriculture	0.1011	0.3014
Nursing & Social Work	0.0520	0.2221
Nursing	0.6391	0.4807
Social Work	0.3609	0.4807
Other	0.0669	0.2498
Panel B: Other Characteristics		
Nber Seats	61	113
With Dorm	0.0572	0.2322
Observations	10,917	

NOTES. This table presents summary statistics of programs available on the platform in 2019, located in metropolitan France.

Table A.3: Summary Statistics: Applications, Offers and Enrollment

	Mean	St. Dev.	25^{th} Pctile	50^{th} Pctile	75^{th} Pctile
	(1)	(2)	(3)	(4)	(5)
Nber Applications	10.587	9.291	5.000	9.000	13.000
Nber Offers	4.203	4.261	2.000	3.000	5.000
Distance of Enrollment	65.368	109.780	8.809	25.979	72.981

NOTES. This table presents summary statistics regarding applications, offers and enrollment of students in high school in 2019, living in metropolitan France. Characteristics of this sample are summarized in Table A.1.

Table A.4: Summary Statistics: Program Type Enrollment

	Mean	St. Dev.
	(1)	(2)
Three-Year University	0.3920	0.4882
Two-Year Elite	0.0700	0.2552
Engineering/Business	0.0461	0.2098
Two-Year Technical	0.0896	0.2856
Two-Year Vocational	0.1685	0.3743
Nursing	0.0262	0.1597
Other	0.0178	0.1320
Unmatched	0.1898	0.3921
Observations	505,069	

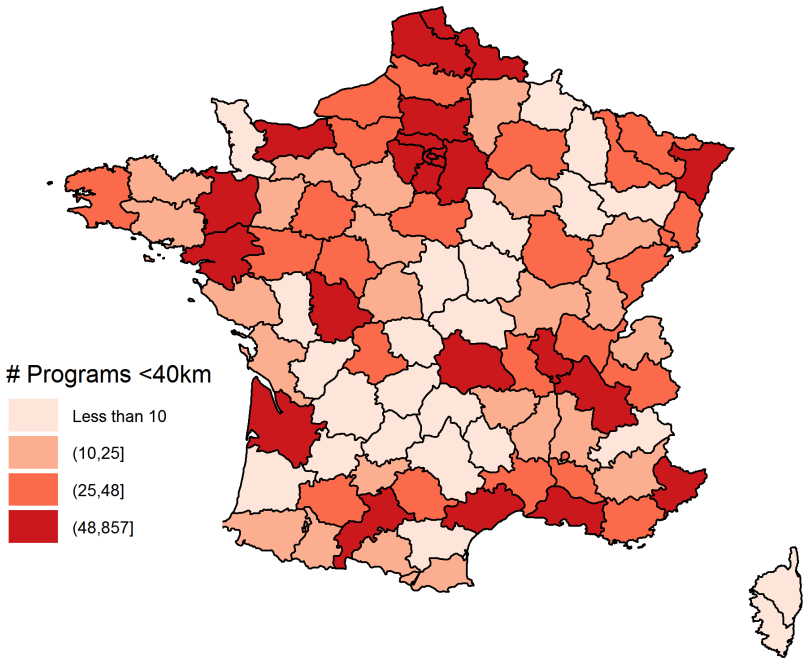
NOTES. This table presents summary statistics regarding the program of enrollment of students in high school in 2019, living in metropolitan France. Characteristics of this sample are summarized in Table A.1.

Table A.5: Summary Statistics: Entry-Level Workers

	Mean	St. Dev.	Min	Max
	(1)	(2)	(3)	(4)
Panel A: Work and Study Locations				
Study Home	0.51			
Work Home	0.64			
Work and Study Home	0.40			
Work Home if Study Home	0.82			
If Study Out of Home Location:				
Work Home	0.46			
Work in Study Location	0.17			
Work Elsewhere	0.36			
Panel B: Earnings				
Monthly Earnings	1,477	804	0	14,000
Nber Individuals	26,347			

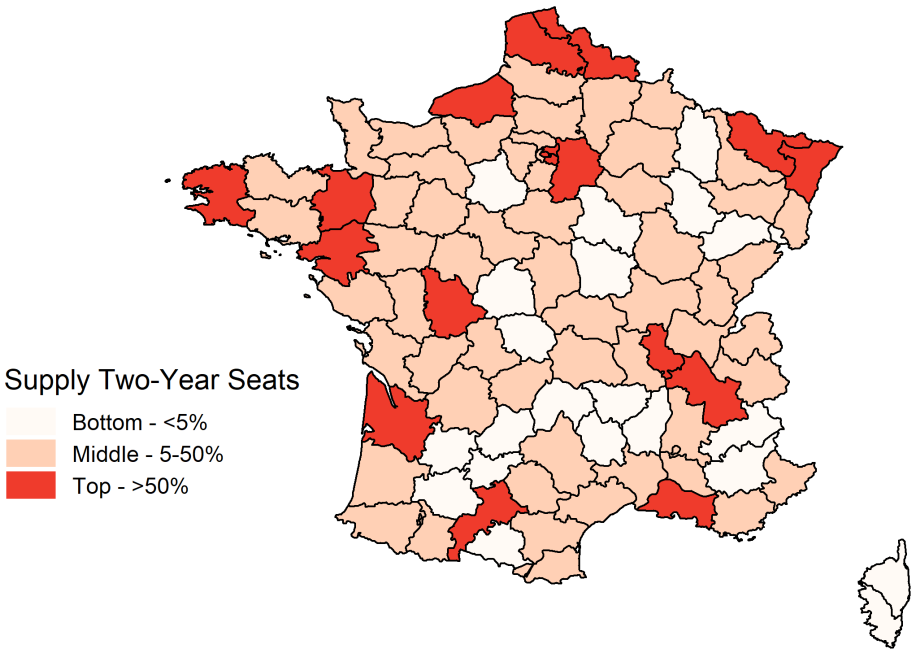
NOTES. This table provides summary statistics of the study and work flows of individuals who exited the education system, as well as of their earnings. Locations are defined at the province level. Study (work, respectively) home refers to the share of individuals who studied (who are working, respectively) in their home province. 'Work and Study Home' refers to the share of individuals who both studied and work in their home province. The table then restricts the sample to students who studied out of their home province, and describes the share who moved back home to work, who stayed in their study location, or who entered the labor market outside their study or home province (work elsewhere).

Figure A.8: Number of Academic Programs Within Commuting Distance



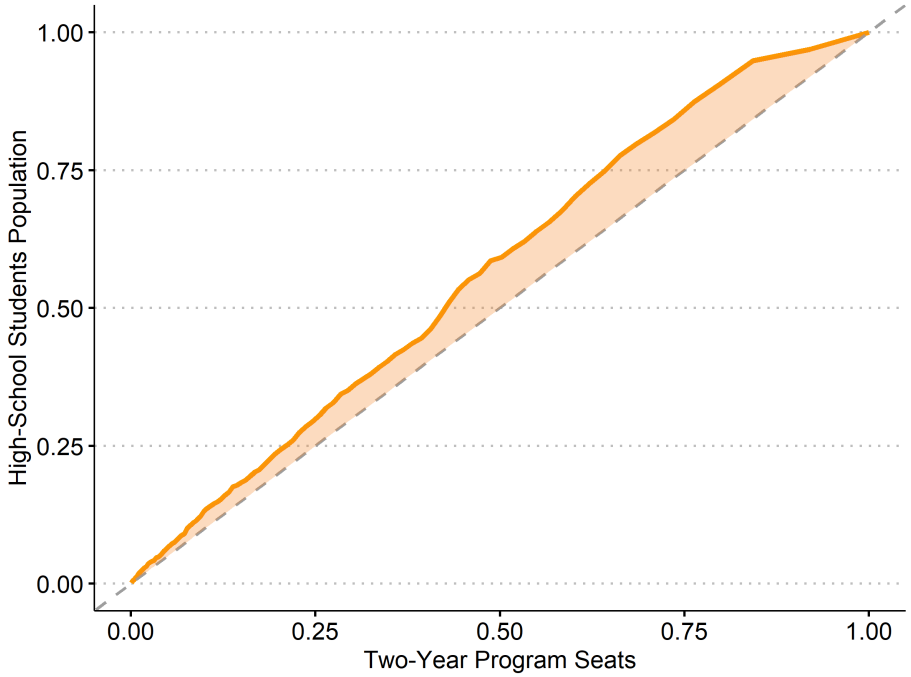
NOTES. This map plots the number of academic programs the mean student of a given province has access to within a 40-kilometer radius from her home.

Figure A.9: Spatial Distribution of Two-Year Technological and Vocational Programs' Seats



NOTES. This figure maps the distribution of two-year technological and vocational programs' seats, at the province level. Provinces are ranked according to their position in the distribution of these programs' seats. Provinces in white are at the bottom of this distribution: they jointly account for less than 5% of the total supply. In contrast, provinces in red are at the top of this distribution: half of the total supply of two-year technological and vocational seats is concentrated there.

Figure A.10: Cumulative Distribution of Two-Year Technological and Vocational Programs' Seats & Student Population



NOTES. This figure plots the relationship between the spatial distributions of two-year technological and vocational programs' seats and of high school students. It depicts the cumulative distribution of the supply of these seats across provinces on the x-axis, and the corresponding cumulative distribution of the high school student population on the y-axis. Provinces are ranked according to the share of vocational and technological seats they offer.

Table A.6: Minimum Distance to Programs

	Quantile			
	5^{th}	10^{th}	25^{th}	50^{th}
	(1)	(2)	(3)	(4)
Three-Year University Programs				
Law	62	50	32	14
Economics	73	61	41	17
Medicine	108	92	62	30
Sports	77	63	43	18
Mathematics	90	73	46	18
Physics & Chemistry	97	78	48	20
Two-Year Elite Programs				
Sciences	57	46	26	11
Humanities	85	69	43	17
Economics & Business	67	56	37	15
Two-Year Technical Programs				
Legal Careers	256	210	150	73
Marketing	74	63	41	18
Chemistry	190	144	94	52
IT	98	81	56	27
Two-Year Vocational Programs				
Real Estate	110	93	60	28
Accounting	39	31	19	8
Construction	89	79	55	27
Engineering Schools	69	56	35	14
Management Schools	116	102	72	32
Nursing Schools	32	26	17	7

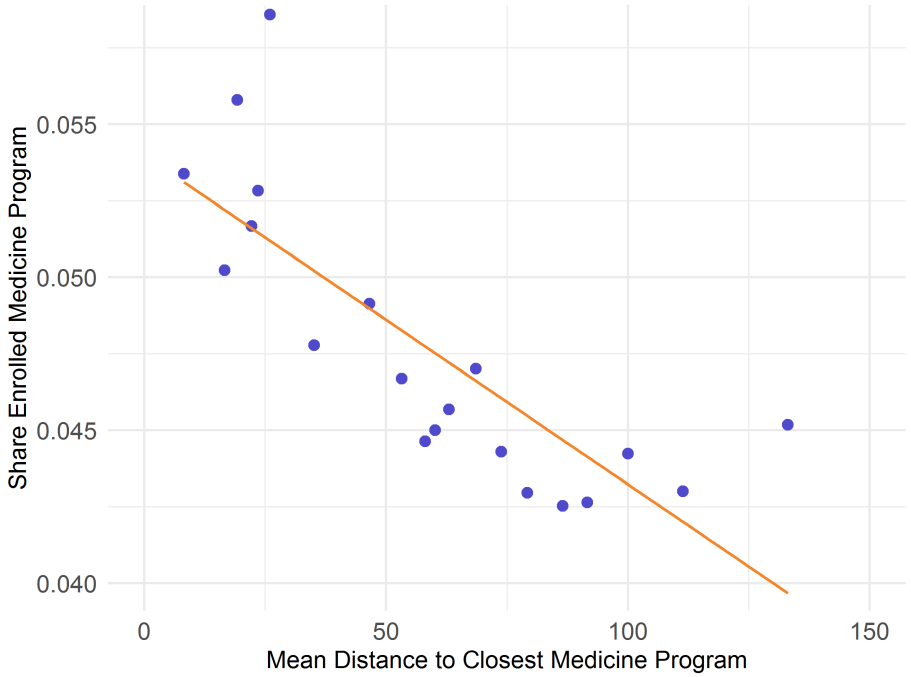
NOTES. Minimum distance to travel, by type of programs. For example, 10% of students have to travel at least 92 kilometers to reach a medicine program.

Table A.7: Gravity Model

	Enrollment Flows	
	OLS	PPML
	(1)	(2)
Distance$_{o,d}$	-1.912	-2.473
	(0.022)	(0.044)
Origin FE	Yes	Yes
Destination FE	Yes	Yes
Observations	5,878	8,930
Adjusted/Pseudo R-Square	0.7503	0.8734

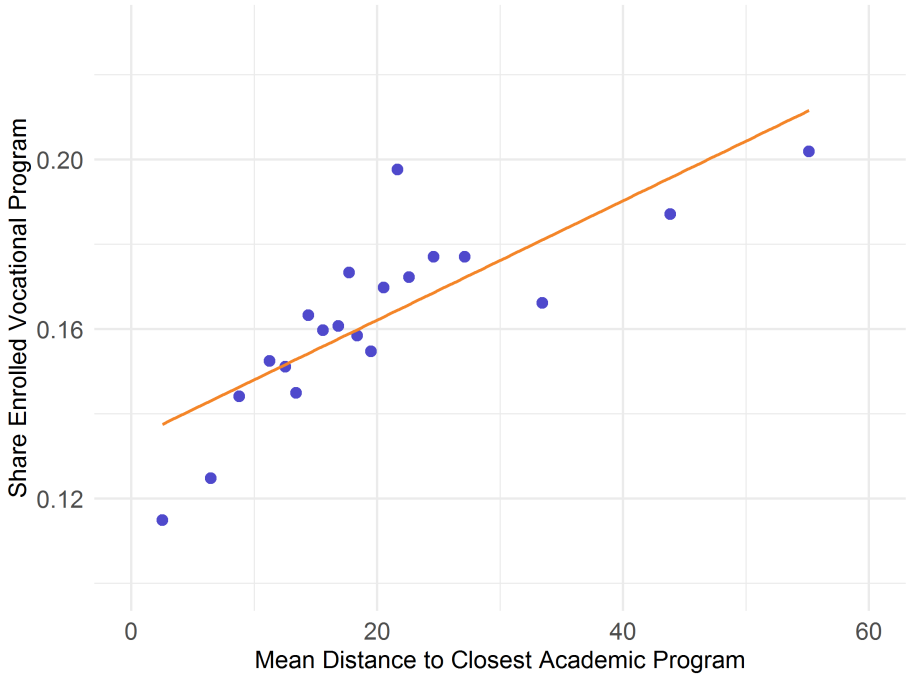
NOTES. This table presents estimates of a gravity equation. It regresses students' enrollment flows between origin province o and destination province d on the distance (in kilometers) between the centroids of o and d, controlling for origin and destination fixed effects. Column (1) shows results from an estimation using OLS, while Column (2) presents results using PPML, as recommended by Silva and Tenreyro (2006). Robust standard errors are shown in parenthesis.

Figure A.11: Enrollment in Medicine Program and their Local Availability



NOTES. This figure is a binned scatter plot, at the province level, of the relationship between the share of students from a province enrolled in an medicine program and the mean distance to the closest medicine program for the average student of the province.

Figure A.12: Enrollment in Two-Year Vocational Program and Local Availability of Academic Programs



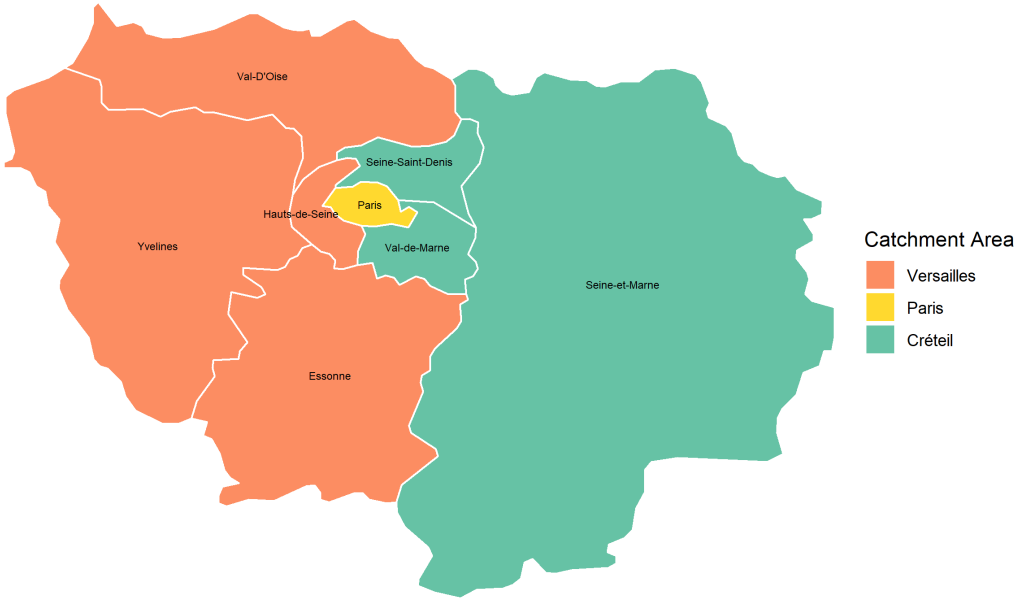
NOTES. This figure is a binned scatter plot, at the province level, of the relationship between the share of students from a province enrolled in a two-year vocational program and the mean distance to the closest academic program for the average student of the province.

Table A.8: Effect of the Mobility Scholarship

		Out-of-Catchment Area		
	Distance	Applications	Offers	Accepted Offers
	(1)	(2)	(3)	(4)
β_{2019}	11.3616	0.0306	0.0073	-0.0248
	(2.8061)	(0.0089)	(0.0128)	(0.0246)
β_{2017}	0.8575	-0.0084	-0.0138	0.0039
	(2.8914)	(0.0096)	(0.0135)	(0.0333)
β_{2016}	-3.8352	-0.0250	-0.0443	-0.0882
	(3.0376)	(0.0100)	(0.0197)	(0.0312)
β_{2015}	-2.9885	-0.0045	0.0348	-0.0043
	(3.2062)	(0.0104)	(0.0205)	(0.0332)
Observations	3,675,961	3,675,961	907,240	226,926

NOTES. This table presents parameter estimates of β_τ from Equation (1). It shows the effect of the mobility subsidy, implemented in 2019, on the mean application distance (Column (1), see also Figure 4), on the probability to submit an of out-of-catchment area application (Column (2)), to receive an out-of-catchment area offer (Column (3)) and to accept an out-of-catchment area offer (Column (4)). Results shown correspond to defining low-supply areas as the five locations at the bottom of the supply distribution. Effects are robust to extending this definition to the ten locations with the least supply, while the magnitude of the estimates is slightly smaller. High-supply areas are defined as the ten locations at the top of this distribution. Results are robust to extending this set. Robust standard errors are shown in parenthesis.

Figure A.13: Map of the Catchment Areas - Greater Paris Area



NOTES. The Greater Paris Area is composed of three catchment areas: Versailles, Paris and Créteil.

Table A.9: Descriptive Statistics: Greater Paris Area Programs

	Catchment Area			
	Paris	Versailles	Créteil	Greater Paris Area
University				
Number University Programs	167	92	81	340
Number Universities/Branches	10	8	7	25
Number Ranked Applicants	3,073	2,884	2,635	2,923
Rank Last Admitted	1,000	1,224	1,033	1,064
% High-Ability Overall	27.17	14.38	8.32	19.22
% High-Ability from Paris	5.81	0.92	0.48	3.22
% High-Ability from Versailles	4.92	11.40	0.94	5.72
% High-Ability from Créteil	4.82	1.31	5.35	3.99
Non-University				
Number Programs	437	499	446	1,382
Number Institutions	113	186	158	457
Number Ranked Applicants	1,121	784	748	879
Rank Last Admitted	156	94	90	111
% High-Ability Overall	48.32	29.24	21.41	32.75
% High-Ability from Paris	13.62	2.21	1.20	5.49
% High-Ability from Versailles	10.94	19.85	3.38	11.72
% High-Ability from Créteil	6.85	2.28	14.01	7.53

NOTES. Descriptive statistics of the programs offered in the Greater Paris area in 2018. The shares correspond to the mean percentage of high-ability students overall and from Paris/Versailles/Créteil admitted by each type of programs.

Table A.10: Institutional Barriers to Mobility: Greater Paris Area

	Program's Catchment Area		
	Paris	Versailles	Créteil
	(1)	(2)	(3)
All Students			
From Versailles	-483	197	-180
From Créteil	-157	-373	171
From Paris	943	-400	-111
High-Ability Students			
From Versailles	-807	73	-200
From Créteil	-470	-472	91
From Paris	407	-522	-93

NOTES. Average difference between the rank of an applicant before and after the implementation of geographic priorities in 2018. On average, the application of a student from Versailles to a university program located in Paris looses 483 ranks after the implementation of geographic priorities.

Table A.11: Removing Barriers to Mobility: Application Effects

	Share High-Ability Applicants		Share Low-Ability
	from Versailles	from Créteil	from Paris
	(1)	(2)	(3)
β_{Paris}	0.007***	0.002	-0.007**
	(0.002)	(0.002)	(0.004)
$\beta_{\text{Versailles}}$	-0.016***	0.004***	0.008***
	(0.003)	(0.001)	(0.001)
$\beta_{\text{Créteil}}$	0.003***	-0.009***	0.007***
	(0.001)	(0.002)	(0.002)
Baseline Paris	0.064	0.043	0.168
Baseline Versailles	0.143	0.019	0.048
Baseline Créteil	0.024	0.073	0.064
Program FE	Yes	Yes	Yes
Observations	680	680	680

NOTES. This table presents estimates from Equation (2). I study the effect of removing barriers to mobility on the share of high-ability students from Versailles (Column (1)), the share of high-ability students from Créteil (Column (2)) and the share of low-ability students from Paris (Column (3)) applying to university programs located in Paris, Versailles and Créteil. Standard errors clustered at the program level in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.12: Removing Barriers to Mobility: Sorting Effects

	Share High-Ability		Share Low-Ability
	from Versailles	from Créteil	from Paris
	(1)	(2)	(3)
$\beta^{DD}_{\text{Paris}}$	0.0360***	0.0061	-0.0787***
	(0.0082)	(0.0085)	(0.0173)
$\beta^{DD}_{\text{Versailles}}$	-0.0136***	0.0044	0.0195***
	(0.0128)	(0.0043)	(0.0063)
$\beta^{DD}_{\text{Créteil}}$	0.0099	0.0020	0.0232***
	(0.0042)	(0.0066)	(0.0069)
Baseline Paris	0.0492	0.0482	0.2205
Baseline Versailles	0.1140	0.0131	0.0303
Baseline Créteil	0.0094	0.0535	0.0472
Program FE	Yes	Yes	Yes
Observations	2,764	2,764	2,764

NOTES. This table presents estimates from Equation (19). I study the effect of removing barriers to mobility on the share of high-ability students from Versailles (Column (1)), the share of high-ability students from Créteil (Column (2)) and the share of low-ability students from Paris (Column (3)) enrolling in programs located in Paris, Versailles and Créteil. Standard errors clustered at the program level in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.13: Removing Barriers to Mobility: Application Effects

	Share High-Ability Applicants		Share Low-Ability
	from Versailles	from Créteil	from Paris
	(1)	(2)	(3)
$\beta^{DD}_{\text{Paris}}$	0.0132***	0.0005	-0.0068
	(0.0026)	(0.0020)	(0.0043)
$\beta^{DD}_{\text{Versailles}}$	-0.0091***	0.0032	0.0043**
	(0.0128)	(0.0011)	(0.0017)
$\beta^{DD}_{\text{Créteil}}$	0.0039	-0.0076	0.0056***
	(0.0013)	(0.0021)	(0.0021)
Baseline Paris	0.0636	0.0432	0.1685
Baseline Versailles	0.1433	0.0186	0.0484
Baseline Créteil	0.0245	0.0735	0.0643
Program FE	Yes	Yes	Yes
Observations	2,764	2,764	2,764

NOTES. This table presents estimates from Equation (19). I study the effect of removing barriers to mobility on the share of high-ability students from Versailles (Column (1)), the share of high-ability students from Créteil (Column (2)) and the share of low-ability students from Paris (Column (3)) applying to programs located in Paris, Versailles and Créteil. Standard errors clustered at the program level in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.14: Students' Preferences - Value

		Heterogeneity								
		Female	Medium High SES	Medium Low SES	Low SES	Schol-arship	High Honors	Honors	Pass	Voc/Tech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
University	-1.681	0.212	0.745	0.744	0.635	0.550	0.609	0.829	0.756	-2.354
	(0.167)	(0.083)	(0.126)	(0.110)	(0.122)	(0.119)	(0.175)	(0.162)	(0.153)	(0.096)
Two-Year Elite	0.868	-0.975	0.193	0.313	-0.225	0.191	0.079	-0.569	-1.536	-2.164
	(0.183)	(0.141)	(0.211)	(0.183)	(0.256)	(0.250)	(0.194)	(0.208)	(0.274)	(0.249)
Two-Year Technical	-2.196	-0.720	0.642	0.513	0.315	0.304	1.536	1.807	1.567	-0.573
	(0.284)	(0.120)	(0.172)	(0.154)	(0.176)	(0.167)	(0.291)	(0.279)	(0.278)	(0.128)
Nursing Schools	-6.085	2.108	0.586	0.861	0.342	-0.128	1.817	1.911	0.941	1.429
	(0.562)	(0.318)	(0.313)	(0.253)	(0.302)	(0.273)	(0.497)	(0.488)	(0.517)	(0.217)
Two-Year Vocational	-4.403	-0.416	0.736	0.870	0.854	0.220	0.996	1.402	1.314	1.412
	(0.275)	(0.098)	(0.164)	(0.138)	(0.146)	(0.127)	(0.285)	(0.265)	(0.260)	(0.117)
Engineering/Business	0.114	-0.881	0.312	0.196	-0.029	-0.089	0.825	0.432	-0.661	-2.001
	(0.233)	(0.156)	(0.224)	(0.202)	(0.250)	(0.280)	(0.239)	(0.239)	(0.272)	(0.215)
Other	-3.161	-0.645	0.078	1.257	1.076	0.197	1.276	0.787	0.866	-0.416
	(0.593)	(0.245)	(0.491)	(0.320)	(0.338)	(0.302)	(0.562)	(0.564)	(0.539)	(0.245)
Number Students	10,234									

NOTES. Standard errors in parentheses. Parameters correspond to $\frac{1}{\sigma}u(x_i, z_j)$. The estimated parameter for σ can be found in Table A.15.

Table A.15: Students' Preferences - Mobility Frictions

		Heterogeneity				
		Female	Medium High SES	Medium Low SES	Low SES	Scholarship
	(1)	(2)	(3)			
Distance (100km)	2.154	0.075	0.341	0.441	0.896	0.007
	(0.061)	(0.059)	(0.000)	(0.077)	(0.091)	(0.000)
Distance^2	-0.166	-0.004	-0.029	-0.025	-0.070	-0.003
	(0.008)	(0.008)	(0.013)	(0.010)	(0.012)	(0.010)
σ^{-1}	2.170					
	(0.135)					
Number Students	10,234					

NOTES. Standard errors in parentheses. Note that the function capturing mobility frictions enters $\mathcal{U}_{ij}$ with a negative sign. Positive parameters associated with distance thus indicate a distaste for this variable. The negative parameters associated with the square of distance imply that these costs are concave. Parameters associated with Distance and Distance^2 correspond to $\frac{1}{\sigma}c(x_i, d_{ij})$.

Table A.16: Students' Preferences - Compensation to Enroll 100km Away from Home

	Average	Female	High SES	Low SES	Scholarship
	(1)	(2)	(3)		
Monthly Subsidy (€)	1,102	1,125	933	1,317	1,192

NOTES. This table presents the monthly compensation, in euros, required by students to be willing to enroll in a program located 100 kilometers away from their home location. It is computed using parameters estimates in Table A.15. Note that the continuation value is expressed in monthly euros, while its associated parameter is normalized to one in $\mathcal{U}_{ij}$. Parameters of $u(.)$ and $c(.)$ can thus be interpreted in monthly euros.

Table A.17: Programs' Preferences

	University	Two-Year Elite	Two-Year Technical	Nursing	Two-Year Vocational	Engineering/Business	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	1.733	-1.543	0.846	1.743	2.018	1.461	2.486
	(0.062)	(0.080)	(0.063)	(0.081)	(0.015)	(0.053)	(0.059)
Grade	0.506	0.628	0.472	0.286	0.331	0.296	0.257
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)
Female	0.218	0.110	0.258	0.059	0.238	0.183	0.193
	(0.004)	(0.006)	(0.005)	(0.018)	(0.003)	(0.008)	(0.010)
Technological Track	-1.051	-1.093	-1.311	-0.424	-0.481	0.037	-0.501
	(0.008)	(0.051)	(0.074)	(0.013)	(0.007)	(0.010)	(0.012)
Vocational Track	-1.164	-1.990	-1.717	-0.856	-1.028	-0.506	-0.501
	(0.0146)	(0.187)	(0.018)	(0.018)	(0.011)	(0.015)	(0.012)
Medium-High SES	0.032	-0.000	0.054	-0.070	0.033	0.061	0.019
	(0.005)	(0.008)	(0.006)	(0.018)	(0.004)	(0.010)	(0.015)
Medium Low SES	0.009	0.031	0.028	-0.098	0.035	0.031	-0.004
	(0.005)	(0.007)	(0.005)	(0.016)	(0.003)	(0.009)	(0.012)
Low SES	0.034	0.080	0.037	-0.128	0.035	-0.007	-0.016
	(0.006)	(0.010)	(0.006)	(0.017)	(0.003)	(0.012)	(0.014)
With Scholarship	0.417	0.400	0.247	0.024	0.068	0.054	0.081
	(0.005)	(0.009)	(0.006)	(0.015)	(0.003)	(0.011)	(0.012)
Same Catchment Area	0.293						
	(0.004)						
High School with HE Program		0.133			-0.003		
		(0.006)			(0.003)		
Same High School		0.448			0.361		
		(0.012)			(0.004)		
Number Programs	10,917						

NOTES. Standard errors in parentheses.

Table A.18: Preferences over Local Labor Markets

Home Bias		
High School Diploma × Home Location	5.689	(0.046)
Two-Year Degree × Home Location	5.312	(0.051)
Bachelor's Degree and More × Home Location	4.214	(0.027)
Moving Costs		
High School Diploma × Graduation Location	3.877	(0.060)
Two-Year Degree × Graduation Location	3.463	(0.070)
Bachelor's Degree and More × Graduation Location	2.953	(0.034)
High School Diploma × Home Location × Graduation Location	-3.234	(0.099)
Two-Year Degree × Home Location × Graduation Location	-2.844	(0.119)
Bachelor's Degree and More × Home Location × Graduation	-2.195	(0.063)
Scale		
θ	1.425	(0.145)
Location FE	Yes	
Observations	2,502,965	
Number Individuals	26,347	

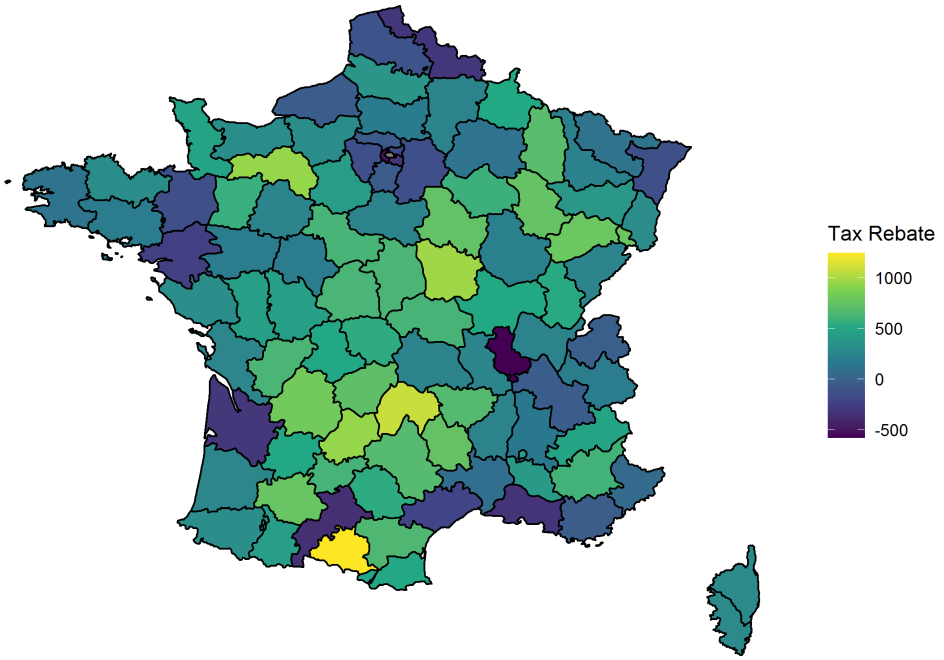
NOTES. Standard errors in parentheses.

Table A.19: Transition Probabilities

	Two-Year Degree	Bachelor and More
	(1)	(2)
Entry Location	5.578 (0.004)	
Program Choice		
University	-0.301 (0.025)	2.387 (0.020)
Two-Year Elite	1.421 (0.034)	3.593 (0.030)
Two-Year Technical	2.300 (0.029)	3.295 (0.026)
Nursing	2.988 (0.039)	
Two-Year Vocational	2.719 (0.027)	2.547 (0.025)
Engineering/Business	1.350 (0.039)	3.823 (0.034)
Other	1.144 (0.040)	2.271 (0.039)
Outside Option	-0.749 (0.025)	0.678 (0.021)
Baseline Characteristics		
Female	0.061 (0.010)	0.148 (0.009)
With Scholarship	-0.089 (0.012)	-0.143 (0.011)
Medium-High SES	-0.051 (0.015)	-0.103 (0.013)
Medium-Low SES	-0.048 (0.013)	-0.165 (0.011)
Low SES	-0.062 (0.014)	-0.221 (0.013)
Medium-High GPA	-0.208 (0.025)	-0.404 (0.021)
Medium-Low GPA	-0.492 (0.024)	-0.964 (0.020)
Low GPA	-0.990 (0.023)	-1.888 (0.019)
Technical Track	-0.409 (0.012)	-1.335 (0.012)
Vocational Track	-1.195 (0.016)	-2.835 (0.020)
Province FE	Yes	
Observations	136,489,065	
Number Students	478,909	

NOTES. Standard errors in parentheses.

Figure A.14: Location Choices - Moving Costs



NOTES. This map uses estimated preferences over local labor markets to compute the tax rebate, in monthly euros, an individual from a given province would need to receive to be willing to move back home rather than to stay in Paris, conditional on having studied in Paris and having reached at least a bachelor's degree. It corresponds to Column (2) of Tables A.20-A.21. It abstracts from wage differences across locations.

Table A.20: Compensation to Move to Paris - Three-Year Degree

	Studied Home	Studied Paris	Wage Premium Paris
	(1)	(2)	(3)
Ain	2,369.6129	-233.8147	326.3984
Aisne	2,368.6639	-234.7637	355.2361
Allier	1,985.5966	-617.8309	471.2733
Alpes de Hte Provence	2,001.6312	-601.7962	548.2294
Hautes Alpes	2,125.5078	-477.9197	665.6326
Alpes Maritimes	2,544.4763	-58.9512	330.3785
Ardèche	2,371.7680	-231.6596	607.5127
Ardennes	2,086.5887	-516.8389	401.0415
Ariège	1,358.9583	-1,244.4690	312.4867
Aube	2,022.0723	-581.3550	430.4088
Aude	1,950.3682	-653.0594	380.2688
Aveyron	1,924.8845	-678.5429	459.1324
Bouches du Rhône	2,928.8074	325.3799	417.2416
Calvados	2,289.4302	-313.9972	399.6028
Cantal	1,519.6078	-1,083.8197	362.2968
Charente	1,973.1458	-630.2817	365.7993
Charente Maritime	2,346.5526	-256.8749	513.4595
Cher	1,968.0151	-635.4125	417.8051
Corrèze	1,879.9699	-723.4577	418.7350
Corse	2,315.2206	-288.2070	622.1647
Côte d'Or	2,391.8662	-211.5612	425.7309
Côtes d"Armor	2,294.1312	-309.2964	519.4637
Creuse	2,060.5421	-542.8852	842.7283
Dordogne	1,782.8343	-820.5934	335.3272
Doubs	2,352.7405	-250.6870	339.9949
Drôme	2,455.5481	-147.8794	511.8137
Eure	2,294.8684	-308.5591	428.7651
Eure et Loir	2,175.4474	-427.9801	330.5469
Finistère	2,483.8316	-119.5958	489.8322
Gard	2,521.8089	-81.6187	494.3485
Haute Garonne	2,953.8333	350.4058	323.7789
Gers	1,832.4528	-770.9747	511.5211
Gironde	2,908.4976	305.0702	467.9077
Hérault	2,819.9723	216.5449	501.8954
Ille et Vilaine	2,734.8472	-131.4197	515.6054
Indre	1,973.4576	-629.9698	502.4423
Indre et Loire	2,419.2800	-184.1474	381.1048
Isère	2,644.9495	41.5221	440.0371
Jura	2,075.2228	-528.2046	478.8349
Landes	2,343.6603	-259.7672	490.7403
Loir et Cher	1,983.7581	-619.6693	466.3047
Loire	2,351.3026	-252.1251	418.0523
Haute Loire	1,926.1790	-677.2485	434.1151
Loire Atlantique	2,849.8087	246.3813	474.7519
Loiret	2,372.1628	-231.2647	324.5332
Lot	1,656.4006	-947.0268	372.4734
Total	2,537.3571	-66.0703	372.4073

NOTES. This table presents monthly compensation payments, by home location, required for individuals to accept to enter the labor market in Paris rather than in their home location, if they studied home (Column (1)) or in Paris (Column (2)). Column (3) shows the wage premium between Paris and the other provinces.

Table A.21: Compensation to Move to Paris - Three-Year Degree (Continued)

	Studied Home	Studied Paris	Wage Premium Paris
	(1)	(2)	(3)
Lot et Garonne	2,091.8518	-511.5757	471.4930
Lozère	1,851.6222	-751.8053	690.9455
Maine et Loire	2,424.8839	-178.5436	485.0795
Manche	2,126.3413	-477.0860	300.9559
Marne	2,482.1343	-121.2931	407.1520
Haute Marne	1,849.2807	-754.1468	330.7110
Mayenne	2,035.1841	-568.2434	419.8071
Meurthe et Moselle	2,383.3641	-220.0634	291.3181
Meuse	1,907.2369	-696.1907	457.0153
Morbihan	2,418.4473	-184.9802	532.3172
Moselle	2,490.5786	-112.8488	336.0319
Nièvre	1,630.8758	-972.5516	422.4279
Nord	2,912.8714	309.4440	384.7555
Oise	2,432.8463	-170.5809	195.1116
Orne	1,656.6796	-946.7479	320.8997
Pas de Calais	2,716.4795	113.0522	426.5190
Puy de Dôme	2,370.8833	-232.5442	371.9368
Pyrénées Atlantiques	2,282.8366	-320.5909	507.9615
Hautes Pyrénées	2,169.2061	-434.2213	549.2835
Pyrénées Orientales	2,096.8928	-506.5347	484.0320
Bas Rhin	2,740.4122	136.9845	340.6232
Haut Rhin	2,300.4759	-302.9515	246.9669
Rhône	3,184.0545	580.6269	390.7863
Haute Saône	1,812.4154	-791.0120	427.8329
Saône et Loire	2,086.4920	-516.9353	483.6682
Sarthe	2,354.2532	-249.1742	610.4579
Savoie	2,412.0451	-191.3823	459.0726
Haute Savoie	2,633.2440	29.8163	223.3103
Seine Maritime	2,645.9545	42.5270	353.5218
Seine et Marne	2,744.5728	141.1452	214.3282
Yvelines	2,740.9037	137.4763	122.6240
Deux Sèvres	2,158.9117	-444.5156	545.1390
Somme	2,235.0758	-368.3516	168.7533
Tarn	2,062.4704	-540.9571	493.1672
Tarn et Garonne	1,991.0916	-612.3359	469.2621
Var	2,653.2386	49.8111	530.9038
Vaucluse	2,193.4653	-409.9623	507.2162
Vendée	2,285.2377	-318.1898	574.0239
Vienne	2,162.4033	-441.0241	473.1853
Haute Vienne	2,090.1821	-513.2454	470.5154
Vosges	2,214.1920	-389.2355	517.9851
Yonne	1,858.8254	-744.6021	409.8497
Territoire de Belfort	1,817.0413	-786.3862	467.1307
Essonne	2,654.3795	50.9520	180.7714
Hauts de Seine	3,111.4564	508.0290	-20.3760
Seine St Denis	2,783.2324	179.8049	153.5027
Val de Marne	2,915.1990	311.7717	128.1345
Val d'Oise	2,661.1420	57.7145	182.9899
Total	2,537.3571	-66.0703	372.4073

NOTES. This table presents monthly compensation payments, by home location, required for individuals to accept to enter the labor market in Paris rather than in their home location, if they studied home (Column (1)) or in Paris (Column (2)). Column (3) shows the wage premium between Paris and the other provinces.

Table A.22: Compensation to Move to Paris - Two-Year Degree

	Studied Home	Studied Paris	Wage Premium Paris
	(1)	(2)	(3)
Ain	3,042.4593	178.2033	94.9097
Aisne	3,041.5105	177.2544	282.6605
Allier	2,658.4430	-205.8130	331.2574
Alpes de Hte Provence	2,674.4778	-189.7785	302.0740
Hautes Alpes	2,798.3544	-65.9017	419.4772
Alpes Maritimes	3,217.3228	353.0668	84.2231
Ardèche	3,044.6145	180.3585	376.0240
Ardennes	2,759.4352	-104.8209	266.3717
Ariège	2,031.8050	-832.4512	181.7255
Aube	2,694.9191	-169.3370	295.7390
Aude	2,623.2148	-241.0414	213.7589
Aveyron	2,597.7313	-266.5247	328.3712
Bouches du Rhône	3,601.6540	737.3981	171.0862
Calvados	2,962.2767	98.0208	226.7728
Cantal	2,192.4544	-671.8016	222.2809
Charente	2,645.9922	-218.2638	93.2114
Charente Maritime	3,019.3993	155.1430	240.8716
Cher	2,640.8617	-223.3945	208.6330
Corrèze	2,552.8164	-311.4397	254.1644
Corse	2,988.0671	123.8110	113.9858
Côte d'Or	3,064.7129	200.4569	122.6522
Côtes d"Armor	2,966.9777	102.7216	225.6494
Creuse	2,733.3889	-130.8674	678.1577
Dordogne	2,455.6808	-408.5753	51.8349
Doubs	3,025.5872	161.3310	128.0431
Drôme	3,128.3947	264.1385	280.3250
Eure	2,967.7151	103.4589	227.6143
Eure et Loir	2,848.2939	-15.9622	121.3749
Finistère	3,156.6785	292.4223	196.0179
Gard	3,194.6556	330.3993	327.8386
Haute Garonne	3,626.6800	762.4239	193.0176
Gers	2,505.2995	-358.9567	380.7599
Gironde	3,581.3444	717.0881	184.4153
Hérault	3,492.8190	628.5629	335.3855
Ille et Vilaine	3,407.6937	543.4377	221.7911
Indre	2,646.3043	-217.9519	293.2704
Indre et Loire	3,092.1267	227.8706	171.9328
Isère	3,317.7960	453.5401	208.5485
Jura	2,748.0695	-116.1867	266.8831
Landes	3,016.5067	152.2507	207.2480
Loir et Cher	2,656.6049	-207.6513	257.1327
Loire	3,024.1490	159.8929	186.5636
Haute Loire	2,599.0256	-265.2304	294.0991
Loire Atlantique	3,522.6555	658.3994	136.2557
Loiret	3,045.0092	180.7533	115.3612
Lot	2,329.2474	-535.0088	241.7122
Total	3,210.2038	345.9477	194.0919

NOTES. This table presents monthly compensation payments, by home location, required for individuals to accept to enter the labor market in Paris rather than in their home location, if they studied home (Column (1)) or in Paris (Column (2)). Column (3) shows the wage premium between Paris and the other provinces.

Table A.23: Compensation to Move to Paris - Two-Year Degree (Continued)

	Studied Home	Studied Paris	Wage Premium Paris
	(1)	(2)	(3)
Lot et Garonne	2,764.6984	-99.5578	188.0007
Lozère	2,524.4689	-339.7871	524.4356
Maine et Loire	3,097.7306	233.4745	146.5833
Manche	2,799.1880	-65.0682	128.1259
Marne	3,154.9809	290.7249	272.4822
Haute Marne	2,522.1273	-342.1289	196.0412
Mayenne	2,708.0308	-156.2255	81.3109
Meurthe et Moselle	3,056.2107	191.9547	102.0846
Meuse	2,580.0833	-284.1727	267.7819
Morbihan	3,091.2937	227.0378	238.5029
Moselle	3,163.4253	299.1691	146.7984
Nièvre	2,303.7225	-560.5337	119.3491
Nord	3,585.7182	721.4620	253.9108
Oise	3,105.6931	241.4370	122.5359
Orne	2,329.5260	-534.7300	148.0696
Pas de Calais	3,389.3263	525.0701	295.6743
Puy de Dôme	3,043.7298	179.4737	231.9208
Pyrénées Atlantiques	2,955.6833	91.4272	224.4692
Hautes Pyrénées	2,842.0529	-22.2032	418.5222
Pyrénées Orientales	2,769.7395	-94.5168	317.5221
Bas Rhin	3,413.2586	549.0024	192.4934
Haut Rhin	2,973.3226	109.0664	98.8371
Rhône	3,856.9011	992.6450	159.2976
Haute Saône	2,485.2621	-378.9940	215.8811
Saône et Loire	2,759.3388	-104.9174	180.5895
Sarthe	3,027.0998	162.8437	271.9618
Savoie	3,084.8918	220.6357	227.5839
Haute Savoie	3,306.0904	441.8345	-8.1784
Seine Maritime	3,318.8013	454.5452	152.3710
Seine et Marne	3,417.4193	553.1633	214.3282
Yvelines	3,413.7505	549.4943	122.6241
Deux Sèvres	2,831.7585	-32.4976	272.5511
Somme	2,907.9226	43.6664	96.1777
Tarn	2,735.3169	-128.9391	362.4060
Tarn et Garonne	2,663.9383	-200.3179	338.5008
Var	3,326.0853	461.8291	284.7484
Vaucluse	2,866.3118	2.0558	261.0608
Vendée	2,958.0843	93.8284	235.5277
Vienne	2,835.2502	-29.0061	200.5974
Haute Vienne	2,763.0287	-101.2275	305.9449
Vosges	2,887.0388	22.7826	328.7516
Yonne	2,531.6721	-332.5841	106.7710
Territoire de Belfort	2,489.8878	-374.3681	255.1788
Essonne	3,327.2261	462.9701	180.7715
Hauts de Seine	3,784.3031	920.0469	-20.3760
Seine St Denis	3,456.0793	591.8230	153.5027
Val de Marne	3,588.0456	723.7896	128.1345
Val d'Oise	3,333.9886	469.7326	182.9900
Total	3,210.2038	345.9477	194.0919

NOTES. This table presents monthly compensation payments, by home location, required for individuals to accept to enter the labor market in Paris rather than in their home location, if they studied home (Column (1)) or in Paris (Column (2)). Column (3) shows the wage premium between Paris and the other provinces.

Table A.24: Compensation to Move to Paris - High School Diploma

	Studied Home	Studied Paris	Wage Premium Paris
	(1)	(2)	(3)
Ain	-3,324.2799	152.7627	78.7502
Aisne	-3,323.3308	151.8136	329.0525
Allier	-2,940.2634	-231.2536	255.1376
Alpes de Hte Provence	-2,956.2981	-215.2191	328.9836
Hautes Alpes	-3,080.1748	-91.3423	446.3868
Alpes Maritimes	-3,499.1432	327.6260	111.1327
Ardèche	-3,326.4350	154.9179	359.8644
Ardennes	-3,041.2555	-130.2615	280.7475
Ariège	-2,313.6253	-857.8918	33.5004
Aube	-2,976.7397	-194.7776	310.1148
Aude	-2,905.0350	-266.4821	200.3853
Aveyron	-2,879.5517	-291.9655	180.1461
Bouches du Rhône	-3,883.4744	711.9572	197.9958
Calvados	-3,244.0972	72.5801	87.6995
Cantal	-2,474.2748	-697.2423	146.1611
Charente	-2,927.8127	-243.7043	39.3705
Charente Maritime	-3,301.2196	129.7024	187.0307
Cher	-2,922.6822	-248.8352	182.9081
Corrèze	-2,834.6369	-336.8804	109.4091
Corse	-3,269.8875	98.3703	-69.6015
Côte d'Or	-3,346.5333	175.0161	84.8087
Côtes d"Armor	-3,248.7981	77.2809	172.1978
Creuse	-3,015.2093	-156.3080	533.4024
Dordogne	-2,737.5013	-434.0159	3.4210
Doubs	-3,307.4076	135.8903	51.8389
Drôme	-3,410.2152	238.6980	264.1655
Eure	-3,249.5355	78.0182	264.2183
Eure et Loir	-3,130.1144	-41.4028	95.6499
Finistère	-3,438.4989	266.9817	142.5664
Gard	-3,476.4760	304.9587	314.4651
Haute Garonne	-3,908.5004	736.9834	44.7925
Gers	-2,787.1199	-384.3973	232.5348
Gironde	-3,863.1646	691.6475	136.0014
Hérault	-3,774.6394	603.1222	322.0120
Ille et Vilaine	-3,689.5142	517.9971	168.3395
Indre	-2,928.1247	-243.3925	267.5453
Indre et Loire	-3,373.9472	202.4299	146.2078
Isère	-3,599.6165	428.0994	192.3888
Jura	-3,029.8899	-141.6272	190.6789
Landes	-3,298.3272	126.8101	158.8341
Loir et Cher	-2,938.4252	-233.0920	231.4077
Loire	-3,305.9694	134.4523	170.4040
Haute Loire	-2,880.8460	-290.6711	217.9793
Loire Atlantique	-3,804.4759	632.9587	71.0329
Loiret	-3,326.8297	155.3127	89.6362
Lot	-2,611.0679	-560.4494	93.4871
Total	-3,492.0242	320.5070	167.3803

NOTES. This table presents monthly compensation payments, by home location, required for individuals to accept to enter the labor market in Paris rather than in their home location, if they studied home (Column (1)) or in Paris (Column (2)). Column (3) shows the wage premium between Paris and the other provinces.

Table A.25: Compensation to Move to Paris - High School Diploma (Continued)

	Studied Home	Studied Paris	Wage Premium Paris
	(1)	(2)	(3)
Lot et Garonne	3,046.5187	-124.9983	139.5868
Lozère	2,806.2893	-365.2278	511.0620
Maine et Loire	3,379.5511	208.0337	81.3605
Manche	3,081.0085	-90.5090	-10.9474
Marne	3,436.8015	265.2843	286.8581
Haute Marne	2,803.9478	-367.5695	210.4170
Mayenne	2,989.8513	-181.6661	16.0880
Meurthe et Moselle	3,338.0311	166.5140	99.6413
Meuse	2,861.9038	-309.6133	265.3386
Morbihan	3,373.1141	201.5971	185.0514
Moselle	3,445.2458	273.7285	144.3551
Nièvre	2,585.5428	-585.9744	81.5056
Nord	3,867.5385	696.0213	249.9462
Oise	3,387.5136	215.9964	168.9280
Orne	2,611.3466	-560.1707	8.9963
Pas de Calais	3,671.1468	499.6294	291.7096
Puy de Dôme	3,325.5504	154.0332	155.8010
Pyrénées Atlantiques	3,237.5036	65.9864	176.0553
Hautes Pyrénées	3,123.8734	-47.6440	270.2972
Pyrénées Orientales	3,051.5596	-119.9575	304.1485
Bas Rhin	3,695.0791	523.5619	175.7847
Haut Rhin	3,255.1429	83.6257	82.1284
Rhône	4,138.7217	967.2043	143.1380
Haute Saône	2,767.0827	-404.4348	139.6769
Saône et Loire	3,041.1593	-130.3581	142.7460
Sarthe	3,308.9203	137.4031	206.7389
Savoie	3,366.7123	195.1950	211.4243
Haute Savoie	3,587.9109	416.3938	-24.3379
Seine Maritime	3,600.6215	429.1044	188.9750
Seine et Marne	3,699.2398	527.7227	214.3282
Yvelines	3,695.5710	524.0537	122.6241
Deux Sèvres	3,113.5789	-57.9382	218.7102
Somme	3,189.7430	18.2258	142.5697
Tarn	3,017.1373	-154.3797	214.1810
Tarn et Garonne	2,945.7586	-225.7584	190.2758
Var	3,607.9054	436.3884	311.6579
Vaucluse	3,148.1322	-23.3850	287.9704
Vendée	3,239.9048	68.3876	170.3049
Vienne	3,117.0705	-54.4468	146.7565
Haute Vienne	3,044.8490	-126.6681	161.1896
Vosges	3,168.8590	-2.6581	326.3083
Yonne	2,813.4923	-358.0248	68.9275
Territoire de Belfort	2,771.7083	-399.8088	178.9746
Essonne	3,609.0467	437.5295	180.7714
Hauts de Seine	4,066.1235	894.6063	-20.3760
Seine St Denis	3,737.8996	566.3823	153.5027
Val de Marne	3,869.8662	698.3489	128.1345
Val d'Oise	3,615.8090	444.2919	182.9899
Total	3,492.0242	320.5070	167.3803

NOTES. This table presents monthly compensation payments, by home location, required for individuals to accept to enter the labor market in Paris rather than in their home location, if they studied home (Column (1)) or in Paris (Column (2)). Column (3) shows the wage premium between Paris and the other provinces.

Table A.26: Model Fit

	Data (1)	Model (2)
Panel A: Higher Education Market		
University	49.17	49.23
Two-Year Elite	8.68	9.57
Two-Year Technical	11.03	10.89
Two-Year Vocational	19.69	19.42
Nursing School	3.60	3.04
Ingeneering/Business	5.63	5.36
Other	2.20	2.49
Distance	67.21	69.88
Panel B: Work Location		
Same as Home & Study Location	40.31	40.34
Same as Home Location Only	23.55	23.56
Same as Study Location Only	9.02	8.81
Neither	27.11	27.28

NOTES. This table evaluates the fit of the model by comparing statistics related to the match on the higher education market (Panel A) and to location choices at entry on the labor market (Panel B). Column (1) and Column (2) present the statistics observed in the data and in the simulated status quo, respectively.

Table A.27: Model Fit: Gravity Model

	Enrollment Flows	
	Data	Model
	(1)	(2)
Distance$_{o,d}$	-2.506	-2.271
	(0.056)	
Origin FE	Yes	Yes
Destination FE	Yes	Yes
Obs.	8,930	8,930

NOTES. This table presents estimates of a gravity equation. It regresses students' enrollment flows between origin province o and destination province d on the distance (in kilometers) between the centroids o and d, controlling for origin and destination fixed effects. Column (1) shows results from an estimation using the estimation sample, while Column (2) presents results where the same model is fitted using the same sample, but where enrollment flows are determined by the province of the matched program in the simulated match. Estimation is performed using PPML, as recommended by Silva and Tenreyro (2006). Robust standard errors in parenthesis.

Table A.28: Quantification - Brain Drain

	Counterfactual	Change
Panel A: No Mobility Frictions		
Work Home	0.56	−12%
From Desert - Work Hub	0.47	+14%
Panel B: No Mobility Frictions + No Admission Restrictions		
Work Home	0.53	−17%
From Desert - Work Hub	0.50	+20%
Panel C: No Mobility Frictions + No Moving Costs		
Work Home	0.69	+8%
From Desert - Work Hub	0.45	+9%

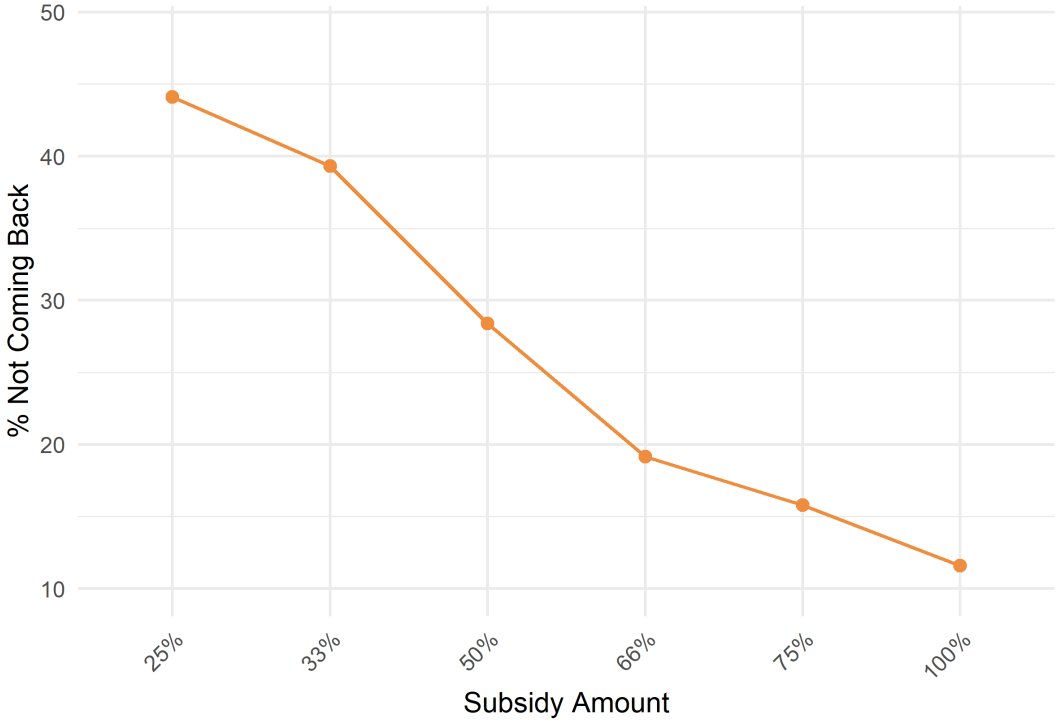
NOTES. This table presents changes in the share of workers entering the labor force in their home location, and in the share of workers from higher education deserts entering the labor force in a higher education hub. Panel A presents results from a counterfactual where mobility frictions within the higher education market are removed. Panel B presents results from a counterfactual additionally eliminating admission restrictions: all students are admitted in their preferred program in stage 1. Panel C presents results from a counterfactual where both mobility frictions within the higher education as well as moving costs at the location choice stage are removed.

Table A.29: Quantification - Labor Force in Paris

	Status Quo	No Mobility Frictions	No Admission Restrictions	No Moving Costs
	(1)	(2)	(3)	(4)
Share Work Paris	7.70	+11%	+44%	−9%

NOTES. This table presents changes in the share of workers entering the labor force in Paris. Column (1) presents the share of workers entering the labor market in Paris in the status quo. Column (2) presents results from a counterfactual where mobility frictions within the higher education market are removed. Column (3) presents results from a counterfactual additionally eliminating admission restrictions: all students are admitted in their preferred program in stage 1. Column (4) presents results from a counterfactual where both mobility frictions within the higher education as well as moving costs at the location choice stage are removed.

Figure A.15: Policy Counterfactual - Share Repaying



NOTES. This figure shows the results of the counterfactual in which students are offered a distance-based scholarship, which they have to reimburse if not returning home after graduation. It plots, for different values of the subsidy, the share of individuals from higher education deserts deciding to pay back the scholarship and entering the labor market outside of their home location.

B Context: Additional Details

B.1 High School Tracks and End-of-High School Exam

In the French high school system, students have three main educational tracks to choose from: general, technological, and vocational.

General track: In the general track, students can choose to specialize in one of three fields: sciences, social sciences, or humanities. While students in the general track share common classes, like English, they also have specialized courses tailored to their chosen field. For instance, a strong emphasis is made on mathematics, biology, and physics for students in the sciences field.

Technological track: This track focuses on applying scientific and technological knowledge to practical skills. Students can specialize in areas such as information technology, chemistry, or agronomy.

Vocational track: This track is designed to provide students with practical skills, with a particular focus on internships. They can specialize in various areas, such as automotive technology, hospitality, construction, agriculture, or healthcare.

The track and specialization of the student determine the centralized exam (*baccalauréat*) they take at the end of the three-year secondary education period. For example, students in the sciences general track will take tests particularly targeted at evaluating their knowledge in mathematics, biology and physics. The final score, between zero and 20, is associated to an Honors system (*Mentions).* The passing score is 10. A score between 12 and 14 corresponds to graduating with honors (*Mention Assez Bien*). With a score between 14 and 16, the student graduates with high honors (*Mention Bien*). A student graduates with highest honors (*Mention Très Bien*) when reaching a score of 16 or above. Table A.1 summarizes the share of students receiving each honors type, conditional on passing.

B.2 Program Types

There exist six main types of programs. Half of them are targeted at students willing to acquire a master's degree. First, students can apply to first-year university programs - *Licences*. Most universities are public, and tuition fees are very low. They amount to 260€/year and are waived if the student is eligible for a scholarship. The selectivity of such programs varies a lot, depending on its institution and on its major. These programs are designed such that students can first graduate with a bachelor's degree, after three year, and can continue to get a master's degree, after five years.

Second, students can apply to two-year elite programs, or *Classes Préparatoires aux Grandes Ecoles (CPGE)*. These programs are highly selective, last two to three years and prepare students to take the competitive exams for admission to the most prestigious public and private higher education institutions (*Grandes Écoles*), such as the engineering schools *École Polytechnique* and *École des Ponts ParisTech*. They are offered by high school institutions. Tuition fees are the same as in university programs.

Third, there exist business and engineering schools, which offer admission after high school. They are often private, and their tuition fees and selectivity vary.

The three other main types of programs are targeted at providing a more technical and vocational training. First, there are technology-oriented programs, which last for two years and deliver a *Diplôme Universitaire de Technologie* (*DUT*). They are provided by public institutions (*Institut Universitaire de Technologie, IUT*). Their selectivity vary according to the institution and major, and tuition fees correspond to those in university programs.

There are also two-year vocational programs, offered by high school institutions. They are free, and are aimed at delivering a degree called *Brevet de Technicien Supérieur* (*BTS*).

Finally, there are social work and nursing schools. They can be public or private, with varying tuition fees.

B.3 Admission System: History

In France, the first online admission platform - 'Admission Post-Bac' (APB) - was introduced in 2002. It was specifically designed to match students to one type of programs: two-year elite programs. In 2009, the platform was extended to manage admission to other types of programs.

Within APB, students had to rank programs, before a Deferred Acceptance algorithm was run, taking into account students' ranking as well as programs' admission choices. Contrary to other programs, universities were legally forbidden from selecting students. The ranking of students by universities was determined by priorities, taking into account the rank at which the program was listed and the catchment area of the student. If over-subscribed, a lottery was run.

Since 2018, the APB platform has been replaced by Parcoursup. Two main changes were introduced. First, an admission algorithm is not used anymore to match students to programs. Students do not have to rank applications, and can receive several offers at the same time. Second, university programs are now allowed to choose applicants based on their own selection criteria.

C Proofs

C.1 Evaluation of the Moving Scholarship: Discussion of the Identifying Assumptions

Using a potential outcome framework, the assumption for the triple differences used in Section 3.2.1 to be valid writes:

$$\begin{aligned} &E\left[(Y_{L,E,t}(0) - Y_{L,E,t-1}(0)) - (Y_{L,NE,t}(0) - Y_{L,NE,t-1}(0))\right] \\ =&E\left[(Y_{H,E,t}(0) - Y_{H,NE,t-1}(0)) - (Y_{H,NE,t}(0) - Y_{H,NE,t}(0))\right] \end{aligned}$$

where $Y_{s,e,t}(0)$ denotes the average potential outcome of students with eligibility status $e \in \{E, NE\}$ living in provinces with supply level $s \in \{H, L\}$ in period t when not treated.

Under this parallel trends assumption, which can be tested, β_{2019} identifies the following object:

$$\begin{aligned} &E\left[[Y_{L,E,2019}(1) - Y_{L,NE,2019}(0)] - [Y_{H,E,2019}(1) - Y_{H,NE,2019}(0)]\right] \\ &= ATT_{L,E,2019} - ATT_{H,E,2019} \end{aligned} \tag{18}$$

That is, it identifies the difference between the ATT of the eligible students living in low-supply areas, denoted $ATT_{L,E,2019}$, and the ATT of the eligible students living in high-supply areas, $ATT_{H,E,2019}$. The triple differences estimator thus identifies the differences in treatment effects of the policy in low-supply versus high-supply areas. While being eligible, it seems however safe to assume that the reform should not have impacted the application behavior of scholarship-eligible students living in high-supply areas. The scholarship was indeed very small, while these students are low-income students living in places where they can easily access higher education programs. Overall, the policy is unlikely to have an effect on students already living in a high-supply area, such that we can expect the ATT to be null in the latter locations. In that case, β_{2019} would identify the average treatment effect of the moving subsidy for students living in low-supply areas.

To limit concerns regarding a potential non-null effect of the subsidy on students part of the comparison group, I consider areas at the very top and bottom of the program supply distribution. I define low-supply areas as the five locations at the bottom of the supply

distribution. High-supply areas are defined as the ten locations at the top of this distribution. The latter definition is chosen as a way to minimize the extent with which students in these areas may have benefited from the scholarship. Results are robust to restricting and extending this set. Regarding low-supply areas, the effects displayed in Table A.8 are robust to extending the definition to the ten locations with the least supply, while the magnitude of the estimates is slightly smaller.

If we consider that the ATT in high-supply areas was non-zero but positive, β_τ would then identify the ATT in low-supply areas net of the one in high-supply areas. As long as the latter is positive, the fact that we observe a positive β_τ thus suggest that the treatment effect is positive for students living in low-supply areas, and larger than the one of those living in high-supply areas. If the treatment instead decreased the application distance of eligible students in high-supply areas, the difference in ATT would then be more difficult to interpret. However, there is no economic rationale for such a negative effect to arise.

C.2 Reverse Difference-in-Differences

Other factors than the reform discussed in Section 3.2.2 may have affected admission outcomes between 2018 and 2019. To control for them, I use a group of programs which admission criteria stayed the same over time: non-university programs, for which geographical priorities were never implemented. I thus augment the model as follows:

$$y_{j,\ell,t} = \alpha_j + \lambda_{\ell,t} + \sum_{\ell} \beta_\ell^{DD} \times D_{\ell,t} + \epsilon_{j,\ell,t} \tag{19}$$

where $\lambda_{\ell,t}$ captures location-specific trends in admission outcomes common to university and non-university programs. This is akin to implementing a difference-in-differences where the groups compared share the same treatment status at endline, but not at baseline (see Kim and Lee (2019) and Fabre (2023) for a discussion of reverse difference-in-differences). In particular, it compares the evolution of admission outcomes in university programs - for which institutional barriers to mobility were removed in 2019 - to those in non-university programs which never implemented such barriers.

I now discuss the identification assumptions required for such a comparison to identify the ATT of removing barriers to mobility for the group switching treatment status. Let us consider the following potential outcome framework. Program j belongs to group S if

the program switched from implementing geographic barriers to mobility in period 2018 to not using such rules in 2019. This is the group switching treatment status. Program j belongs to group C if the program implemented non-geographic admission criteria in 2018 and 2019. $Y_{j,g,t}(d)$ is the potential outcome of program j belonging to group $g \in \{S, C\}$ in period t under treatment status $d \in \{0, 1\}$, where $d = 1$ under non-geographic admission criteria and zero otherwise. $Y_{g,t}(d)$ is the average potential outcome for group g in period t: $Y_{g,t}(d) = \frac{1}{n_g} \sum_{j \in g} Y_{j,g,t}(d)$, where n_g is the number of programs in group g.

In standard difference-in-differences, the treatment status of the two groups is the same at baseline and differs ex post. In contrast, here, the treatment status of the two groups differs at baseline, but is the same at endline. Kim and Lee (2019) and Fabre (2023) show that one can still identify the treatment effect of interest in this framework, under the following parallel trends assumption:

$$E\left[[Y_{S,t}(1) - Y_{S,t-1}(1)] - [Y_{C,t}(1) - Y_{C,t-1}(1)]\right] = 0 \tag{20}$$

That is, the potential outcomes of the two groups would have evolved similarly across time under non-geographic admission criteria. Note that, as the two groups do not have the same treatment status at baseline, one cannot test this assumption using periods prior to the implementation of the reform. However, one can test this assumption using outcomes posterior to the switch.[30]

Under this assumption, β^{DD} from Equation (19) identifies the ATT of non-geographic admission criteria for university programs:

$$\begin{aligned}
\beta^{DD} &= E\left[Y_{S,2019} - Y_{S,2018}\right] - E\left[Y_{C,2019} - Y_{C,2018}\right] \\
&= E\left[Y_{S,2018}(1) - Y_{S,2018}(0)\right] \\
&+ E\left[Y_{S,2019}(1) - Y_{S,2018}(1)\right] - E\left[Y_{C,2019}(1) - Y_{C,2018}(1)\right] \\
&= E\left[Y_{S,2018}(1) - Y_{S,2018}(0)\right]
\end{aligned} \tag{21}$$

β^{DD} thus identifies the ATT, for programs belonging to the switching group S, of removing institutional barriers to mobility.

Note that, given the nature of the market, one of the assumptions required for any

[30] I plan on testing this assumption with administrative data from the online admission platform from 2020 and onward.

difference-in-differences to be valid might not be satisfied in practice: the comparison group may be affected by the reform. Indeed, students' flows might respond to the removal of barriers to mobility by shifting away from other type of programs toward university programs located within Paris. To limit such concerns, I implement this difference-in-differences at the catchment area level. In that case, we would recover the effect of removing barriers to mobility in Paris, even if the reform would impact programs in Versailles.[31]

C.3 Identification of Preferences over Locations

Taking the logarithm on both sides of Equation (10), we have:

$$\log(\Pr(\ell^* = \ell | h_i, y_i, \boldsymbol{m}, \boldsymbol{w}_i)) = \theta(w_{i\ell} + \omega(h_i, y_i, m_\ell)) - \log(\sum_{\kappa \in \mathcal{L}} \exp(\theta(w_{i\kappa} + \omega(h_i, y_i, m_\kappa)))) \tag{22}$$

The same equation can be evaluated for $\ell = \ell_0$, the location choice for which we normalize $\omega(h_i, y_i, m_{\ell_0})$ to be equal to zero. Taking the difference of Equation (22) evaluated at location ℓ and ℓ_0, and considering $w_{i\ell_0} = 0$ we have:

$$\begin{aligned} &\log(\Pr(\ell^* = \ell | h_i, y_i, \boldsymbol{m}, \boldsymbol{w}_i)) - \log(\Pr(\ell^* = \ell_0 | h_i, y_i, \boldsymbol{m}, \boldsymbol{w}_i)) \\ &= \theta(w_{i\ell} + \omega(h_i, y_i, m_\ell)) \end{aligned}$$

where the left-hand side of the equation is directly observed in data from realized location choices. In particular, taking the derivative of this object with respect to $w_{i\ell}$ allows us to identify θ. Given θ, ω can then be identified.

C.4 Identification of Program-Specific Students' Score

Taking the logarithm on both sides of Equation (11), we have:

$$\log(\Pr(i^*_{j,r} = i | \boldsymbol{x}, \boldsymbol{h}, z_j)) = v(x_i, h_i, z_j) - \log\big(\sum_{a \in \mathcal{A}_j \setminus \{i^*_{j,k}\}_{k=1}^{r-1}} \exp(v(x_a, h_a, z_j))\big) \tag{23}$$

[31] For example, if an increase of students from Versailles admitted to programs in Paris is compensated by a decrease of students from Versailles admitted to non-university programs in Versailles, the comparison would still be valid. Note that it would, however, be a concern if this increase is rather compensated by a decrease of high-ability students from Versailles admitted to non-university programs in Paris.

The same equation can be evaluated for $i = 0_{\mathcal{I}}$, the outside option of the program, for which the flow utility is normalized to zero. Taking the difference of Equation (23) evaluated for student i and $0_{\mathcal{I}}$, we have:

$$\begin{aligned}
&\log(\Pr(i^*_{j,r} = i|\boldsymbol{x}, \boldsymbol{h}, z_j)) - \log(\Pr(i^*_{j,r} = 0_{\mathcal{I}}|\boldsymbol{x}, \boldsymbol{h}, z_j)) \\
&= v(x_i, h_i, z_j) - v(x_{0_{\mathcal{I}}}, h_{0_{\mathcal{I}}}, z_j) \\
&= v(x_i, h_i, z_j))
\end{aligned}$$

where the left-hand side of the equation is directly observed in data from realized rankings of applicants, such that $v(.)$ can be recovered.

C.5 Identification of σ

This section details the proof of Proposition 1. Consider a student i and a student o, with $x_i = x_o$ and $h_i \neq h_o$. Consider a program j such that $u(x_i, z_j) - c(x_i, d_{ij}) = u(x_o, z_j) - c(x_o, d_{oj})$.

Let us start by considering student i. Let us take the ratio of the probabilities associated with enrolling in program j and the outside option:

$$\begin{aligned}
&\frac{\Pr(\mu(i) = j|x_i, h_i, \boldsymbol{z})}{\Pr(j \in \mathcal{F}(x_i, h_i, \boldsymbol{z}, \boldsymbol{\eta})|x_i, h_i, \boldsymbol{z}) \Pr(\mu(i) = 0_{\mathcal{J}}|x_i, h_i, \boldsymbol{z})} \\
=&\frac{\int \frac{\exp(\frac{1}{\sigma}(u(x_i,z_j)-c(x_i,d_{ij})+\frac{1}{\sigma}\bar{U}(x_i,h_i,z_j)))}{\sum_{k\in\mathcal{F}(x_i,h_i,\eta)\bigcup 0_{\mathcal{J}}}\exp(\frac{1}{\sigma}(u(x_i,z_k)-c(x_i,d_{ik})+\bar{U}(x_i,h_i,z_k)))} g(\eta)d\eta}{\int \frac{\exp(\frac{1}{\sigma}(u(x_i,z_{0_{\mathcal{J}}})-c(x_i,d_{i0_{\mathcal{J}}})+\bar{U}(x_i,h_i,z_{0_{\mathcal{J}}})))}{\sum_{k\in\mathcal{F}(x_i,h_i,\eta)\bigcup 0_{\mathcal{J}}}\exp(\frac{1}{\sigma}(u(x_i,z_k)-c(x_i,d_{ik})+\bar{U}(x_i,h_i,z_k)))} g(\eta)d\eta} \\
=&\frac{\exp(\frac{1}{\sigma}(u(x_i, z_j) - c(x_i, d_{ij}) + \bar{U}(x_i, h_i, z_j)))}{\exp(\frac{1}{\sigma}(u(x_i, z_{0_{\mathcal{J}}}) - c(x_i, d_{i0_{\mathcal{J}}}) + \bar{U}(x_i, h_i, z_{0_{\mathcal{J}}})))}
\end{aligned} \tag{24}$$

Taking the logarithm and subtracting from Equation (24) the same object evaluated at

(x_o, h_o), we find:

$$
\begin{aligned}
&\log\left(\frac{\Pr(\mu(i)=j|x_i,h_i,\boldsymbol{z})}{\Pr(j\in\mathcal{F}(x_i,h_i,\boldsymbol{z},\boldsymbol{\eta})|x_i,h_i,\boldsymbol{z})\Pr(\mu(i)=0_{\mathcal{J}}|x_i,h_i,\boldsymbol{z})}\right)\\
&-\log\left(\frac{\Pr(\mu(o)=j|x_o,h_o,\boldsymbol{z})}{\Pr(j\in\mathcal{F}(x_o,h_o,\boldsymbol{z},\boldsymbol{\eta})|x_o,h_o,\boldsymbol{z})\Pr(\mu(o)=0_{\mathcal{J}}|x_o,h_o,\boldsymbol{z})}\right)\\
=&\frac{1}{\sigma}(u(x_i,z_j)-c(x_i,d_{ij})-(u(x_o,z_j)-c(x_o,d_{oj})))\\
&+\frac{1}{\sigma}\left[\left[\bar{U}(x_i,h_i,z_j)-\bar{U}(x_i,h_i,z_{0_{\mathcal{J}}})\right)\right]-\left[\bar{U}(x_o,h_o,z_j)-\bar{U}(x_o,h_o,z_{0_{\mathcal{J}}})\right]\right]\\
=&\frac{1}{\sigma}\left[\left[\bar{U}(x_i,h_i,z_j)-\bar{U}(x_i,h_i,z_{0_{\mathcal{J}}})\right]-\left[\bar{U}(x_o,h_o,z_j)-\bar{U}(x_o,h_o,z_{0_{\mathcal{J}}})\right]\right]
\end{aligned}
$$

where the first equality stems from the fact that $u(x_i, z_{0_{\mathcal{J}}}) - c(x_i, di0_{\mathcal{J}}) = 0$, $\forall x_i$, and the second equality from the fact that $u(x_i, z_j) - c(x_i, d_{ij}) = u(x_o, z_j) - c(x_o, d_{oj})$. $\bar{U}(.)$ can be identified from the parameters identified from data over location choices and transition probabilities. We can thus express σ as a function of objects observed in the data and parameters previously identified, as long as $\bar{U}(x_i, h_i, z_j) - \bar{U}(x_i, h_i, z_{0_{\mathcal{J}}}) \neq \bar{U}(x_o, h_o, z_j) - \bar{U}(x_o, h_o, z_{0_{\mathcal{J}}})$. This is made plausible by the fact that the home location enters in $\bar{U}(.)$, while students i and o have different home locations, $h_i \neq h_o$.

Note that, I include the distance between student i and program j in $c(.)$. The identification argument thus relies on considering a program j located at the same distance from both student i and student o's respective home location. $c(.)$ could include, on top, a home bias - i.e. a dummy capturing whether the program is located in the same province as the student's home. In this case, the identification argument would rely on finding a program j which is located out of students i and o's respective home province and equidistant to both of them. Note that the flow utility associated with a program can also depend freely on the location of the program, for example through location fixed effects.

The identification argument would also go through by using two different programs, j' and j'', as long as $u(x_i, z_{j'}) - c(x_i, d_{ij'}) = u(x_o, z_{j''}) - c(x_o, d_{oj''})$ and $\bar{U}(x_i, h_i, z_{j'}) - \bar{U}(x_i, h_i, z_{0_{\mathcal{J}}}) \neq \bar{U}(x_o, h_o, z_{j''}) - \bar{U}(x_o, h_o, z_{0_{\mathcal{J}}})$. In particular, this requires the characteristics of programs j' and j'' to be the same, i.e. $z_{j'} = z_{j''}$. It also requires the distance between student i and program j' to be equal to the one between student o and program j''.

C.6 Identification of u(.) and c(.)

Taking the ratios $\Pr(\mu(i)=j|x_i,h_i,\boldsymbol{z})$ and $\Pr(\mu(i)=0_{\mathcal{J}}|x_i,h_i,\boldsymbol{z})$, we have:

$$\begin{aligned}
&\frac{\Pr(\mu(i)=j|x_i,h_i,\boldsymbol{z})}{\Pr(j\in\mathcal{F}(x_i,h_i,\boldsymbol{z},\boldsymbol{\eta})|x_i,h_i,\boldsymbol{z})\Pr(\mu(i)=0_{\mathcal{J}}|x_i,h_i,\boldsymbol{z})}\\
=&\frac{\int \frac{\exp(\frac{1}{\sigma}(u(x_i,z_j)-c(x_i,d_{ij})+\bar{U}(x_i,h_i,z_j)))}{\sum_{k\in\mathcal{F}(x_i,h_i,\eta)\bigcup 0_{\mathcal{J}}}\exp(\frac{1}{\sigma}(u(x_i,z_k)-c(x_i,d_{ik})+\bar{U}(x_i,h_i,z_k)))}g(\eta)d\eta}{\int \frac{\exp(\frac{1}{\sigma}(u(x_i,z_{0_{\mathcal{J}}})-c(x_i,d_{i0_{\mathcal{J}}})+\bar{U}(x_i,h_i,z_{0_{\mathcal{J}}})))}{\sum_{k\in\mathcal{F}(x_i,h_i,\eta)\bigcup 0_{\mathcal{J}}}\exp(\frac{1}{\sigma}u(x_i,z_k)-c(x_i,d_{ik})+\bar{U}(x_i,h_i,z_k))}g(\eta)d\eta}\\
=&\frac{\exp(\frac{1}{\sigma}(u(x_i,z_j)-c(x_i,d_{ij})+\bar{U}(x_i,h_i,z_j)))}{\exp(\frac{1}{\sigma}(u(x_i,z_{0_{\mathcal{J}}})-c(x_i,d_{i0_{\mathcal{J}}})+\bar{U}(x_i,h_i,z_{0_{\mathcal{J}}})))}
\end{aligned} \tag{25}$$

Taking logarithms, this writes:

$$\begin{aligned}
&\log(\Pr(\mu(i)=j|x_i,h_i,\boldsymbol{z}))-\log(\Pr(\mu(i)=0_{\mathcal{J}}|x_i,h_i,\boldsymbol{z})\Pr(j\in\mathcal{F}(x_i,h_i,\boldsymbol{z},\boldsymbol{\eta})|x_i,h_i,\boldsymbol{z}))\\
&=\frac{1}{\sigma}\left[u(x_i,z_j)-c(x_i,d_{ij})+\bar{U}(x_i,h_i,z_j)\right]-\frac{1}{\sigma}\left[u(x_i,z_{0_{\mathcal{J}}})-c(x_i,d_{i0_{\mathcal{J}}})+\bar{U}(x_i,h_i,z_{0_{\mathcal{J}}})\right]\\
&\iff \sigma\left[\log(\Pr(\mu(i)=j|x_i,h_i,\boldsymbol{z}))-\log(\Pr(\mu(i)=0_{\mathcal{J}}|x_i,h_i,\boldsymbol{z}))\right]-\left[\bar{U}(x_i,h_i,z_j)-\bar{U}(x_i,h_i,z_{0_{\mathcal{J}}})\right]\\
&=u(x_i,z_j)-c(x_i,d_{ij})
\end{aligned} \tag{26}$$

where $\Pr(\mu(i)=j|x_i,h_i,\boldsymbol{z})$ and $\Pr(\mu(i)=0_{\mathcal{J}}|x_i,h_i,\boldsymbol{z})$ are directly identified from data on realized matched and $\bar{U}(x_i,h_i,z_j)-\bar{U}(x_i,h_i,z_{0_{\mathcal{J}}})$ is identified in a first step and σ is identified (see Appendix C.5). $\Pr(j\in\mathcal{F}(x_i,h_i,\boldsymbol{z},\boldsymbol{\eta})|x_i,h_i,\boldsymbol{z})$ is also identified as we identified programs' preferences, while we know the set of applicants to each program and the distribution of η. Thus, the left-hand side of this equation is observed. Normalizing $c(x_i,d_{ij})=0$ if $d_{ij}=0$ ensures that we can separately identify $u(.)$ and $c(.)$.

D Estimation Details

D.1 Estimation Sample

For computational tractability, students' preferences are estimated using a random sub-sample of 10,234 students. Table D.1-D.3 present the same summary statistics over students' characteristics and their enrollment outcomes as in Table A.1 and Tables A.3-A.4. It contrasts those statistics for the full sample and the random sub-sample, and show that all characteristics are very close in the two samples.

Table D.1: Summary Statistics: Full vs. Random Sample

	Full Sample	Random Sub-Sample
	(1)	(2)
Female	0.5396	0.5479
Socio-Economic Characteristics		
With Scholarship	0.1939	0.1921
High SES	0.3139	0.3098
Medium High SES	0.1566	0.1588
Medium Low SES	0.3119	0.3155
Low SES	0.2177	0.2158
End-of-High School Exam:		
With Highest Honors	0.0946	0.0957
With High Honors	0.1744	0.1759
With Honors	0.2963	0.2958
Pass	0.4347	0.4326
High School Track:		
General HS Track	0.6257	0.6282
Technological HS Track	0.2222	0.2198
Vocational HS Track	0.1521	0.1518
Observations	505,069	10,235

NOTES. This table presents summary statistics of high school students, living in metropolitan France in 2019. Column (1) focuses on the full sample while Column (2) presents the statistics for a random sample.

Table D.2: Summary Statistics: Applications, Offers & Enrollment

	Mean	St. Dev.	25^{th} Pctile	50^{th} Pctile	75^{th} Pctile
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
Nber Applications	10.587	9.291	5.000	9.000	13.000
Nber Offers	4.203	4.261	2.000	3.000	5.000
Distance of Enrollment	65.368	109.780	8.809	25.979	72.981
Panel B: Random Sub-Sample					
Nber Applications	10.664	9.505	5.000	9.000	13.000
Nber Offers	4.250	4.332	2.000	3.000	5.000
Distance of Enrollment	66.701	113.148	9.145	26.145	74.1497

NOTES. This table presents summary statistics regarding applications, offers and enrollment of students in high school in 2019, living in metropolitan France. Characteristics of this sample are summarized in Table A.1. Panel A and Panel B show these statistics for the full sample and random sub-sample, respectively.

Table D.3: Summary Statistics: Program of Enrollment

	Full Sample	Random Sub-Sample
	(1)	(2)
Three-Year University	0.3920	0.3904
Two-Year Elite	0.0700	0.0706
Engineering/Business	0.0461	0.0481
Two-Year Technical	0.0896	0.0916
Two-Year Vocational	0.1685	0.1591
Nursing	0.0262	0.0275
Other	0.0178	0.0197
Unmatched	0.1898	0.1930
Observations	505,069	10,235

NOTES. This table presents summary statistics regarding the program of enrollment of students in high school in 2019, living in metropolitan France. Column (1) focuses on the full sample, while Column (2) presents the statistics for a random sample.

D.2 Estimation of Transition Probabilities

I use the universe of applicants to the online platform in 2019, regardless of their match status, and match them to the higher education census thanks to the student unique identifier. I am able to match 82% of students. 94% of students matched to a program on Parcoursup in 2019 are recovered in the higher education census dataset. This implies that 6% of the students who are matched to an on-platform program either do not register to their matched program, or do so but cannot be recovered in the census.

Note that the latter dataset allows me to track some unmatched students, as I observe whether i) they match to one of the few programs off-platform but present in the census or ii) whether they match to an on-platform program in the following years, implying they participated again to the admission process. Given that the administrative census gathers the large majority of higher education programs in France, I consider that a student who was unmatched on the platform in 2019 and who cannot be found in the censuses of the years 2019-2021 stayed out of the higher education system. I assign the home location of these students as their graduation location.

D.3 Extension: Adding Unobserved Heterogeneity

I augment the model in order to capture persistent unobserved preferences over locations over time. It may indeed be important to take into account such unobserved preferences when modeling location choices, as they often display persistence. Allowing for unobserved heterogeneity would help disentangle the stickiness in location choices coming from unobserved preferences from state dependence (Heckman, 1981). I thus augment the model in the second stage as follows:

$$\begin{aligned}\omega(h_i, \alpha_i, y_i, m_\ell) = \mathbf{Degree}_i'\boldsymbol{\phi_1}\mathbb{1}\{\ell = \ell_i^G, \ell = \ell_i^H\} + \mathbf{Degree}_i'\boldsymbol{\phi_2}\mathbb{1}\{\ell \neq \ell_i^G, \ell = \ell_i^H\} \\ + \mathbf{Degree}_i'\boldsymbol{\phi_3}\mathbb{1}\{\ell = \ell_i^G, \ell \neq \ell_i^H\} + \alpha_i a_\ell\end{aligned} \tag{27}$$

where a_ℓ is an amenity index, and $\alpha_i \sim \mathcal{N}(0, \zeta)$. α_i is a persistent unobserved idiosyncratic taste for amenities.

Given the parameters of Equation (27) and a draw of $\alpha_i, \forall i$, one can compute the expected discounted continuation value associated with choosing the optimal location in the second stage. Further assuming full persistence of the taste for the amenity index, the utility from

enrolling in program j writes:

$$\mathcal{U}_{ij} = u(x_i, z_j) - c(x_i, d_{ij}) + \alpha_i a_j + \sigma\epsilon_{ij} + \bar{U}(x_i, h_i, \alpha_i, z_j)$$

where a_j is the amenity index associated with the location of program j. The probability that student i matches with program j simply rewrites:

$$\Pr(\mu(i) = j | x_i, h_i, \boldsymbol{z}) = \int \Pr(\mu(i) = j | x_i, h_i, \alpha_i, z) f(\alpha_i|\zeta) d\alpha_i$$

where:

$$\Pr(\mu(i) = j | x_i, h_i, \alpha_i, \boldsymbol{z}) = \int \Pr(\mu(i) = j | \mathcal{F}(x_i, h_i, \boldsymbol{\eta}), x_i, h_i, \alpha_i, \boldsymbol{z}, j \in \mathcal{F}(x_i, h_i, \boldsymbol{\eta})) g(\boldsymbol{\eta}) d\boldsymbol{\eta}$$

where:

$$\begin{aligned}
&\Pr(\mu(i) = j | \mathcal{F}(x_i, h_i, \boldsymbol{\eta}), x_i, h_i, \alpha_i, \boldsymbol{z}, j \in \mathcal{F}(x_i, h_i, \boldsymbol{\eta})) \\
&= \frac{\exp(\frac{1}{\sigma}(u(x_i, z_j) - c(x_i, d_{ij}) + \alpha_i a_j + \bar{U}(x_i, \alpha_i, h_i, z_j)))}{\sum_{k \in \mathcal{F}(x_i, h_i, \boldsymbol{\eta}) \bigcup 0_{\mathcal{J}}} \exp(\frac{1}{\sigma}(u(x_i, z_k) - c(x_i, d_{ik}) + \alpha_i a_k + \frac{1}{\sigma}\bar{U}(x_i, \alpha_i, h_i, z_k)))}
\end{aligned}$$

Estimation of preferences in this framework would be more computationally costly, as it would require to jointly estimate preferences in stages one and two.

E Counterfactuals: Details

E.1 Counterfactuals: Simulation Details

This section describes how both the higher education market equilibrium and individuals' location choices are computed in counterfactual exercises.

Higher Education Market Equilibrium I use the estimated parameters and a draw of idiosyncratic shocks to simulate students' utility associated to each program, from Equation (4), as well as their program-specific score, from Equation (6).

In particular, when removing mobility frictions within the higher education system, the utility of student i from enrolling in program j becomes:

$$\mathcal{U}_{ij}^{\mathcal{C}^1} = u(x_i, z_j) + \sigma\epsilon_{ij} + \bar{U}(x_i, h_i, z_j) \tag{28}$$

This allows us to generate each student's ranking of programs, as well as each program's ranking of students. I feed these two rankings, together with programs' number of seats, into a student-proposing Deferred Acceptance algorithm, which matches each student to a unique program. This algorithm allows us to derive the student-proposing stable match. The properties of this market entails that it essentially has a unique stable equilibrium.

Higher Education Market Equilibrium - Change in Second Stage Payoffs Note that some counterfactual exercises directly modify payoffs in the second stage of the model — such as the counterfactual where mobility costs between the individual's graduation and home location are eliminated. In such cases, one needs to update the continuation value associated with each program before computing students' utility from Equation (4). I thus start by computing the new utility from entering each location ℓ in stage 2 from Equation (3), before using it to compute the log-sum formula, which is used to derive the continuation value. Taking the example of the counterfactual where mobility costs between the individual's graduation and home location are eliminated, denoted $\mathcal{C}^2$, the new utility from entering the labor market in location ℓ for individual i writes:

$$\mathcal{W}_{i\ell}^{\mathcal{C}^2} = w_{i\ell} + \omega(h_i, y_i, m_\ell) + \mathbf{Degree}_i^{'}\boldsymbol{\phi}_3 \mathbb{1}\{\ell = \ell_i^H, \ell_i^H \neq \ell_i^G\} + \frac{1}{\theta}\nu_{i\ell} \tag{29}$$

where the term $\mathbf{Degree}_i^{'}\boldsymbol{\phi}_3\mathbb{1}\{\ell = \ell_i^H, \ell_i^H \neq \ell_i^G\}$ is added to remove moving costs between the graduation location of individual i, ℓ_i^G, and her home location, ℓ_i^H.

The continuation value of a program with characteristics z_j now becomes:

$$\bar{U}^{\mathcal{C}^2}(x_i, h_i, z_j) = \int \beta^{t(y_i)} \mathbb{E}\left[\max_{\ell \in \mathcal{L}} \mathcal{W}_{i\ell}^{\mathcal{C}_2} | y_i\right] f\left(y_i | x_i, h_i, z_j\right) dy_i \tag{30}$$

In this case, we can then derive each student's ranking of programs by computing the following object, for each i:

$$\mathcal{U}_{ij}^{\mathcal{C}^2} = u(x_i, z_j) + \sigma\epsilon_{ij} + \bar{U}^{\mathcal{C}^2}(x_i, h_i, z_j)$$

Higher Education Market Equilibrium - No Admission Restrictions One of the counterfactual exercises eliminates mobility frictions, while preventing programs from rejecting any students. In this case, each student can be admitted to their preferred program, regardless of capacity constraints and programs' preferences. The equilibrium is such that each student i matches to a program $\mu(i)$, such that:

$$\mu(i) = \arg\max_{\mathcal{J} \bigcup 0_{\mathcal{J}}} \mathcal{U}_{ij}^{\mathcal{C}^1}$$

Location Decisions at Entry on the Labor Market Once the new higher education market equilibrium is simulated, one can compute the counterfactual transition probabilities, and use Equation (3) to simulate the counterfactual location choice of individual i.

Note that all idiosyncratic shocks are kept fixed across the different simulation exercises, and are the same as the ones used to simulate the status quo paths.

E.2 Counterfactuals: Outcomes

Inequalities Between Students with Different Home Locations: Each counterfactual exercise is evaluated by comparing outcomes between the new equilibrium and the status quo simulation. In order to capture inequalities across individuals with different home location, I compute the share of individuals from a given province graduating with a bachelor's

degree or more as follows:

$$s_{\ell}^{Home} = \frac{\sum_i \mathbb{1}\{\ell_i^H = \ell, \text{Degree}_i = \text{Bachelor}\}}{\sum_i \mathbb{1}\{\ell_i^H = \ell\}}$$

where $\mathbb{1}\{\ell_i^H = \ell, \text{Degree}_i = \text{Bachelor}\}$ is a dummy equal to one if ℓ is the home location of individual i and individual i graduates with at least a bachelor's degree. $\mathbb{1}\{\ell_i^H = \ell\}$ is a dummy equal to one if ℓ is the home location of individual i. I thus have 96 observations of the variable s_{ℓ}^{Home}, one for each province: I compute the variance of these values.

On top of looking at the variance, I also compare the share of individuals from higher education deserts and hubs graduating with at least a bachelor's degree as follows:

$$\frac{\sum_{i \in \{i:\ell_i^H \in Hubs\}} \mathbb{1}\{\text{Degree}_i = \text{Bachelor}\}}{n_{Hubs}} - \frac{\sum_{i \in \{i:\ell_i^H \in Deserts\}} \mathbb{1}\{\text{Degree}_i = \text{Bachelor}\}}{n_{Deserts}}$$

where $\mathbb{1}\{\text{Degree}_i = \text{Bachelor}\}$ is a dummy equal to one if individual i graduates with at least a bachelor's degree, *Hubs* is the set of education hubs, *Deserts* is the set of education deserts, n_{Hubs} is the number of individuals from higher education hubs and $n_{Deserts}$ is the number of individuals from higher education deserts.

Additionally, I compute the mean welfare of students in different provinces as follows:

$$\bar{W}_{\ell} = \frac{\sum_{i \in \{i:\ell_i^H = \ell\}} \mathcal{U}_{ij^*}}{\sum_i \mathbb{1}\{\ell_i^H = \ell\}}$$

where j^* correspond to the program where student i is matched in the scenario considered.

I compute the variance of this measure across provinces ℓ. I also contrast the mean welfare of students from hubs and deserts:

$$\frac{\sum_{i \in \{i:\ell_i^H \in Hubs\}} \mathcal{U}_{ij^*}}{n_{Hubs}} - \frac{\sum_{i \in \{i:\ell_i^H \in Deserts\}} \mathcal{U}_{ij^*}}{n_{Deserts}}$$

where *Hubs* is the set of education hubs, *Deserts* is the set of education deserts, n_{Hubs} is the number of individuals from higher education hubs and $n_{Deserts}$ is the number of individuals from higher education deserts.

Inequalities across Local Labor Markets: In order to capture inequalities across local labor markets, I first look at the composition of their labor force. To do that, I compute the

share of individuals who graduated with at least a bachelor's degree and who entered the labor market in province ℓ, that is:

$$s_\ell^{Work} = \frac{\sum_i \mathbb{1}\{\ell_i^* = \ell, \text{Degree}_i = \text{Bachelor}\}}{\sum_i \mathbb{1}\{\ell_i^* = \ell\}}$$

where $\mathbb{1}\{\ell_i^* = \ell, \text{Degree}_i = \text{Bachelor}\}$ is a dummy equal to one if ℓ is the work location of individual i and individual i graduates with at least a bachelor's degree. $\mathbb{1}\{\ell_i^* = \ell\}$ is a dummy equal to one if ℓ is the work location of individual i. To measure inequalities across local labor markets, I compute the variance of s_ℓ^{Work} across the 96 provinces of metropolitan France. Additionally, I also compare the share of workers in hubs and deserts as follows:

$$\frac{\sum_{i \in \{i:\ell_i^* \in Hubs\}} \mathbb{1}\{\text{Degree}_i = \text{Bachelor}\}}{L_{Hubs}} - \frac{\sum_{i \in \{i:\ell_i^* \in Deserts\}} \mathbb{1}\{\text{Degree}_i = \text{Bachelor}\}}{L_{Deserts}}$$

where L_{Hubs} is the number of entry-level workers entering the labor market in a higher education hub, and $L_{Deserts}$ is the number of entry-level workers entering the labor market in a higher education desert.

The second measure I consider to capture inequalities across local labor markets is the sum of the wages of the entry-level workers in a given location:

$$Y_\ell = \sum_{i \in \{i:\ell_i^* = \ell\}} w_{i\ell}$$

I compute the variance of Y_ℓ across provinces, and additionally compare the sum of wages of entry-level workers in hubs and deserts:

$$\sum_{\ell \in Hubs} Y_\ell - \sum_{\ell \in Deserts} Y_\ell$$

E.3 Additional Policy Counterfactual

Distance-Based Subsidies and Commitment to Come Back As an alternative policy counterfactual, I consider contracts offering a distance-based scholarship conditional on coming back, with perfect enforcement. In particular, conditional on accepting the contract, students have to enter the labor market in their home location and cannot deviate.

To evaluate such a policy, I simulate the counterfactual match of a student by replacing the lifetime utility associated with a given program j, $\mathcal{U}_{ij}$, by the utility associated with this program under the contract. In particular, the subsidy compensates for (parts of) the disutility from traveling distance d_{ij}. Regarding the continuation value, it captures the fact that the student cannot choose where to enter the labor market anymore, as they commit to come back home. The utility from enrolling in program j under such a contract thus writes:

$$u(x_i, z_j) - (1-\tau)c(x_i, d_{ij}) + \sigma\epsilon_{ij} + \frac{1}{\theta}\int \beta^{t(y_i)}(\gamma + \theta(w_{i\ell^h} + \omega(h_i, y_i, m_{\ell^H})))f(y_i|x_i, h_i, z_j)dy_i \quad (31)$$

where $\tau \in [0, 1]$ is the percentage of mobility frictions that the subsidy covers the cost for. Students take into account that, when taking this scholarship, they have to enter the labor market in their home location. I simulate students' match outcome in stage one when their utility is replaced by Equation (31), and denote the welfare associated to this choice $\mathcal{U}^{\mathcal{C}_3}(\tau)$, $\forall i$. The welfare of individual i associated to the choice made under the status quo is denoted $\mathcal{U}^{\mathcal{SQ}}$.

To evaluate the impact of such a contract on the welfare of students living in low opportunities areas, I thus contrast the average utility under the contract with subsidy τ to the one under the status quo as follows:

$$\Omega^{\mathcal{C}_3}_{\mathcal{D}}(\tau) = \frac{\sum_{i\in\{i:\ell^H_i \in Deserts\}}\left[\mathcal{U}^{\mathcal{C}_3}_i(\tau) - \mathcal{U}^{SQ}_i\right]}{n_{Deserts}} \quad (32)$$

As long as $\mathcal{U}^{\mathcal{C}_3}_i(\tau) \geq \mathcal{U}^{SQ}_i$, student i is at least better off under the contract than in the status quo. The student would thus accept to tie her hands in the second stage to benefit from the subsidy. In contrast, if $\mathcal{U}^{\mathcal{C}_3}_i(\tau) < \mathcal{U}^{SQ}_i$, the student would not accept the contract, as she would be better off in the status quo. For the student to accept the contract, higher education deserts would need to compensate for this loss in welfare by offering tax rebates

to students once they return home. I compute the tax rebates as follows:

$$\mathcal{T}_i^{\mathcal{C}}(\tau) = \begin{cases} \mathcal{U}_i^{SQ} - \mathcal{U}_i^{\mathcal{C}^3}(\tau) & \text{if } \mathcal{U}_i^{\mathcal{C}_3}(\tau) < \mathcal{U}_i^{SQ} \\ 0 & \text{if } \mathcal{U}_i^{\mathcal{C}_3}(\tau) \geq \mathcal{U}_i^{SQ} \end{cases} \tag{33}$$

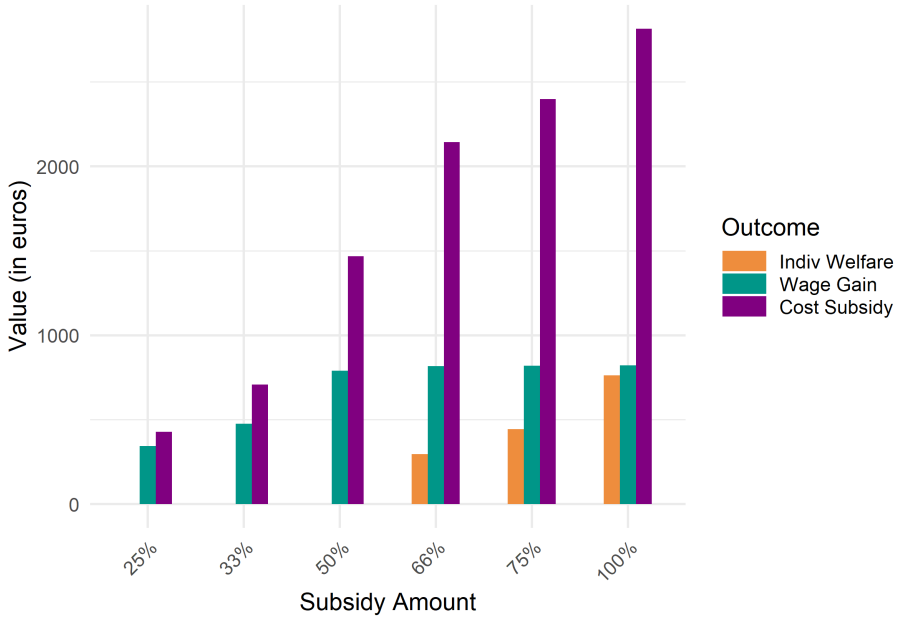
Taking into account these tax rebates, I finally compute the average gain in terms of wages from making one student come back home thanks to the contract. To do that, I take into account that a student taking the contract may have decided to come back under the status quo. The average wage returns for low opportunity areas is thus defined as follows:

$$\begin{aligned} \mathcal{G}_{\mathcal{D}}^{\mathcal{C}_3}(\tau) = & \frac{1}{n_{Deserts}} \sum_{i \in \{i: \ell_i^H \in Deserts\}} \left[\left(\int w_{i,\ell_i^H} f(y_i | x_i, h_i, z_{ij}^{\mathcal{C}^3}) dy_i \right) \right. \\ & \left. - \left(\int w_{i,\ell^{\mathcal{SQ}}(y_i)} \mathbb{1}\{\ell^{\mathcal{SQ}}(y_i) = \ell_i^H\} f(y_i | x_i, h_i, z_{ij}^{\mathcal{SQ}}) dy_i \right) - \mathcal{T}_i^{\mathcal{C}^3}(\tau) \right] \end{aligned} \tag{34}$$

where $z_{ij}^{\mathcal{C}^3}$ and $z_{ij}^{\mathcal{SQ}}$ are the vectors of characteristics of the program chosen by student i under the contract and in the status quo, respectively. $\ell^{\mathcal{SQ}}(y_i)$ corresponds to the location at entry on the labor market that an individual with characteristics y_i, collecting the degree and location at graduation, would choose in the status quo. The first integral thus corresponds to the wage that an individual with characteristics y_i would earn when returning home. The second term of this equation takes into account that, with some probability, the student would have already chosen to return home upon graduation in the status quo. In this case, the contract would not benefit education deserts, as they would not manage to attract an additional worker through the contract. Finally, the last term takes into account that, in some cases, places will have to offer a tax rebate to students for them to accept the contract.

Figure E.1 plots the average gain of this policy for students and places, as well as its cost for different values of τ, i.e. more or less generous subsidies. Offering the scheme covering 100% of the disutility associated with distance would allow the average student to benefit from an increase in welfare equivalent to 763 euros/month compared to the status quo. Such a student would not need any additional tax rebates to accept the contract. In this context, making one individual come back would allow education deserts to receive an additional wage of 822 euros/month on average. The cost associated with the distance-based subsidy is however very large, being equivalent to 2,816 euros/month.

Figure E.1: Counterfactual: Distance-Based Scholarship Conditional on Coming Back Home



NOTES. This figure shows the results of the counterfactual in which students are offered a contract under which they benefit from a distance-based scholarship, under the condition of coming back home upon graduation. It plots, for different values of the subsidy, the average welfare gain for a student taking the contract relatively to the status quo (in orange), the average wage gain for educational deserts from offering the scheme to one student (in green), and the total cost of the subsidy (in purple). All values are expressed in equivalent monthly euros.

As τ decreases, making the subsidy less generous, the cost associated with this policy decreases. The welfare gain for students born in educational deserts, however, also drops: when $\tau = \frac{2}{3}$, the average student accepting the contract would only get a welfare increase equivalent to 297 euros/month compared to the status quo. For subsidies covering 50% of the moving costs or less, tax rebates have to be offered for the average student to be willing to return home upon graduation. This implies that the net wage gain for low opportunity areas to make one student come back decreases. It reaches 344 euros/month when $\tau = 0.25$.