# Migration of high school graduates: How relevant are the degree type and field of study?*

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**Abstract**

This paper examines the migration choices of Chilean students pursuing higher education from 2011 to 2017. Using a gravity model approach, our findings provide novel insights into the forces shaping location and programmatic decisions. The estimates reveal disparities in how vocational degrees attract students from their own and neighboring regions compared to universities offering bachelor's degrees. The analysis of the fields of study suggests that Education, Health, and Technology and Engineering tend to attract students from their local communities. The results also indicate the regional polarization in educational resources, with the capital region disproportionately attracting more students from other regions.

**Keywords:** Migration, Higher Education, Choice.
**JEL:** R23, I23, J24.

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# 1 Introduction

Over the last decades, most developed and developing economies have experienced a rapid expansion of higher education. This expansion, strongly linked with human capital accumulation, has affected economic development by impacting, among others, economic growth, salaries, and innovation (Florida et al., 2008; Galor & Tsiddon, 1997). Chile is not the exception; since the early 1980s, the creation of private institutions at the professional and university level has impacted the overall coverage of post-secondary education. Between 1984 and 2015, the total enrollment in higher education has increased by more than 500% and the percentage of people aged 18–24 years enrolled in higher education has increased from 7.5% to 53.1% (SIES, 2021). Alongside these changes, in the last two decades, the country has promoted several educational policies that aimed to increase access and reduce the economic barriers to attaining higher education.[1]

The economic benefits of expanding higher education require a high level of coordination between the demand and supply of the labor market. In countries with an increasing number of highly educated workers, as in the Chilean case, overqualification is prevalent on the labor market, where higher educated workers are also likely to maintain working positions for which they are overeducated for prolonged periods of time(Sevilla et al., 2021).[2] Furthermore, as the demand for highly skilled workers does not increase as fast as enrollment in higher education, vocational post-secondary graduates are more likely to take jobs for which they far exceed the required qualifications (Sevilla & Farías, 2020).

A similar pattern is observed in science, technology, engineering, and math (STEM), where technological advances are incorporated faster in the educational system than in the labor market. In this context, higher education institutions play a significant role in the labor market mismatch (Ortiz et al., 2020), as they can also shape regional inequalities by promoting immigration from more distant areas and impacting local labor markets (Faggian et al., 2017; Kazakis & Faggian, 2017). In this context, the concentration of educational opportunities, mainly in urban and metropolitan

[1]One of the most significant policy changes include those related to college-financing programs offered by the Ministry of Education, such as traditional university loans and State Guaranteed Loans (see Card & Solis (2022); Solis (2017)).

[2]A worker is classified as overeducated if in a certain period (month), her years of education are one standard deviation above the mean of all the workers in the same occupation (Sevilla et al., 2021).

areas, has also promoted economic disparities between regions or states (Glaeser & Shapiro, 2003; Simon & Nardinelli, 2002).

This paper analyzes the interregional migration of students pursuing post-secondary education in Chile by exploring in detail the education supply of both the type of higher education institution and the field of study. Both dimensions allow us to construct a unique dataset of disaggregated interregional migration flows of Chilean high school graduates. The vast literature on interregional student migration has mainly focused on analyzing different determinants of migration across regions (see Cullinan & Duggan, 2016; Faggian & Franklin, 2014; Piras, 2017; Poot et al., 2016; Sá et al., 2004; Sá et al., 2006). As migration flows are inherently dependent on the underlying attributes of the origin and destination, as well as bilateral factors, the gravity model is widely used to analyze aggregate migration flows between places. Previous literature has shown that distance deters migration and that students tend to prefer to migrate to regions contiguous to their home region. In addition to geographical factors, the quality, type, and availability of post-secondary programs offered in one region can create barriers to students' choices whenever there is a scarcity of alternatives located close by.

Our analysis is divided into four parts. The first analyzes the effect of the main geographical variables on migration. In addition to distance, we incorporate two variables: a binary variable that captures whether two regions are contiguous and another binary variable that captures whether the enrollment choice occurs within the home region. We label the former variable as the Contiguity effect and the latter as the Within effect. The second component of our analysis extends the previous literature by exploring the heterogeneous effects of the aforementioned geographical effects by the type of higher education. We test whether the geographical effects are equal among vocational education, professional, and bachelor's degrees. Third, we conduct a similar heterogeneity analysis by fields of study. Finally, the last part simultaneously incorporates heterogeneous effects by the type of higher education and field of study.

The main findings suggest that the type of higher education and the field of study are important attributes to explain migration flows, even after accounting for time-variant origin and destination characteristics, fixed effects that control for time-invariant origin and destination factors, and year-fixed effects. Institutions that offer professional and bachelor's degrees have a larger and more significant impact on migration flows than institutions that offer vocational degrees. Similarly, the results by field of study indicate that the average effect on migration flows of the field which includes Social Sciences, Law, and Humanities, is the lowest among all fields of study. Furthermore, the estimations show that there are differences in how geography affects migration decisions as we show that distance, contiguity, and within effects are also statistically significant in explaining migration flows.

The heterogeneity analysis shows that the within effect—the effect of attending a higher educational institution in their region of origin—is statistically larger for vocational/technical institutions than for universities. Additionally, students are more likely to choose a contiguous region when choosing a vocational institution than when choosing a university. Moreover, Bachelor's degrees offered by universities outside the centralized admission system are less affected by the within and contiguity effects than any other degree type. Regarding fields of study, the largest within effect is on the field of Education, while the field of Social Sciences, Law, and Humanities presents the lowest within effect. The heterogeneity analysis that jointly compares geographical effects with the type of institution and field of study concludes that, in the case of vocational degrees, the effect geographical variables on migration flows are similar across all fields of study. In contrast with bachelor's or professional degrees, where the magnitude of the geographical effects are more diverse by fields.

The descriptive results in this paper also highlight the relative importance of the center of the country (*Región Metropolitana*) as this region serves as a focal point attracting students from all the rest of the regions. Chile is characterized by high levels of economic concentration and spatial disparities around the *Metropolitana* region. This region is home to 35.5% of the country's population and accounts for 46% of the national GDP. Much of Chile's concentration problem traces back to the fact that the majority of the economic and political decisions are made in this region, and the central government has taken few policy steps to mitigate this problem (Aroca & Hewings, 2002; Aroca & Rodríguez, 2013). Regional inequalities have been well documented in several indicators, such as income levels (Paredes et al., 2016) and quality of life (Aroca et al., 2017). The descriptive approach in this paper shows that, for example, more than half of the students located in the southernmost region—more than 800 miles away from the *Metropolitana* region—decide to enroll in a bachelor's degrees offered by private universities located in the capital.

This article contributes to different dimensions of the student migration literature. First, to our knowledge, it provides one of the first analyses of student migration that incorporates the entire tertiary education system. This allows us to offer a more complete assessment of migration determinants than existing analyses, as they focus on a subset of the higher education system. Second, by incorporating both inter- and intraregional migration flows jointly, this paper builds on the existing work, which largely focuses solely on inter-regional migration.[3] The inclusion of the within effect is a key component that ensures the adding up constraint and,[4] importantly, it reduces the selection bias resulting from only observing students who leave their home region. Third, this article offers a disaggregated analysis of migration flows by type of higher education and by field of study. Although previous evidence has suggested the existence of heterogeneous effects by the type of higher education institutions, less is known about the heterogeneity originating from differences in program fields. Finally, as most of the evidence on the determinants of student migration has focused on developed countries, this paper contributes to understanding migration patterns in a middle-income country such as Chile, a country characterized by high spatial inequalities and the concentration of economic activity around its capital.

# 2 Student Migration

Interregional migration has been widely analyzed in the literature through approaches based on both individual-level (Faggian et al., 2007; Niu, 2015; Ono, 2003) and aggregate-level data (Cooke & Boyle, 2011; Faggian & Franklin, 2014; Mixon, 1992; Tuckman, 1970; Ullis & Knowles, 1975). In both approaches, there is a broad consensus on the use of human capital theory to explain education choices and migration (Becker, 1975, 2009). According to this theory, an agent will invest in education and migrate to a location if the expected utility of the net present value of the move is greater than in any other location (Mixon & Hsing, 1994). Empirical evidence on the determinants of interregional migration supports the notion that both regional differences in

[3]See for example Baryla E.A. & Dotterweich (2001); Faggian & Franklin (2014); Sá et al. (2004).

[4]The adding-up constraint refers to having a model consistent with the gravity model theory that imposes that the total number of students residing in a region equals the combined count of immigrant students and those who choose to remain in the same region. See Yotov (2022) for further details.

economic indicators, natural amenities, quality of life, and individual characteristics such as age, education, and income, are all relevant factors that determine migration choices.

Despite the relevance of other factors, this paper focuses primarily on the geographical variables that explain interregional migration. Among them, distance is the most important variable, and it has been dealt with through different approaches. Under individual or school-level analyses, distance to the nearest institution is commonly included as a proxy for spatial accessibility of higher education. It is widely accepted that the closer the supply is, the larger is the propensity that students enroll in post-secondary education (Alm & Winters, 2009; Ashworth & Olabisi, 2023; Frenette, 2006; Sá et al., 2011, 2006; Spiess & Wrohlich, 2010), with just a few exceptions as in Gibbons & Vignoles (2012). Alternatively, in the aggregate analysis of interregional migration, distance is a crucial component of the theory behind the gravity model, which relates flows from one region to another to a set of push and pull factors in the source and destination regions, and bilateral factors that impede or encourage migration between regions. Distance is typically incorporated as the distance between geographical units such as cities, states, or regions. In this theory, larger distances between units are correlated with lower migration flows between them. Different economic interpretations have been given to this variable, which can reflect transaction costs related to monetary, information, and search costs (Cullinan et al., 2013).

The transition from high school to post-secondary education usually involves a wide range of decisions. It has been widely studied how the type of institution and its quality, the degree level, and the field of study affect labor market outcomes and future earnings (Andrews et al., 2016; Black & Smith, 2006). Depending on the educational context, different dimensions can characterize the higher educational options available to students, such as two-year or four-year colleges, universities, technical institutions, among others. From this perspective, it is plausible that geographical variables can have differential effects on migration decisions depending on the institution's characteristics, degree type, or field of study.

Although the heterogeneous analyses that researchers can conduct depend mostly on the educational context, the literature on this topic has found, in both individual or aggregate data, evidence of heterogeneous effects of distance originating from different dimensions of student or institution quality. Avery & Hoxby (2004) shows that high-aptitude students are less affected by distances when it comes to college choices, while Alm & Winters (2009) and Faggian & Franklin (2014) found that distance does not play a meaningful role in enrollment decisions. In other words, these types of institutions are able to attract both local and non-local students, for which the distance dimension is not statistically significant. Using a bivariate probit model and data from Portugal, Sá et al. (2011) show that when institutions are closer to students, there is a high probability that students stay at home rather than leaving, and consistent with our results, students who left the home region are more likely to choose a university rather than a polytechnic institution.

Despite the relevance of fields of study in explaining future labor market outcomes, the migration literature that incorporates this dimension remains small. The little empirical evidence that has focused on heterogeneous effects is mainly centered on individual choice models. In these studies, Suhonen (2014), Flannery & Cullinan (2014), and Denzler & Wolter (2011) show that field of study matters in the distance deterrence effect. However, there is no evidence of other geographical heterogeneous effects when using this type of program classification.

Given the Chilean educational system, our first heterogeneity analysis is based on the type of degree offered. To our knowledge, there has been no previous analysis of migration patterns using this classification. Rodríguez et al. (2016) found heterogeneous economic returns of the degrees offered in Chile. Thus, all else equal, degrees with higher returns are likely to attract students from farther away locations. Additionally, heterogeneous effects for other geographic variables besides from distance have been less documented in the literature. An exception is Faggian & Franklin (2014) which shows that high-performing students are less affected not only by distance, but also by whether the destination is in a contiguous state.

# 3 Chilean Context

The Chilean secondary education encompasses four years, and schools can be categorized as public, private subsidized (voucher schools), and private. It is widely recognized that students enrolled in private schools tend to be students from high income levels, voucher schools typically educate middle-income students, and public schools serve students from the lowest income levels (OECD, 2009).

Regarding the transition from high school to higher education, although there are no mandatory tests or required choices that must be made with respect to student paths, most students take at the end of the last year of high school a standardized test for admission to college (*Prueba de Selección Universitaria*, or PSU). This test allows students to apply to universities using a centralized admission system in which all of the public and traditional universities and 9 of the country's 43 private universities participate. The rest of the institutions are free to design their own selection processes, although some of them also rely on the PSU scores.

The postsecondary system has different types of higher education institutions (HEI) based on the degree type they offer. Technical Formation Centers are those that offer two-year vocational degrees, while professional institutes are those that offer four-year Professional degrees. These two types of institutions are private institutions and do not receive any public funding.[5] The next type of institution are universities that offer five-year bachelor's degrees. We classify universities into two types. The first group consists of universities that are part of the centralized admission system (we define them as "Bachelor's Degree - Centralized Admission System, CAS"), while the rest are private universities outside the centralized system (we define them as "Bachelor's Degree - Private System, PS").[6]

In general, tuition costs are high for all higher education alternatives, but Bachelor's Degrees from private universities are typically the most expensive options. Annual tuition fees for the case of universities represent around 50% of the average per capita income of the country, while the tuition fees of CFTs or IPs correspond to 28% of the average per capita income.[7]

Figure 1 shows the net migration for all 15 Chilean regions.[8] According to this figure, *Metropolitana*, *Valparaíso*, and *Bio-Bio* are the only regions displaying positive net migration while the region

[5] Since 2018, the Chilean government has promoted the creation of public vocational institutions, however the data analyzed in this paper are from before that period.

[6] Bachelor's degrees from universities which are part of the centralized admission system are mostly traditional and public institutions, but there are also private institutions that are part of this group. In contrast, universities outside the centralized system are all private.

[7] Average fees are calculated using data from the Ministry of Education, Chile. Annual per capital income is retrieved from the Ministry of Social Development and Family, CASEN Survey (2017).

[8] In September 2018, a new region, *"Región del Ñuble,"* was created. The data used in this paper considers only 15 regions because our data cover the period of 2011–2017.

of *O'Higgins* presents the largest emigration of students.[9] Figure 1 also displays, after each region's name, the regional share of high school graduates in each region and the share of high school graduates that enroll in post-secondary education. As expected, a large share (39.1%) of the high school graduates live in the capital of the country, however, there are no substantial differences in the proportion of students pursuing higher education. Importantly, the *Metropolitana* region hosts 186 out of the 553 post-secondary education institutions (33.6%) in the country.

Data allow us to identify programs' fields based on an OECD classification of educational fields of study and areas of knowledge provided by the Ministry of Education. Specifically, the fields of study are: (1) Social Sciences, Humanities, Architecture, (2) Agriculture and Basic Sciences, (3) Administration and Business, (4) Education, (5) Health, (6) Technology and Engineering. nrollment data from the period 2011–2017 shows that, on average, the three main fields of study accounting for 70% of the enrollment are Technology and Engineering (28%), Health (23%), and Social Sciences, Humanities, and Architecture (21%). The field with the lowest share is Agriculture and Basic Sciences (5%).

As in many educational settings, socioeconomic background significantly influences postsecondary educational choices. However, analyzing how specific socioeconomic variables impact migration requires individual-level data, which is beyond the scope of this paper. Consequently, we are unable to isolate the influence of idiosyncratic factors such as household income or parents' education on migration decisions. Nevertheless, it is worth noting the socioeconomic disparities among the group of students who migrate within this educational system.

According to administrative data from the Ministry of Education, the enrollment rates in higher education for the year following graduation in 2017 were significantly different between private and public schools. In private schools, 76.5% of students enrolled in higher education, whereas only 41.9% of students from public schools did the same. Additionally, in terms of migration, 6% of students from public schools and 14% of students from private schools enrolled and migrated in the

[9] Net migration in Figure 1 is calculated as the difference between the number of students who immigrate and the number of students who emigrate. The region of origin considers the location of students at high school, the region of destination considers the region of enrollment of students at post-secondary education.

year after high school graduation.[10]

During the transition from high school to post-secondary education, almost 50% of the students in public schools opt for vocational and professional degrees, whereas less than 10% of the students in private schools make the same choice (refer to Appendix Figure A.1). Furthermore, we observe that the distribution of enrollment by field does not significantly differ between public and voucher schools. The preferred choices for both types of schools are Technology and Engineering and Health. However, in the case of private schools, the most notable difference is observed in the field of Social Sciences, Humanities, and Architecture, with approximately 36% of students from private schools selecting this field (see Appendix Figure A.2).

Another important aspect that distinguishes the groups in tertiary education is the average performance of students during high school. Students pursuing vocational and professional degrees tend to have the lowest average GPA, whereas those enrolled in bachelor's degrees through centralized admission achieve the highest average GPA. However, there are no significant variations in GPA across different fields of study (refer to Appendix Figures A.3 and A.4).

# 4 Data Construction and Descriptive Statistics

## 4.1 Dependent Variable

The main dependent variable in our analysis is the interregional migration flow, which refers to the total number of students who move from one region to another, including cases where the region of origin and destination are the same.[11] The following paragraphs provide detailed explanations of the aggregation levels from the individual-level data and how the dependent variables are constructed.

[10] Apart from the type of high school, financial aid can serve as a useful indicator of income levels. Nearly half of the students enrolled in vocational, professional, and bachelor's degrees in the centralized system receive tuition waivers. In contrast, only 13% of students enrolled in a bachelor's degree through private admission receive this type of financial aid. In terms of migrant students, a mere 11% of those enrolled in private bachelor's degrees receive financial aid, while 52% of migrant students enrolled through centralized admission in a bachelor's degree benefit from financial assistance.

[11] When the region of origin and destination are the same, it means that the student decided to enroll in an institution in the same region where they currently reside during high school. We do not exclude these cases from our data since they represent a significant portion of the overall distribution of destination choices. Additionally, as explained in section 5, the within-region flow is an essential element of our identification strategy.

We estimate four models with different dependent variables, all representing the migration flows. These variables are derived from aggregating administrative data at various levels. The procedure begins by utilizing individual-level data from the Ministry of Education to identify the entire population of high school students in their last year between 2010 and 2016. This data allows us to determine the region of residence for each student, which serves as the region of origin.

Next, we use unique student IDs to match each student with their subsequent year of enrollment in higher education (2011–2017). This data provides us with information about the location of the campus or institution where the students enroll, representing the region of destination.

The next step involves aggregating the data according to the desired level of analysis. For instance, if we are interested in examining the total migration between each pair of regions, irrespective of institution type or field of study, we tally the number of students enrolled in post-secondary education for all possible combinations of origin and destination regions. As a result, we can calculate the number of observations in the final dataset as follows: Considering that Chile consists of 15 regions and we have seven years of data, there are a total of 225 possible combinations of interregional migration ($15 \times 15 = 225$), leading to a final dataset with $225 \times 7 = 1575$ observations.

The example provided in the preceding paragraph illustrates the initial and fundamental level of aggregation, which considers interregional and intra-regional migration flows between all pairs of origin and destination regions. The second level of aggregation includes the type of higher education in addition to the origin-destination pair. At this level, each observation in the dataset represents the total number of students migrating from one region to another for a specific type of higher education. Consequently, the final dataset at this aggregation level multiplies the total number of region-to-region by the number of available higher education types in the system.

The third level of aggregation incorporates the field of study. Each observation in this dataset represents the total number of students migrating from one region to another within a particular field of study. Lastly, the last dataset takes into account both the type of higher education and the field of study simultaneously. In this case, each entry of the dependent variable represents, for instance, the total number of students moving from region $i$ to region $j$ to pursue a program in the field of sciences at a private university.

Following this procedure, we obtain four datasets aggregated at different levels. Figure 2 displays a heat map illustrating the migration patterns between different regions in Chile. The $y$-axis represents the origin region, while the $x$-axis represents the destination region. Each pair $(x, y)$ indicates the percentage of students from the origin region $y$ who enroll in the destination region $x$. Panel A of Figure 2 demonstrates that the majority of students tend to remain in their home regions, as indicated by the diagonal line. However, darker red spots off the main diagonal suggest that the regions of *Metropolitana* and *Valparaíso* serve as attractive destinations for students from other regions.

Panels B to E of Figure 2 depict matrix representations of the migration flow for each type of higher education institution. These panels reveal that the migration pattern observed in Panel A is primarily driven by enrollment in bachelor's degree programs. For instance, in Panel D, it can be seen that at least 50% of high school students from *Magallanes*, the southernmost region, enroll in bachelor's degree programs offered by private universities located in the Metropolitan Region. Additionally, at least 25% of students from *Magallanes* choose to study in *Valparaiso*. In contrast, Panel B illustrates that vocational degrees predominantly attract students from the same or neighboring regions. Notably, there is a significant exchange of students between the regions of *Los Rios* and *Los Lagos*.

## 4.2 Geographical Variables

Three geographical variables comprise the main focus of the analysis:

- ***Distance:*** To calculate the distance between regions, we utilize the Euclidean distance in kilometers, which is measured between the centroids of the respective regions. However, when considering intra-regional distance, we adopt the approach outlined by Head & Mayer (2000) to avoid assigning zero as the distance for internal migration. In such cases, the distance within a region, denoted as $d_{ii}$, is determined as $0.67\sqrt{(Area_i)/\pi}$, where $\pi$ represents the irrational number and $Area_i$ denotes the region's area measured in square kilometers.[12]

- ***Contiguity:*** This is a dummy variable that takes a value of one when two regions share a

[12]For instance, considering that the *Metropolitana* region has an area of 15828 $km^2$, the within-distance variable (i.e., when both the region of origin and destination are the *Metropolitana* region) is computed as $0.67\sqrt{15,828/\pi} = 47.56$ km. The rationale behind this calculation assumes that the economic geography of each region can be approximated by a disk, with the radius of the disk being proportional to the square root of the region's area. Alternative measures of internal distance have negligible impacts on our estimates.

common border. For instance, when there is a migration flow from *Valparaíso* to the *Metropolitana* region (refer to Figure 1), the border variable takes a value of one.

- ***Within:*** The intra- or within-region variable is a dummy variable that takes a value of one when the region of origin and destination are the same. In other words, it indicates the occurrence of intra-regional migration.

## 4.3 Control Variables

All of our regressions include controls that capture the characteristics of the origin and destination regions, specifically related to the higher education system and the labor market. Table 1 displays the means and standard deviations of the main variables used to describe the Chilean regions.

From 2011 to 2017, the regional average of students enrolled in the final year of high school is 12,677, with the Metropolitan Region having the highest number of students, exceeding 73,000. The average number of available programs in each region exhibits significant variation. In the *Metropolitana* region, for instance, the combined post-secondary institutions offer nearly 8,000 programs per year, while *Aysén* has an average of 107 programs. Program quality is typically assessed through accreditation conducted by the National Commission of Accreditation (CNA). On average, 20% of the programs received accreditation from the CNA during the 2011-2017 period, with *Atacama* having the lowest accreditation ratio and *Los Ríos* having the highest. Monthly tuition fees do not exhibit drastic variations across regions, although the *Metropolitana* region remains the most expensive for studying purposes.

As part of the control variables related to the labor market, we include unemployment rates and average monthly income. These variables were constructed using data from the National Survey of Employment and the Supplementary Survey of Income, both conducted by the National Institute of Statistics (INE). The average monthly income is 422,178 Chilean pesos,[13] and the average regional unemployment rate is 5.9%.

[13]Approximately 535 US$ as of June 9, 2023.

# 5 Theory and Econometric Estimation

This paper adopts the well-known gravity model approach commonly used in migration and trade studies (Anderson, 1979, 2011; Cushing & Poot, 2004). Equation 5 presents the main equation derived from this theory, which suggests that migration is expected to have a positive relationship with the "size" of both the origin and destination regions, as measured by population, while demonstrating an inverse relationship with distance.

$$M_{ij} = \frac{P_i^{\alpha} P_j^{\beta}}{D_{ij}^{\gamma}}. \tag{1}$$

Here $M_{ij}$ represents the total inter-regional migration flow from location $i$ to location $j$, $P_i$ and $P_j$ refer to the population of origin and destination respectively, and $D_{ij}$ is a measure of distance between these two locations. The economic interpretation of $D_{ij}$ is that it approximates the cost of moving from $i$ to $j$.

In order to estimate Equation 1 econometrically, it is common in the literature to apply a logarithmic transformation to the equation and estimate it using ordinary least squares (OLS). However, this approach is marked by a number of empirical challenges. These issues include inconsistent estimators, heteroskedasticity, and the presence of zero flows. Specifically, work by Santos Silva & Tenreyro (2006) show that the log-linearization of the error term, as used in OLS, can lead to a highly biased distance elasticity estimation. The authors suggest that a proper estimator is the Poisson pseudo-maximum likelihood (PPML), which is robust to different specifications of heteroskedasticity and allows for the inclusion of zero-valued flows.[14]

Similarly to Faggian & Franklin (2014) and Wall (2005), we express migration flows as a Poisson process to model interregional and intra-regional migration flows. Equation 2 describes this process:

[14]While other studies suggest the use of alternative estimation methods such as Negative Binomial and zero-inflated models (Biagi et al., 2011; Burger et al., 2009; Faggian & Franklin, 2014), empirical evidence restricts us from utilizing such methods. Firstly, as noted by Bosquet & Boulhol (2014), estimates obtained using Negative Binomial models are sensitive to the scale of the dependent variable. Secondly, Santos Silva & Tenreyro (2006, 2011) demonstrate that PPML does not require equidispersion of the data, which is a common critique of Poisson estimates. Instead, it requires the conditional mean and variance to be proportional. They also illustrate that the PPML estimator performs well even in the presence of a large number of zero-valued flows.

$$Pr(M_{ij}) = \frac{\exp(-\mu_{ij})\mu_{ij}^{M_{ij}}}{M_{ij}!}, \tag{2}$$

where $E(M_{ij}) = \mu_{ij} = \exp(\alpha + \beta' X_i + \gamma' Z_j)$ and represents the expected value of the inter-regional migration between $i$ and $j$, and where $X_i$ and $Z_j$ are vectors of origin and destination characteristics, respectively.

In this study, we employ the PPML estimator to extend the model proposed by Faggian & Franklin (2014) in two ways. Firstly, we incorporate the type of degree and field of study as additional dimensions that influence migration flows. By considering these dimensions, we capture the influence of educational opportunities and specialization on migration patterns. Secondly, we include intra-regional migration flows in addition to inter-regional migration flows, which distinguishes our study from most previous research in this area. As discussed in the trade literature, Yotov (2022) highlights important reasons for the inclusion of intra-regional migration. This inclusion ensures adherence to the adding-up constraint, exemplified by a model consistent with the gravity model theory, where the total number of students residing in a region equals the combined count of immigrant students and those who choose to remain in the same region. Furthermore, it helps mitigate potential selection biases that may arise from solely observing migrant students. By incorporating both inter- and intra-regional migration, we offer a comprehensive overview of migration patterns while avoiding potential biases in our analysis

# 6 Empirical Strategy

## 6.1 Region-Level model

In the region-level gravity model, the dependent variable $M_{ijt}$ represents the total number of students who migrate from region $i$ to region $j$ at time $t$. We parameterize the conditional mean in equation 2 and add time subscripts to obtain the equation that describes the regression model:

$$M_{ijt} = \exp(\alpha + \beta \log dist_{ij} + \gamma intra_{ij} + \delta border_{ij} + \psi' X_{it} + \rho' Z_{jt} + \theta_i + \omega_j + \tau_t) + \varepsilon_{ijt}. \tag{3}$$

As previously mentioned, the three main variables of interest are the geographical variables. In equation 3, $dist_{ij}$ represents the distance variable, $intra_{ij}$ represents the within-region variable, and $border_{ij}$ is the contiguity variable.

Additionally, $\theta_i$, $\omega_j$, and $\tau_t$ represent origin, destination, and time fixed effects, respectively. The fixed effects from origin and destination variables capture long-term and time-invariant characteristics of the regions, including geographical features, weather conditions, amenities, and other relevant factors. The time fixed effects account for time-specific events that may impact enrollment decisions, such as changes in government financial aid programs. The term $X_{it}$ denotes a vector of time-variant characteristics specific to the origin region, while $Z_{jt}$ represents a vector of time-variant characteristics specific to the destination region. All variables included in both vectors $X_{it}$ and $Z_{jt}$ are the variables described in Table 1.

## 6.2 Region-Degree Level Gravity Model

This section introduces the inclusion of the type of degree in the model. Degrees are indexed by the letter $l$, and include degrees classified as vocational (1), professional (2), bachelor's from the centralized admission system (3), and bachelor's outside the system, i.e., private system (4). $M_{ijlt}$ captures the total flow of students who migrate from region $i$ to region $j$ to study at a degree $l$ in year $t$. The regression model is expressed in equation 4.

$$\begin{aligned} M_{ijlt} = \exp(&\alpha + \beta_1 \log dist_{ij} + \gamma_1 intra_{ij} + \delta_1 border_{ij} + \sum_l \eta^l Type_l + \sum_l \beta_2^l \log dist_{ij} \times Type_l \\ &+ \sum_l \gamma_2^l intra_{ij} \times Type_l + \sum_l \gamma_2^l border_{ij} \times Type_l + \psi' X_{it} + \rho' Z_{jt} + \theta_i + \omega_j + \tau_t) + \varepsilon_{ijlt}. \end{aligned} \tag{4}$$

$Type_l$ is a dummy variable for each degree type. For example, $\eta^2$ captures the average effect of a professional degree program on migration relative to a vocational degree program, which is the excluded category. The coefficients $\beta_1$, $\gamma_1$, and $\delta_1$ capture each geographical variable's average effect on migration when the degree type is vocational. The subsequent terms are interaction terms between the geographical and degree-type variables. For example, the coefficient $\beta_2^2$ captures the difference in the distance elasticity between professional and vocational degrees. Similar to Equation 3, origin, destination, and time-fixed effects are represented by $\theta_i$, $\omega_j$, and $\tau_t$, respectively. $X_{it}$ and $Z_{jt}$ represent the time-varying origin and destination characteristics, respectively.

## 6.3 Region-Field of Study Gravity Model

We next explore the heterogeneous effects by field of study while assuming homogeneous effects across degree types. The model examines whether geographical variables have different impacts on migration depending on the field of study, which is a crucial aspect of the regional distribution of specialization areas. The fields of study are Social Sciences, Humanities, and Architecture (1), Agriculture and Basic Sciences (2), Administration and Business (3), Education (4), Health (5), and Technology and Engineering (6). In the regression analysis, the excluded category is Social Sciences, Humanities, and Architecture.

Equation 5 defines the regression model where the dependent variable $M_{ijkt}$ that represents the total number of students from region $i$ who enroll in region $j$ to study in the field $k$ at time $t$.

$$
\begin{aligned}
M_{ijkt} = \exp(&\alpha + \beta_1 \log dist_{ij} + \gamma_1 intra_{ij} + \delta_1 border_{ij} + \sum_k \lambda^k Field_k \\
&+ \sum_k \beta_2^k \log dist_{ij} \times Field_k + \sum_k \gamma_2^k intra_{ij} \times Field_k + \sum_k \delta_2^k border_{ij} \times Field_k \\
&+ \psi' X_{it} + \rho' Z_{jt} + \theta_i + \omega_j + \tau_t) + \varepsilon_{ijkt}.
\end{aligned}
\tag{5}
$$

$Field_k$ is a dummy variable for each field of study in the data. For example, the coefficient $\lambda^5$ captures the average effect of the field Health on migration relative to the excluded category of Social Sciences, Humanities, and Architecture. Similar to the previous model, Equation 5 includes interaction terms between geographical variables and the fields' dummy variables. Thus, $\delta_2^5$ captures the difference in the border effect between Health and the excluded category. As usual, origin, destination, and time fixed effects are represented by $\theta_i$, $\omega_j$, and $\tau_t$, respectively. $X_{it}$ and $Z_{jt}$ represent time-varying origin and destination characteristics, respectively.

### 6.4 Region-Degree-Field of Study Gravity Model

The final specification involves examining variations by both degree type and field of study, referred to as the State-Degree-Field model. The exponential mean parametrization of the flow is constructed as a fully saturated regression, and the regression model is represented in Equation 6. The excluded categories are vocational degrees for the degree variable and Social Sciences, Humanities, and Architecture for the field variable.

$$
\begin{aligned}
M_{ijlkt} = \exp(&\alpha + \beta_1 \log dist_{ij} + \gamma_1 intra_{ij} + \delta_1 border_{ij} + \sum_l \eta^l Type_l + \sum_k \lambda^k Field_k \\
&+ \sum_l \beta_2^l \log dist_{ij} \times Type_l + \sum_k \beta_3^k \log dist_{ij} \times Field_k + \sum_l \sum_k \beta_4^{lk} \log dist_{ij} \times Type_l \times Field_k \\
&+ \sum_l \gamma_2^l intra_{ij} \times Type_l + \sum_k \gamma_3^k intra_{ij} \times Field_k + \sum_l \sum_k \gamma_4^{lk} intra_{ij} \times Type_l \times Field_k \\
&+ \sum_l \delta_2^l border_{ij} \times Type_l + \sum_k \delta_3^k border_{ij} \times Field_k + \sum_l \sum_k \delta_4^{lk} border_{ij} \times Type_l \times Field_k \\
&+ \psi' X_{it} + \rho' Z_{jt} + \theta_i + \omega_j + \tau_t) + \varepsilon_{ijlkt}.
\end{aligned} \tag{6}
$$

In this model, all combinations of interaction terms are included. For example, $\delta_4^{l=3,k=2}$ captures the difference in border effects of a Bachelor's degree from a university in the centralized admission system in Administration and Business relative to a Vocational degree in Social Sciences, Humanities, and Architecture. Fixed effects by origin, destination, and time are represented by $\theta_i$, $\omega_j$, and $\tau_t$, respectively. $X_{it}$ and $Z_{jt}$ represent time-varying origin and destination characteristics, respectively.

## 7 Results

All of the results are estimated using the PPML estimator, with standard errors clustered at the origin-destination pair. It is important to note that these estimators are nonlinear, which means that the coefficients cannot be directly interpreted as marginal effects. For dummy variables, the marginal effects are computed as $(\exp(\beta) - 1) \times 100\%$. In the case of continuous variables, logarithmic transformations are applied to the variables, enabling the coefficients to be interpreted as elasticities.

Table 2 presents the results of the state-level and state-degree-level gravity models. Columns (1) and (2) display the coefficients and standard errors of the state-level model. In this model, the three geographical variables of interest, namely distance, within, and border, are statistically significant. Consistent with the theoretical expectations, the distance effect acts as a deterrent to migration. This coefficient can be interpreted as an elasticity: a 1% increase in the distance between two regions corresponds to a 0.71% decrease in student migration between them.

The coefficient for *within* indicates a positive relationship between enrollment and remaining in the same region of origin. This result suggests that there is a regional force that encourages students to study in their home region after high school graduation. Additionally, the border coefficient indicates that migration flows between contiguous regions are larger compared to flows between non-neighboring regions. This finding aligns with previous studies such asFaggian & Franklin (2014), Sá et al. (2006), and DesJardins et al. (1999), which suggest that students tend to prefer staying geographically closer to their families and friends and may have better knowledge of institutions in nearby regions.

Table 2 displays the coefficients of various pull and push factors. As anticipated, the results indicate that both the high school population of the origin and destination regions have a positive effect on migration, but only the population of the origin region significantly influences migration flows. In an expanded gravity model, it is necessary to include push and pull variables beyond population. According to Faggian & Franklin (2014), students bound for college tend to prioritize the quality of institutions over labor market conditions, with the latter potentially becoming more relevant after graduation. Table 2 reveals that the ratio of accredited programs to the total programs offered at the destination region is positively and significantly associated at the 1% level. This variable serves as a proxy for the relative quality of institutions in a region and indicates that regions with a higher proportion of accredited programs attract students from other regions.

Labor market variables at the destination exhibit a significant influence on migration. Consistent with Cooke & Boyle (2011), the results suggest that destination income and unemployment have a slightly negative effect on migration. The positive signs on the labor market variables of the origin regions suggest that migration likely occurs from high-income regions to low-income regions and from high-unemployment regions to low-unemployment regions.

Although not shown in Table 2, the effects of the region of origin and destination can provide valuable insights into migration patterns. To examine these effects, Figure 4 presents the coefficients derived from the binary variables representing the origin and destination. The excluded category is the *Metropolitana* region, represented by the solid horizontal line in both panels.

The results indicate that larger coefficients are observed in the northern and southern regions, while smaller coefficients are found in regions located near the center of the country. As expected, all the origin effects are positive and significant, indicating that every region sends out more students than the *Metropolitana* region. Conversely, no region receives as many students as the *Metropolitana* region, except for Valparaiso, a region where the inflow and outflow of students resemble that of the *Metropolitana* region.

Columns (3) and (4) in Table 2 present the results of the State-Degree specification. The coefficients for degree types indicate that all of the degree types are statistically different from Vocational degrees. This suggests that, for instance, private universities outside the centralized system have a greater impact on migration flows compared to vocational institutions.

In terms of the geographical variables, the purpose of this model is to examine whether the main geographical variables have different effects by degree. As mentioned earlier, the interaction terms of each geographical variable with the degree type measure the difference in the effect compared to the excluded category. In Column (3), all of the interaction terms show a negative sign, indicating that all degree types are less affected by these geographical variables relative to Vocational degrees.

Figure 5 presents the point estimates along with the 95% and 90% confidence intervals on the geographical variables for each degree type. These estimates are obtained by combining the corresponding coefficients from Equation 4. For example, the distance elasticity of a professional degree is calculated as the sum of $\beta_1 + \beta_2^2$. Based on the estimates from Table 2, the total effect is $-0.013 + -1.193 = -1.206$,[15] indicating an elastic effect of distance for professional degrees.

Figure 5 reveals significant variations among degree types. Specifically, the results indicate that,

[15]Final estimates and confidence intervals are obtained using the *lincom* command in Stata.

after controlling for the within and contiguity variables, the distance elasticity is not statistically significant for vocational degrees. This finding is consistent with the pattern observed in Figure 2, where enrollment decisions of students from vocational degrees are primarily influenced by whether the institution is located in their home or neighboring region, as indicated by the substantial and significant effects of the contiguity and within variables in Figure 5. These findings suggest that students enrolled in vocational/technical institutions face greater spatial constraints, likely due to the increased transaction costs associated with distance. On average, students attending vocational/technical institutions predominantly come from public schools, which, as highlighted by OECD (2009), typically serve students from lower-income backgrounds. Consequently, these students may have limited financial resources to support relocation to another region, leading them to prefer staying in proximity to their home region.

Furthermore, Figure 5 illustrates that migration flows associated with Bachelor's degrees from the centralized admission system are less sensitive to distance compared to Professional and Private Bachelor's degrees. This finding aligns with previous literature, which has shown that high-performing students tend to be less affected by distance compared to low-performing students (Faggian & Franklin, 2014). This result is consistent with the characteristics of the Chilean educational system, where universities from the centralized admission system are typically considered more selective and capable of attracting high-achieving students (Hastings et al., 2013; Rodríguez et al., 2016).

Table 3 presents the results of the State-Field of Study model. As mentioned earlier, the excluded category in this model is Sciences, Law, Humanities, Arts, and Architecture. Therefore, the coefficients of the dummy variables representing different fields indicate that migration flows in all other fields are lower compared to the base category.

For illustrative purposes, Figure 6 displays the total geographical effects by field of study, following a procedure similar to the one used in Figure 5. The results indicate that Education is the field with the largest Contiguity and Within effect, but these effects are closer and no statistically different than the fields of Health, and Technology and Engineering. Finally, all of the distance elasticity estimates are statistically significant at least at the 90% level, and there are no significant differences across fields.

Tables 4 and 5 present the results of the final model, which includes all interaction terms for the State-Degree-Field of Study specification. The total effects are displayed in Figure 7, where each panel represents a specific geographical variable, and the colors are grouped by degree.

For example, in Panel A of Figure 7, the red confidence intervals represent the total distance elasticity effect of vocational degrees across all fields of study. The results indicate that distance is not statistically significant for any field of study at the vocational degree level, as all the confidence intervals cross zero. Regarding bachelor's degrees, the estimates from the centralized admission system suggest that the effect of distance is inelastic c across all fields of study, as the coefficients are smaller than one in magnitude. However, for bachelor's degrees from the private system, all fields of study except for Health exhibit distance elastic coefficients. Furthermore, degrees from Professional institutes exhibit substantial heterogeneity in the distance effect, with the field of Business and Administration showing the largest distance effect among them.

Panel B of Figure 7 displays the total estimates of the Within effect. The estimates for Vocational degrees exhibit larger confidence intervals and less heterogeneity across fields. On the other hand, Health degrees from Professional Institutes or Universities show a significantly larger Within effect compared to Social Sciences, Humanities, and Architecture, indicating a strong preference for studying in the home region for such degrees.

Finally, Panel C of Figure 7 presents the total estimates of the Contiguity effect. For Professional degrees, many of the estimates cross zero, indicating a null total effect of contiguity between regions on migration flows. In the case of Bachelor's degrees from the centralized system, the figure indicates that Health exhibits the largest contiguity effect, which is statistically different from Social Sciences, Humanities, and Architecture.

# 8 Conclusions

The Chilean tertiary educational system exhibits high levels of spatial concentration, primarily centered around the *Metropolitana* Region (Aroca & Atienza, 2016). This concentration has resulted in the accumulation of high-quality human capital in the central region over the years. The literature has documented various consequences in terms of regional economic growth and development resulting from this concentration (Faggian & McCann, 2009; Faggian et al., 2017; Ishitani, 2011; Kazakis & Faggian, 2017; Kodrzycki, 2001). However, limited evidence exists regarding the types of institutions that attract more students, the regions from which these students originate, and the fields of study that are able to retain students in their home regions.

In this paper, we utilize a unique dataset compiled from various administrative sources, encompassing the entire high school population enrolled in higher education between 2011 and 2017. The main objective of this study is to employ an extended gravity model to examine the influence of geographical variables, including distance, contiguity, and the attractiveness of students' home regions, on migration patterns. We specifically investigate whether these effects exhibit heterogeneity based on the type of degree and fields of study.

Our main findings suggest that, after accounting for factors such as regions' size, availability and quality of higher education, and local labor market conditions, significant differences in migration flows across Chilean regions emerge. Specifically, all regions experience higher levels of out-migration of students compared to the *Metropolitana* region, where the nation's capital is located. Furthermore, no region receives a higher influx of students than the *Metropolitana* region. This concentration of higher education opportunities in a single region has significant implications for the labor market structure and may influence the spatial distribution of high-skill labor (Chacón & Paredes, 2015).

Regarding the impact of geographical variables, the findings suggest that Vocational degrees primarily attract students from the same or contiguous regions. After accounting for these factors, the distance deterrence effect is not significant. On the other hand, Bachelor's degrees from universities in the centralized admission system exhibit the lowest distance elasticity effect, which aligns with previous research indicating that students attending highly competitive institutions are less influenced by distance.

The model that explores heterogeneity by field of study reveals fewer differences among fields compared to the model that solely examines heterogeneity by degrees. The fields of Education, Health, and Technology and Engineering present similar geographical effects without statistical differences.

Our findings provide evidence on how different types of potential human capital move across the country and the institutional characteristics that impact the way geography affects migration. In this sense, as individuals enrolled in vocational institutions are more likely to be low-income and low-performance students compared to those enrolled in public and private universities, our results suggest that their mobility across the country is more limited compared to students enrolled in universities. The results that we establish can be useful in the design of educational policies toward more equitable regional development. One example is the location decision of future higher education institutions and how regions other than the *Metropolitana* region can attract their own human capital.

Further research includes the analysis of migration flows that occur after college graduation. International evidence shows mixed results on whether students are more likely to move or stay after graduation (Faggian & McCann, 2009; Ishitani, 2011; Kodrzycki, 2001; Winters, 2020). In the case of Chile, it is still unclear whether the concentration process towards the *Metropolitana* region is stronger for recent college graduates than for high school graduates. However, such evidence will provide a better understanding of the long-term consequences of students' migration on spatial disparities in the labor market.

# References


Alm, J. & Winters, J. V. (2009). Distance and Intrastate College Student Migration. *Economics of Education Review*, 28(6), 728–738.

Anderson, J. E. (1979). A Theoretical Foundation for the Gravity Equation. *American Economic Review*, 69(1), 106–116.

Anderson, J. E. (2011). The Gravity Model. *Annual Review of Economics*, 3(1), 133–160.

Andrews, R. J., Li, J., & Lovenheim, M. F. (2016). Quantile Treatment Effects of College Quality on Earnings. *Journal of Human Resources*, 51(1), 200–238.

Aroca, P. & Atienza, M. (2016). Spatial Concentration in Latin America and the Role of Institutions. *Investigaciones Regionales: Journal of Regional Research*, (36), 233–253.

Aroca, P., González, P. A., & Valdebenito, R. (2017). The Heterogeneous Level of Life Quality across Chilean Regions. *Habitat International*, 68, 84–98.

Aroca, P. & Hewings, G. J. D. (2002). Migration and Regional Labor Market Adjustment. *Annals of Regional Science*, 36, 197–218.

Aroca, P. & Rodríguez, J. (2013). Population Distribution and Internal Migration Issues in LAC. In J. R. Cuadrado-Roura & P. Aroca (Eds.), *Regional Problems and Policies in Latin America* chapter 15, (pp. 341–358). Springer.

Ashworth, J. & Olabisi, M. (2023). Distance and Mismatch in Graduate School Selection. *Education Economics*, 31(1), 1–30.

Avery, C. & Hoxby, C. M. (2004). *Do and Should Financial Aid Packages Affect Students' College Choices?* University of Chicago Press.

Baryla E.A., J. & Dotterweich, D. (2001). Student Migration: Do Significant Factors Vary by Region? *Education Economics*, 9(3), 269–280.

Becker, G. S. (1975). *Human Capital*. New York, NY, Columbia University Press.

Becker, G. S. (2009). *Human capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. University of Chicago press.

Biagi, B., Faggian, A., & McCann, P. (2011). Long and Short Distance Migration in Italy: The Role of Economic, Social and Environmental Characteristics. *Spatial Economic Analysis*, 6(1), 111–131.

Black, D. A. & Smith, J. A. (2006). Estimating the Returns to College Quality with Multiple Proxies for Quality. *Journal of Labor Economics*, 24(3), 701–728.

Bosquet, C. & Boulhol, H. (2014). Applying the GLM Variance Assumption to Overcome the Scale-Dependence of the Negative Binomial QGPML Estimator. *Econometric Reviews*, 33(7), 772–784.

Burger, M., van Oort, F., & Linders, G. J. (2009). On the Specification of the Gravity Model of Trade: Zeros, Excess Zeros and Zero-inflated Estimation. *Spatial Economic Analysis*, 4(2), 167–190.

Card, D. & Solis, A. (2022). Measuring the effect of student loans on college persistence. *Education Finance and Policy*, 17(2), 335–366.

Chacón, S. & Paredes, D. (2015). Desigualdad Espacial de Ingresos en Chile y su Relación con la Concentración de Capital Humano. *El Trimestre Económico*, 82(326), 351–377.

Cooke, T. J. & Boyle, P. (2011). The Migration of High School Graduates to College. *Educational Evaluation and Policy Analysis*, 33(2), 202–213.

Cullinan, J. & Duggan, J. (2016). A School-Level Gravity Model of Student Migration Flows to Higher Education Institutions. *Spatial Economic Analysis*, 11(3), 294–314.

Cullinan, J., Flannery, D., Walsh, S., & McCoy, S. (2013). Distance Effects, Social Class and the Decision to Participate in Higher Education in Ireland. *Economic and Social Review*, 44(1), 19–51.

Cushing, B. & Poot, J. (2004). Crossing Boundaries and Borders: Regional Science Advances in Migration Modelling. *Papers in Regional Science*, 83(1), 317–338.

Denzler, S. & Wolter, S. C. (2011). *Too Far To Go? Does Distance Determine Study Choices?* Technical report, IZA Discussion Papers No. 5712.

DesJardins, S. L., Dundar, H., & Hendel, D. D. (1999). Modeling the College Application Decision Process in a Land-Grant University. *Economics of Education Review*, 18(1), 117–132.

Faggian, A. & Franklin, R. S. (2014). Human Capital Redistribution in the USA: The Migration of the College-bound. *Spatial Economic Analysis*, 9(4), 376–395.

Faggian, A. & McCann, P. (2009). Universities, Agglomerations and Graduate Human Capital Mobility. *Tijdschrift voor Economische en Sociale Geografie*, 100(2), 210–223.

Faggian, A., Mccann, P., & Sheppard, S. (2007). Human Capital, Higher Education and Graduate Migration: An Analysis of Scottish and Welsh Students. *Urban Studies*, 44(13), 2511–2528.

Faggian, A., Rajbhandari, I., & Dotzel, K. R. (2017). The Interregional Migration of Human Capital and its Regional Consequences: A Review. *Regional Studies*, 51(1), 128–143.

Flannery, D. & Cullinan, J. (2014). Where They Go, What They Do and Why It Matters: The Importance of Geographic Accessibility and Social Class for Decisions Relating to Higher Education Institution Type, Degree level and Field of Study. *Applied Economics*, 46(24), 2952–2965.

Florida, R., Mellander, C., & Stolarick, K. (2008). Inside the Black Box of Regional Development–Human Capital, the Creative Class and Tolerance. *Journal of Economic Geography*, 8(5), 615–649.

Frenette, M. (2006). Too Far to Go On? Distance to School and University Participation. *Education Economics*, 14(1), 31–58.

Galor, O. & Tsiddon, D. (1997). The Distribution of Human Capital and Economic Growth. *Journal of Economic Growth*, 2(1), 93–124.

Gibbons, S. & Vignoles, A. (2012). Geography, choice and participation in higher education in England. *Regional Science and Urban Economics*, 42(1-2), 98–113.

Glaeser, E. L. & Shapiro, J. M. (2003). Urban Growth in the 1990s: Is City Living Back? *Journal of Regional Science*, 43(1), 139–165.

Hastings, J. S., Neilson, C. A., & Zimmerman, S. D. (2013). *Are Some Degrees Worth More Than Others? Evidence From College Admission Cutoffs in Chile*. Technical report, National Bureau of Economic Research.

Head, K. & Mayer, T. (2000). Non-Europe: The Magnitude and Causes of Market Fragmentation in the EU. *Review of World Economics*, 136(2), 284–314.

Ishitani, T. T. (2011). The Determinants of Out-Migration Among In-State College Students in the United States. *Research in Higher Education*, 52(2), 107–122.

Kazakis, P. & Faggian, A. (2017). Mobility, Education and Labor Market Outcomes for U.S. Graduates: Is Selectivity Important? *Annals of Regional Science*, 59(3), 731–758.

Kodrzycki, Y. K. (2001). Migration of Recent College Graduates: Evidence from the National Longitudinal Survey of Youth. *New England Economic Review*, (pp. 13–34).

Mixon, F. G. (1992). Factors Affecting College Student Migration Across States. *International Journal of Manpower*, 13(1), 25–32.

Mixon, F. G. & Hsing, Y. (1994). College student migration and human capital theory: A research note. *Education Economics*, 2(1), 65–73.

Niu, S. X. (2015). Leaving Home State for College: Differences by Race/Ethnicity and Parental Education. *Research in Higher Education*, 56(4), 325–359.

OECD (2009). *Reviews of National Policies for Education. Tertiary Education in Chile.* Technical report.

Ono, H. (2003). in Pursuit of College Quality: Migration Decisions Among College Students in Japan. *Research in the Sociology of Education*, 14, 103–123.

Ortiz, E. A., Kaltenberg, M., Jara-Figueroa, C., Bornacelly, I., & Hartmann, D. (2020). *Local Labor Markets and Higher Education Mismatch.* Technical report, IDB Working Paper Series IDB-WP-01115.

Paredes, D., Iturra, V., & Lufin, M. (2016). A Spatial Decomposition of Income Inequality in Chile. *Regional Studies*, 50(5), 771–789.

Piras, R. (2017). A Long-run Analysis of Push and Pull Factors of Internal Migration in Italy. Estimation of a Gravity Model with Human Capital Using Homogeneous and Heterogeneous Approaches. *Papers in Regional Science*, 96(3), 571–602.

Poot, J., Alimi, O., Cameron, M. P., & Maré, D. C. (2016). The Gravity Model of Migration: The Successful Comeback of an Ageing Superstar in Regional Science. *Investigaciones Regionales*, 2016(36), 63–86.

Rodríguez, J., Urzúa, S., & Reyes, L. (2016). Heterogeneous Economic Returns to Post-Secondary Degrees: Evidence From Chile. *Journal of Human Resources*, 51(2), 416–460.

Sá, C., Amado Tavares, D., Justino, E., & Amaral, A. (2011). Higher Education (related) Choices in Portugal: Joint Decisions on Institution Type and Leaving Home. *Studies in Higher Education*, 36(6), 689–703.

Sá, C., Florax, R. J., & Rietveld, P. (2004). Determinants of the Regional Demand for Higher Education in the Netherlands: A Gravity Model Approach. *Regional Studies*, 38(4), 375–392.

Sá, C., Florax, R. J., & Rietveld, P. (2006). Does Accessibility to Higher Education Matter? Choice Behaviour of High School Graduates in the Netherlands. *Spatial Economic Analysis*, 1(2), 155–174.

Santos Silva, J. M. & Tenreyro, S. (2006). The Log of Gravity. *The Review of Economics and Statistics*, 88(4), 641–658.

Santos Silva, J. M. & Tenreyro, S. (2011). Further Simulation Evidence on the Performance of the Poisson Pseudo-Maximum Likelihood Estimator. *Economics Letters*, 112(2), 220–222.

Sevilla, M.-P. & Farías, M. (2020). Labour Market Mismatch in Emerging Countries: The Case of Chile. *Compare: A Journal of Comparative and International Education*, 50(2), 276–293.

Sevilla, M. P., Farías, M., & Luengo-Aravena, D. (2021). Patterns and Persistence of Educational Mismatch: A Trajectory Approach Using Chilean Panel Data. *Social Sciences*, 10(9), 333.

SIES (2021). Servicio de Información de Educación Superior, Matrícula Historica.

Simon, C. J. & Nardinelli, C. (2002). Human Capital and the Rise of American Cities, 1900–1990. *Regional Science and Urban Economics*, 32(1), 59–96.

Solis, A. (2017). Credit Access and College Enrollment. *Journal of Political Economy*, 125(2), 562–622.

Spiess, C. K. & Wrohlich, K. (2010). Does Distance Determine Who Attends a University in Germany? *Economics of Education Review*, 29(3), 470–479.

Suhonen, T. (2014). Field-of-Study Choice in Higher Education: Does Distance Matter? *Spatial Economic Analysis*, 9(4), 355–375.

Tuckman, H. (1970). Determinants of College Student Migration. *Southern Economic Association*, 37(2), 184–189.

Ullis, J. J. & Knowles, P. L. (1975). A Study of the Intrastate Migration of Washington College Freshmen: A Further Test of the Gravity Model. *The Annals of Regional Science*, 9(1), 112–121.

Wall, H. J. (2005). Voting With Your Feet in the United Kingdom: Using Cross-migration Rates to Estimate Relative Living Standards. *Papers in Regional Science*, 80(1), 1–23.

Winters, J. V. (2020). In-State College Enrollment and Later Life Location Decisions. *Journal of Human Resources*, 55(4), 140–1426.

Yotov, Y. V. (2022). On the Role of Domestic Trade Flows for Estimating the Gravity Model of Trade. *Contemporary Economic Policy*, 40(3), 526–540.

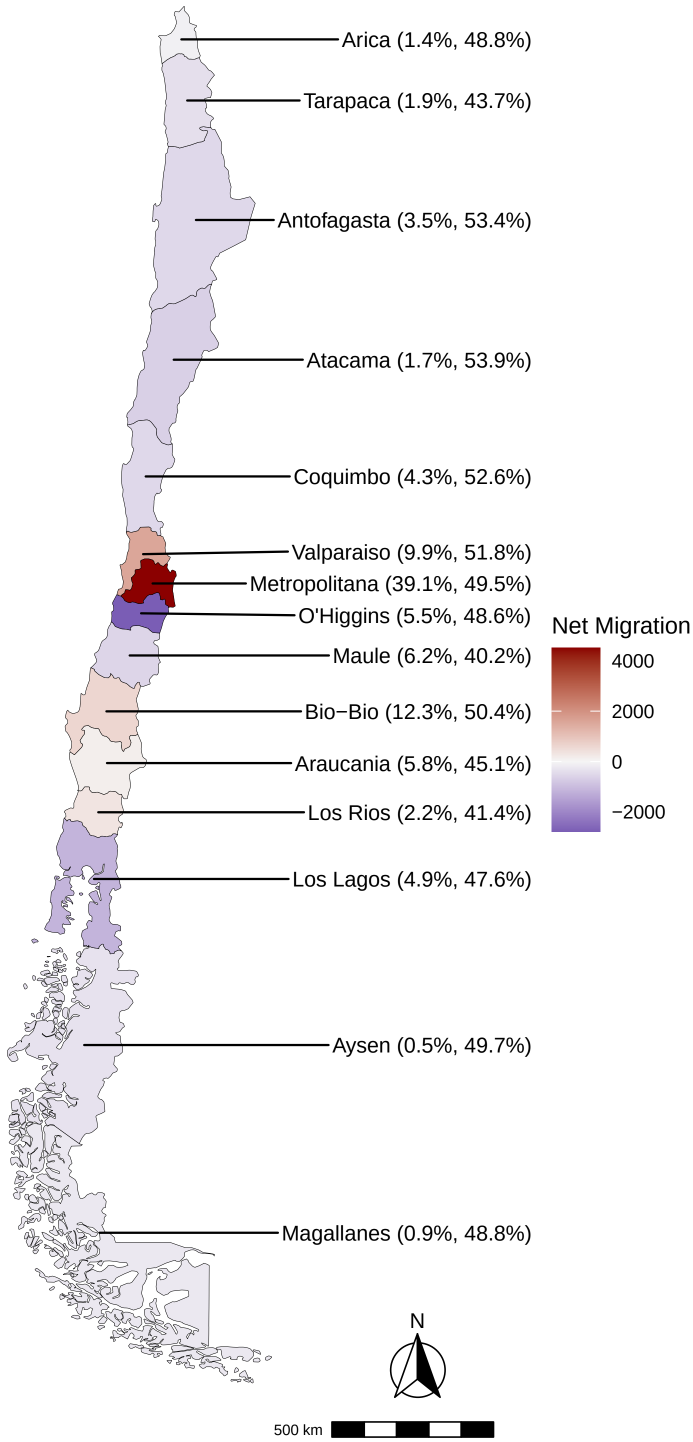


Figure 1: Net migration, share of high school graduates, and percentage of enrollment by region in 2017.

Note: Net migration is calculated using in-migration and out-migration of freshmen enrollment in tertiary education during 2017. After each region's name, the first number in the parentheses is the share of high school students over the total enrollment in the country. The second number in the parentheses is the percentage of students enrolled in tertiary education with respect to high school enrollment by each region. Data from the Ministry of Education, Chile (2017).

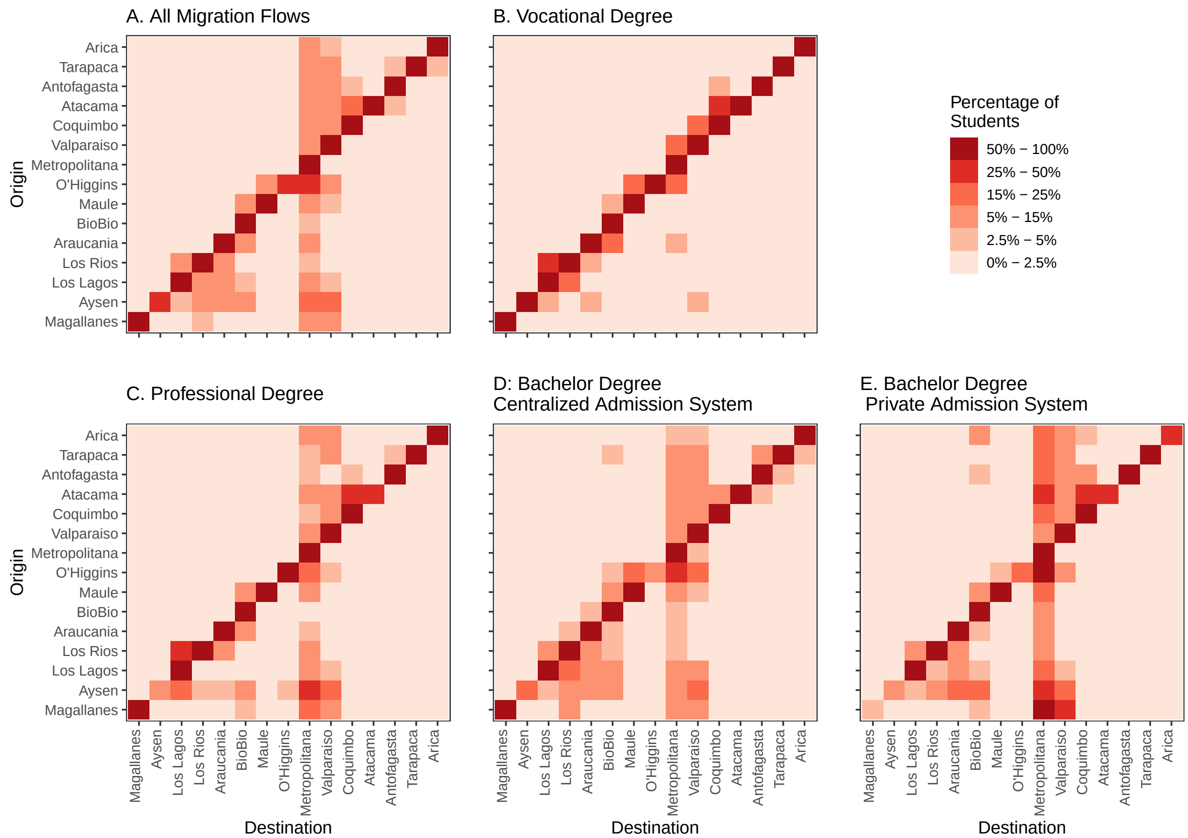


Figure 2: Heat map of the inter- and intraregional migration flows as percentage of population of origin by type of higher education institution in 2017

Note: Calculated using administrative data from Ministry of Education, Chile. Regions are ordered in geographical order, where *Arica* is the northernmost region and *Magallanes* is the southernmost region. All percentages are relative to the population of origin (i.e., row summation equals 100%).

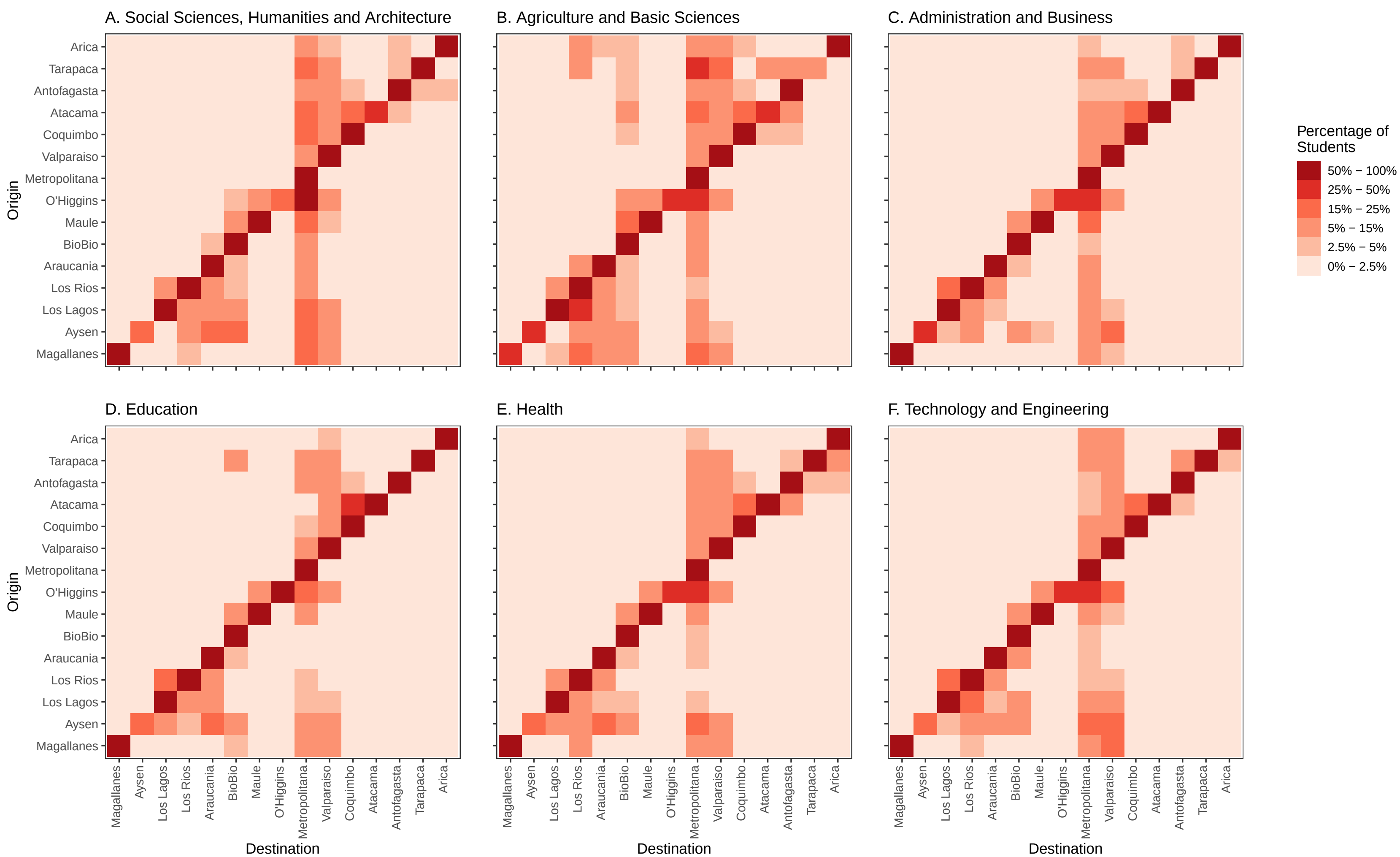


Figure 3: Heat map of the inter- and intra migration flows as percentage of population of origin by field of study in 2017

Note: Calculated using administrative data from Ministry of Education, Chile. Regions are ordered in geographical order, where *Arica* is the northernmost region and *Magallanes* is the southernmost region. All percentages are relative to the population of origin (i.e., row summation equals 100%).

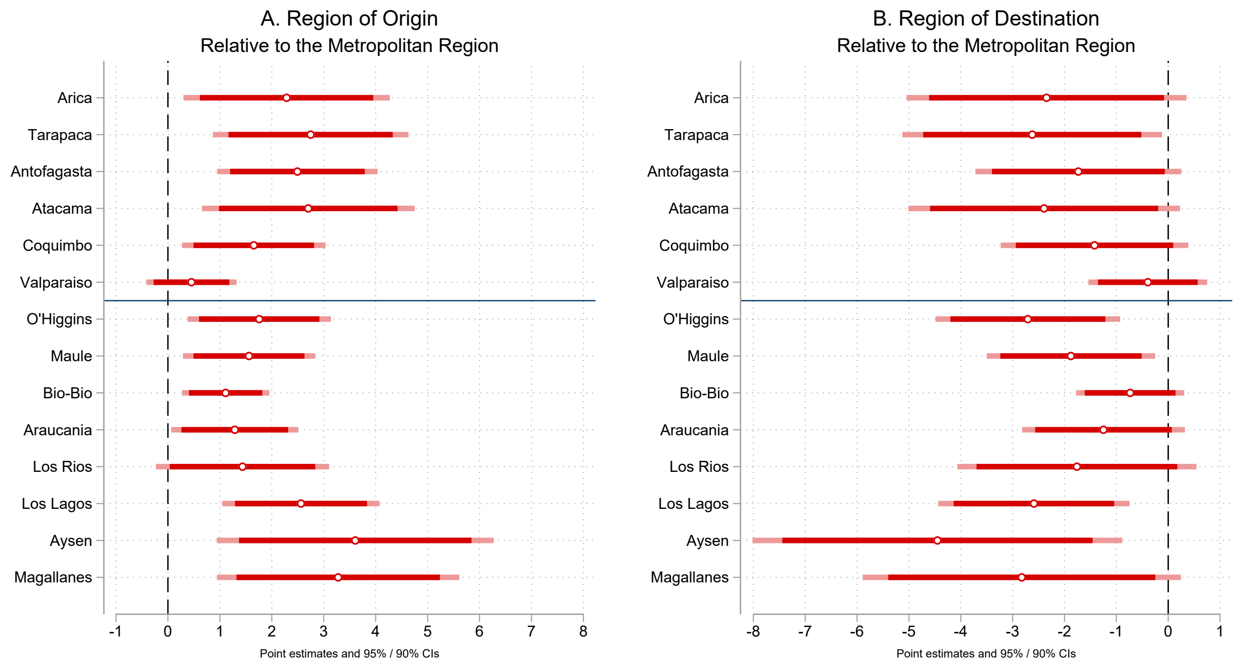


Figure 4: Region of origin and destination effects

Note: This figure shows the region of origin and destination effects obtained from the dummy variables included in the Region-level gravity model. All coefficients are measured relative to the Metropolitan region, which geographical location is represented by the horizontal solid navy line.

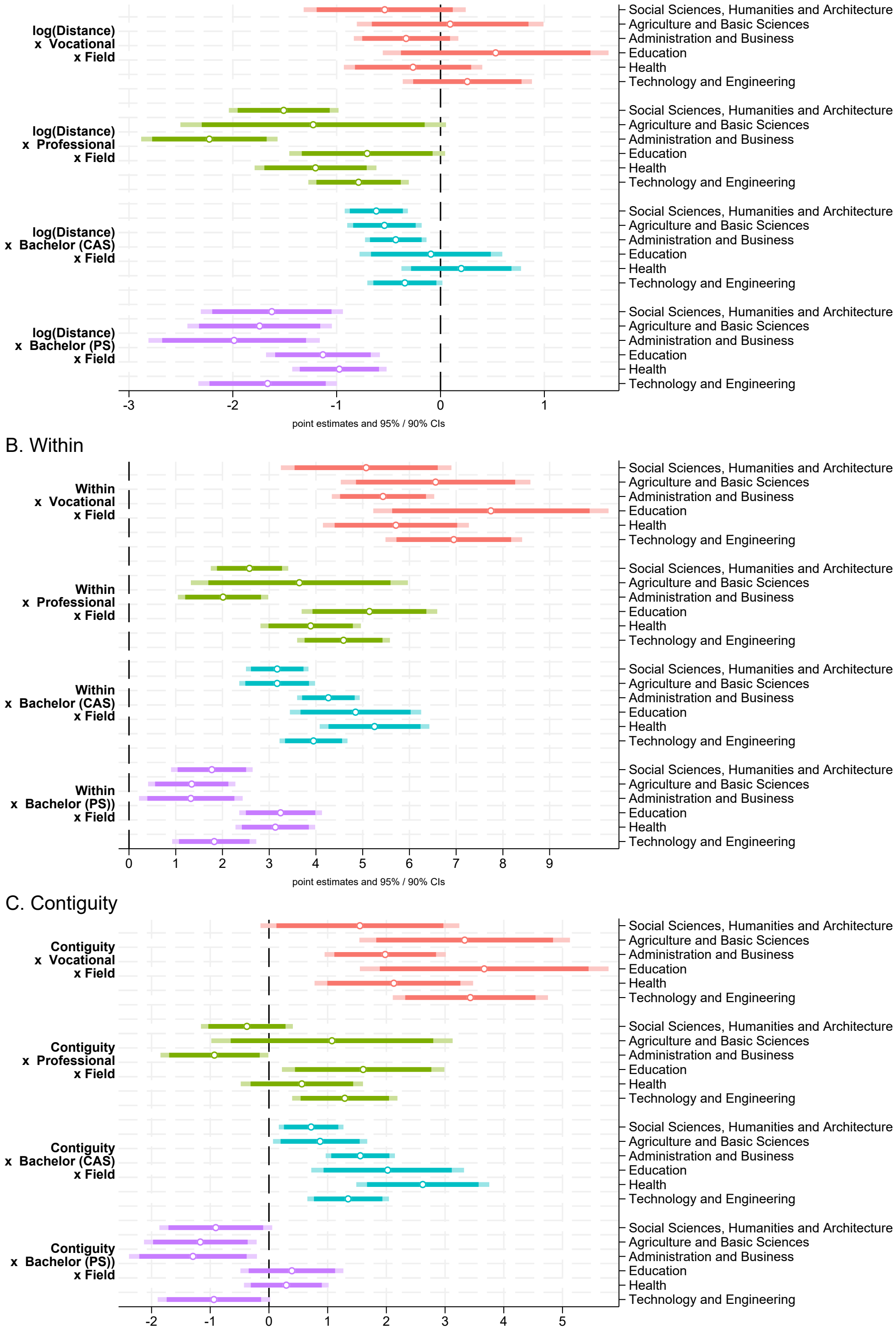


Figure 5: Total effect of geographical variables from the region-degree model

Note: This figure shows the total estimated effect of the geographical variables from the State-Degree Gravity Model. Each estimate and confidence interval is estimated using the *lincom* command in Stata from the respective model.

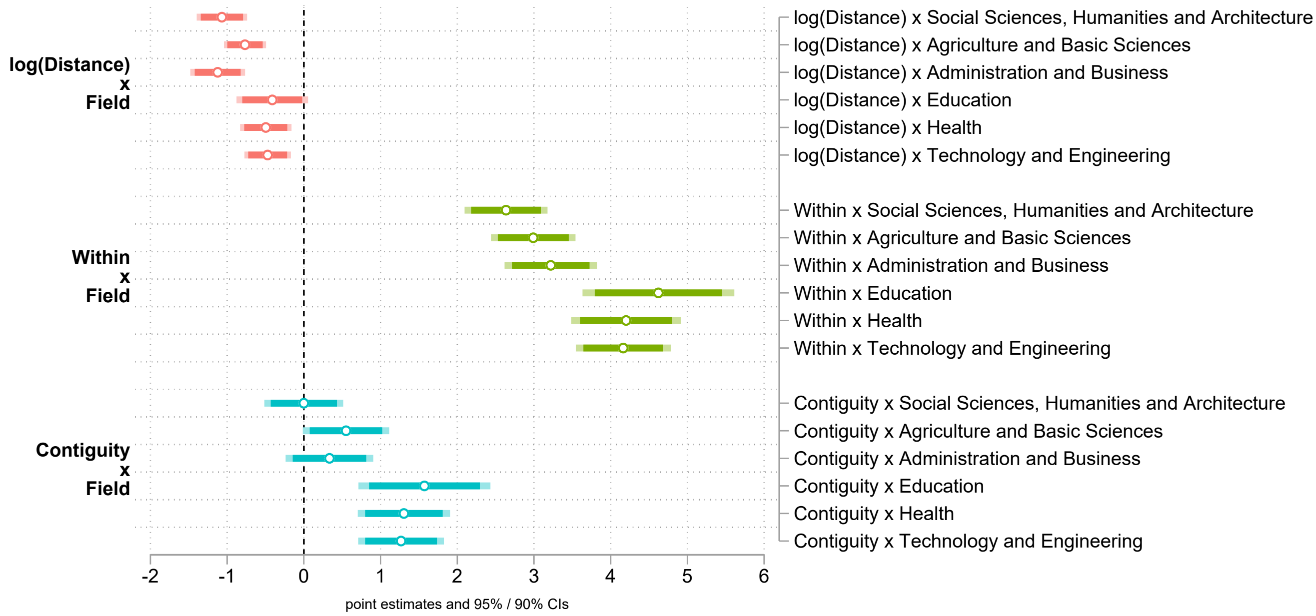


Figure 6: Total effect of geographical variables from the region-field of study model

Note: This figure shows the total estimated effect of the geographical variables from the State-Field Gravity Model. Each estimate and confidence interval is estimated using the *lincom* command in Stata from the respective model.

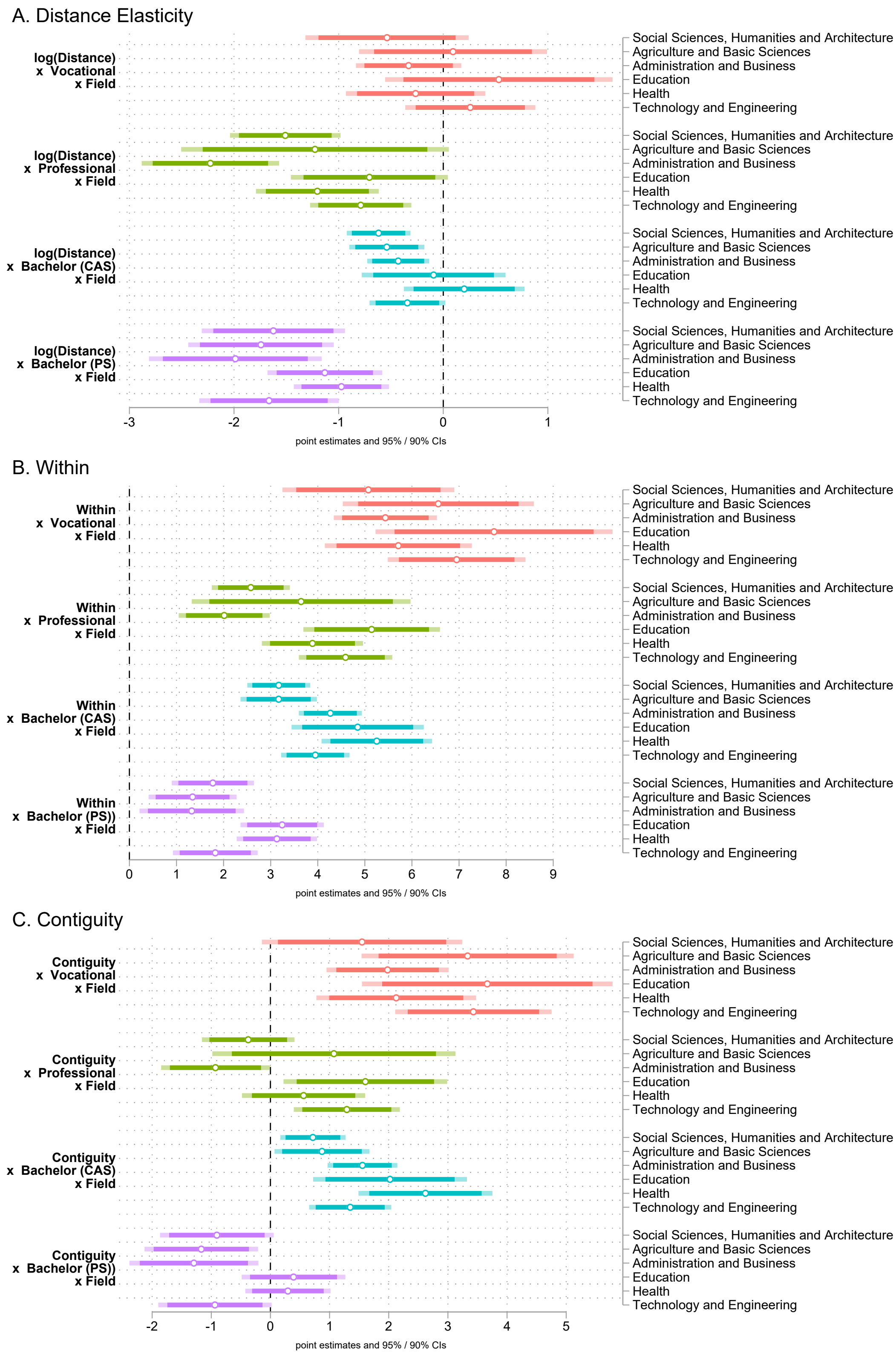


Figure 7: Region-degree-field of study model - geographical variables

Note: This figure shows the total estimated effect of the geographical variables from the State-Field Gravity Model. Each estimate and confidence interval is estimated using the *lincom* command in Stata from the respective model.

Table 1: Descriptive statistics of regional variables over the period 2011–2017

| *Region* | High school students (1) | Programs offered (2) | Accredited programs (%) (3) | Tuition fees (4) | Monthly Income (5) | Unemploy-ment rate (6) |
|---|---|---|---|---|---|---|
| Arica | 2784.00 | 268.29 | 25.14 | 173.86 | 374.22 | 6.00 |
| | (75.87) | (20.09) | (5.07) | (13.05) | (46.78) | (0.75) |
| Tarapaca | 3525.57 | 347.14 | 24.81 | 160.09 | 455.06 | 6.26 |
| | (60.52) | (27.50) | (8.56) | (10.43) | (49.15) | (1.12) |
| Antofagasta | 6762.86 | 773.29 | 20.32 | 158.81 | 585.94 | 6.51 |
| | (161.78) | (67.72) | (10.83) | (21.36) | (87.34) | (1.17) |
| Atacama | 3470.14 | 310.14 | 13.23 | 142.34 | 466.31 | 6.25 |
| | (186.92) | (37.20) | (4.81) | (15.86) | (53.22) | (0.99) |
| Coquimbo | 8577.00 | 854.29 | 18.96 | 133.80 | 391.61 | 7.10 |
| | (237.04) | (61.19) | (8.67) | (11.40) | (33.95) | (0.59) |
| Valparaiso | 18878.86 | 2245.57 | 17.27 | 151.98 | 398.91 | 7.32 |
| | (581.17) | (157.17) | (6.66) | (16.86) | (70.88) | (0.48) |
| Metropolitana | 73099.86 | 5799.57 | 19.60 | 174.27 | 475.27 | 6.52 |
| | (2624.89) | (385.85) | (6.09) | (15.39) | (38.62) | (0.42) |
| O'Higgins | 9692.43 | 691.00 | 20.13 | 123.84 | 350.17 | 5.70 |
| | (253.41) | (94.34) | (14.69) | (15.70) | (50.81) | (0.46) |
| Maule | 11972.43 | 944.71 | 17.88 | 127.16 | 328.71 | 5.70 |
| | (437.80) | (55.24) | (8.15) | (14.29) | (51.64) | (0.57) |
| Bio-Bio | 22633.29 | 2340.29 | 21.07 | 144.40 | 353.92 | 7.71 |
| | (1002.02) | (45.52) | (8.71) | (14.22) | (48.92) | (0.46) |
| Araucania | 11645.86 | 868.43 | 18.84 | 142.87 | 337.50 | 7.08 |
| | (573.40) | (76.61) | (7.97) | (15.37) | (43.86) | (0.61) |
| Los Rios | 4792.43 | 316.86 | 29.83 | 158.11 | 353.68 | 5.30 |
| | (228.15) | (40.61) | (12.85) | (21.61) | (58.43) | (1.05) |
| Los Lagos | 9538.14 | 844.00 | 20.54 | 134.70 | 384.59 | 3.51 |
| | (290.81) | (70.16) | (8.80) | (12.76) | (47.99) | (0.57) |
| Aysen | 972.86 | 107.43 | 14.12 | 131.42 | 551.33 | 3.77 |
| | (39.75) | (34.76) | (13.26) | (19.36) | (54.62) | (0.58) |
| Magallanes | 1813.71 | 252.71 | 22.55 | 150.13 | 525.46 | 3.61 |
| | (71.09) | (38.05) | (13.87) | (16.90) | (37.46) | (0.65) |
| Total | 12677.30 | 1130.91 | 20.29 | 147.19 | 422.18 | 5.89 |
| | (17235.62) | (1410.18) | (10.53) | (22.00) | (95.82) | (1.49) |

*Note:* High school students is the total number of high school of students in their last year of high school. Programs is the total number of programs offered by all type of higher education institutions. Accredited programs is the ratio of accredited programs to the total number of programs, while tuition fees are the average tuition fees charged by all programs-institutions in the region, measured in thousands of Chilean pesos. Income is the average monthly income measured in thousands of Chilean pesos. Unemployment is the monthly unemployment rate. Educational variables are obtained from the Ministry of Education and the National Commission of Accreditation. The economic indicators are obtained from the National Institute of Statistics. Standard deviations are presented in parenthesis.

Table 2: Region and region-degree type, estimation results

| | State | | State-by-degree | |
|---|---|---|---|---|
| *Outcome: Migration flow* | Coefficient (1) | Standard Error (2) | Coefficient (3) | Standard Error (4) |
| *Degree type:* | | | | |
| Professional | | | 8.036*** | (1.855) |
| Bachelor | | | 4.731*** | (1.610) |
| Bachelor Private | | | 10.596*** | (2.384) |
| *Geographical variables:* | | | | |
| log(Distance) | −0.705*** | (0.122) | −0.013 | (0.286) |
| log(Distance) × Professional | | | −1.193*** | (0.297) |
| log(Distance) × Bachelor | | | −0.332 | (0.253) |
| log(Distance) × Bachelor Private | | | −1.413*** | (0.391) |
| Within | 3.666*** | (0.236) | 6.276*** | (0.655) |
| Within × Professional | | | −2.584*** | (0.653) |
| Within × Bachelor | | | −2.314*** | (0.593) |
| Within × Bachelor Private | | | −4.017*** | (0.703) |
| Contiguity | 0.845*** | (0.216) | 2.752*** | (0.603) |
| Contiguity × Professional | | | −2.245*** | (0.553) |
| Contiguity × Bachelor | | | −1.354** | (0.537) |
| Contiguity × Bachelor Private | | | −3.228*** | (0.705) |
| *Origin:* | | | | |
| log(High school enrollment) | 0.831*** | (0.281) | 0.825*** | (0.280) |
| Programs offered | −0.024 | (0.032) | −0.024 | (0.032) |
| Ratio of accredited programs | −0.232 | (0.176) | −0.233 | (0.176) |
| log(Average annual tuition fee) | −0.136 | (0.214) | −0.132 | (0.212) |
| log(annual income) | 0.046 | (0.082) | 0.047 | (0.083) |
| Unemployrment rate | 0.019 | (0.013) | 0.019 | (0.012) |
| *Destination:* | | | | |
| log(High school enrollment) | 0.285 | (0.410) | 0.293 | (0.408) |
| Programs offered | 0.005 | (0.031) | 0.005 | (0.031) |
| Ratio of accredited programs | 0.529** | (0.220) | 0.530** | (0.219) |
| log(Average annual tuition fee) | 0.206 | (0.246) | 0.201 | (0.244) |
| log(annual income) | −0.039** | (0.016) | −0.039** | (0.017) |
| Unemployment rate | −0.038*** | (0.013) | −0.037*** | (0.013) |
| Observations | 1575 | | 6300 | |
| Years FEs | ✓ | | ✓ | |
| Origin FEs | ✓ | | ✓ | |
| Destination FEs | ✓ | | ✓ | |

*Note:* Standard errors clustered by region pair in parentheses. Columns (1) and (2) are the gravity model at region level. The number of observations in this model reflects inter- and intraregional migration flows between the 15 Chilean regions and 7 time periods. Columns (3) and (4) present the results of the region-degree gravity model. Number of observations in this model reflects inter and intra migration flows between the 15 Chilean regions, types of degrees offered by four type of higher education institutions and seven time periods. The base category in the degree type is the technical/vocational degree. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Region-field of study, estimation results

| *Outcome: Migration flow* | Coefficient (1) | Standard Error (2) |
|---|---|---|
| *Field:* | | |
| Agriculture and Basic Sciences | $-2.878^{***}$ | (0.663) |
| Administration and Business | $-0.620^{*}$ | (0.354) |
| Education | $-5.215^{***}$ | (1.826) |
| Health | $-3.733^{***}$ | (1.277) |
| Technology and Engineering | $-3.457^{***}$ | (1.182) |
| *Geographical variables:* | | |
| log(Distance) | $-1.068^{***}$ | (0.168) |
| log(Distance) × Agriculture and Basic Sciences | $0.301^{***}$ | (0.112) |
| log(Distance) × Administration and Business | $-0.055$ | (0.060) |
| log(Distance) × Education | $0.657^{**}$ | (0.299) |
| log(Distance) × Health | $0.572^{***}$ | (0.211) |
| log(Distance) × Technology and Engineering | $0.596^{***}$ | (0.196) |
| Within | $2.636^{***}$ | (0.276) |
| Within × Agriculture and Basic Sciences | $0.355^{*}$ | (0.212) |
| Within × Administration and Business | $0.583^{***}$ | (0.118) |
| Within × Education | $1.986^{***}$ | (0.568) |
| Within × Health | $1.565^{***}$ | (0.394) |
| Within × Technology and Engineering | $1.528^{***}$ | (0.344) |
| Contiguity | $-0.000$ | (0.262) |
| Contiguity × Agriculture and Basic Sciences | $0.550^{**}$ | (0.239) |
| Contiguity × Administration and Business | $0.335^{***}$ | (0.109) |
| Contiguity × Education | $1.572^{***}$ | (0.512) |
| Contiguity × Health | $1.305^{***}$ | (0.356) |
| Contiguity × Technology and Engineering | $1.268^{***}$ | (0.334) |
| Observations | 9450 | |
| Years FEs | ✓ | |
| Origin FEs | ✓ | |
| Destination FEs | ✓ | |

*Note:* Standard errors clustered by region pair in parentheses. Number of observations in this model reflects inter- and intraregional migration flows between the 15 Chilean regions, 5 categories of fields of study, and 7 time periods. The base category in the field of study is an aggregation of fields related to Social Sciences, Law, Humanities, Arts, and Architecture. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: Region-degree-field of study, estimation results

| *Outcome: Migration flow* | Coefficient (1) | Standard Error (2) |
|---|---|---|
| *Degree type:* | | |
| Professional | 8.683*** | (2.191) |
| Bachelor | 5.166** | (2.311) |
| Bachelor Private | 10.714*** | (2.495) |
| *Field:* | | |
| Agriculture and Basic Sciences | −3.776 | (2.765) |
| Administration and Business | 0.912 | (1.663) |
| Education | −6.039* | (3.386) |
| Health | 0.212 | (1.666) |
| Technology and Engineering | −2.543 | (2.461) |
| *Geographical variables:* | | |
| log(Distance) | −0.537 | (0.398) |
| log(Distance) × Professional × Agriculture and Basic Sciences | −0.346 | (0.553) |
| log(Distance) × Professional × Administration and Business | −0.922*** | (0.289) |
| log(Distance) × Professional × Education | −0.265 | (0.320) |
| log(Distance) × Professional × Health | 0.033 | (0.253) |
| log(Distance) × Professional × Technology and Engineering | −0.075 | (0.366) |
| log(Distance) × Bachelor (CAS) × Agriculture and Basic Sciences | −0.552 | (0.447) |
| log(Distance) × Bachelor (CAS) × Administration and Business | −0.019 | (0.289) |
| log(Distance) × Bachelor (CAS) × Education | −0.543** | (0.273) |
| log(Distance) × Bachelor (CAS) × Health | 0.545** | (0.253) |
| log(Distance) × Bachelor (CAS) × Technology and Engineering | −0.521* | (0.291) |
| log(Distance) × Bachelor (PS) × Agriculture and Basic Sciences | −0.749* | (0.451) |
| log(Distance) × Bachelor (PS) × Administration and Business | −0.570* | (0.315) |
| log(Distance) × Bachelor (PS) × Education | −0.577 | (0.453) |
| log(Distance) × Bachelor (PS) × Health | 0.377* | (0.208) |
| log(Distance) × Bachelor (PS) × Technology and Engineering | −0.837** | (0.395) |

*Continued on the next page*

Table 5: Region-degree-field of study, estimation results - *continued from previous page*

| *Outcome: Migration flow* | Coefficient (1) | Standard Error (2) |
|---|---|---|
| Within | 5.074*** | (0.931) |
| Within × Professional × Agriculture and Basic Sciences | −0.418 | (1.068) |
| Within × Professional × Administration and Business | −0.926 | (0.682) |
| Within × Professional × Education | −0.103 | (0.801) |
| Within × Professional × Health | 0.672 | (0.576) |
| Within × Professional × Technology and Engineering | 0.136 | (0.904) |
| Within × Bachelor (CAS) × Agriculture and Basic Sciences | −1.487 | (0.906) |
| Within × Bachelor (CAS) × Administration and Business | 0.734 | (0.691) |
| Within × Bachelor (CAS) × Education | −0.993 | (0.673) |
| Within × Bachelor (CAS) × Health | 1.445** | (0.616) |
| Within × Bachelor (CAS) × Technology and Engineering | −1.098 | (0.712) |
| Within × Bachelor (PS) × Agriculture and Basic Sciences | −1.916** | (0.923) |
| Within × Bachelor (PS) × Administration and Business | −0.810 | (0.731) |
| Within × Bachelor (PS) × Education | −1.198 | (1.094) |
| Within × Bachelor (PS) × Health | 0.722 | (0.523) |
| Within × Bachelor (PS) × Technology and Engineering | −1.824* | (0.942) |
| Contiguity | 1.549* | (0.864) |
| Contiguity × Professional × Agriculture and Basic Sciences | −0.336 | (1.020) |
| Contiguity × Professional × Administration and Business | −0.985 | (0.607) |
| Contiguity × Professional × Education | −0.137 | (0.806) |
| Contiguity × Professional × Health | 0.358 | (0.520) |
| Contiguity × Professional × Technology and Engineering | −0.215 | (0.758) |
| Contiguity × Bachelor (CAS) × Agriculture and Basic Sciences | −1.631* | (0.885) |
| Contiguity × Bachelor (CAS) × Administration and Business | 0.407 | (0.614) |
| Contiguity × Bachelor (CAS) × Education | −0.814 | (0.655) |
| Contiguity × Bachelor (CAS) × Health | 1.325** | (0.577) |
| Contiguity × Bachelor (CAS) × Technology and Engineering | −1.251** | (0.638) |
| Contiguity × Bachelor (PS) × Agriculture and Basic Sciences | −2.048** | (0.876) |
| Contiguity × Bachelor (PS) × Administration and Business | −0.820 | (0.602) |
| Contiguity × Bachelor (PS) × Education | −0.821 | (0.947) |
| Contiguity × Bachelor (PS) × Health | 0.623 | (0.491) |
| Contiguity × Bachelor (PS) × Technology and Engineering | −1.914** | (0.776) |
| Observations | 37800 | |
| Year FEs | ✓ | |
| Origin FEs | ✓ | |
| Destination FEs | ✓ | |

*Note:* Standard errors clustered by region pair in parentheses. Number of observations in this model reflects inter- and intraregional migration flows between the 15 Chilean regions, 6 categories of fields of study, and 4 degree types, and 7 time periods. The base category for higher education type is technical degree and for field of study is an aggregated field that includes social sciences, law, humanities, arts and architecture. CAS stands for Centralized Admission System, and PS stands for private system. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

# A Characterization of the Chilean Educational System

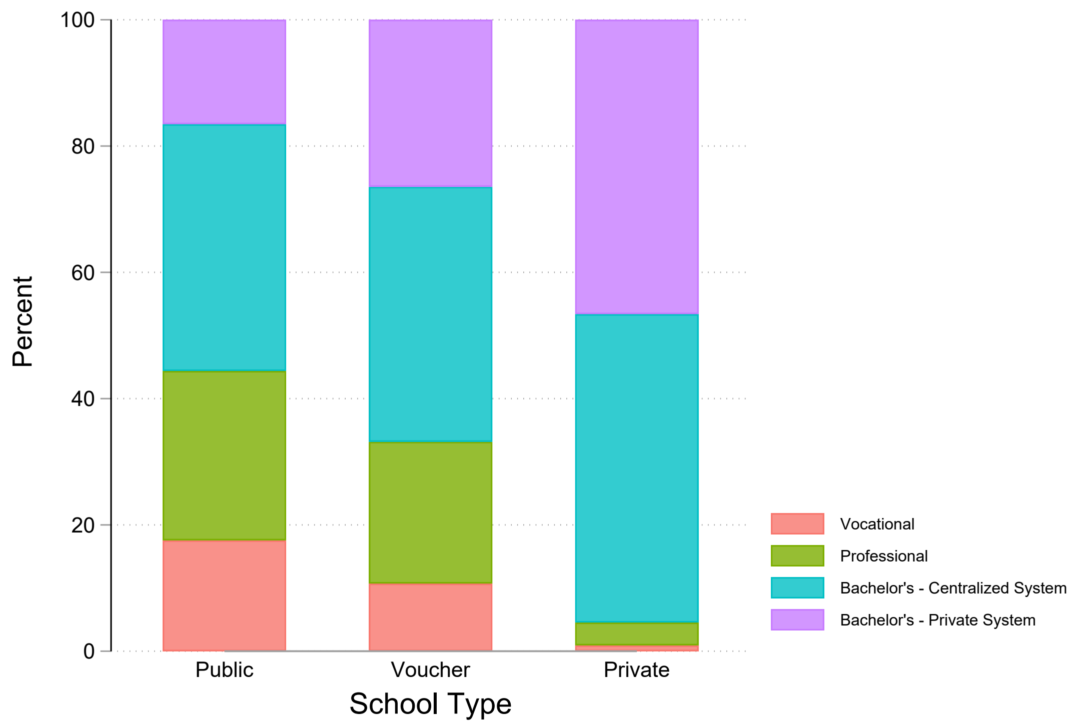


Figure A.1: Freshmen enrollment composition by degree from different school type (2017)

*Note:* Own elaboration based on administrative data from the Ministry of Education, Chile.

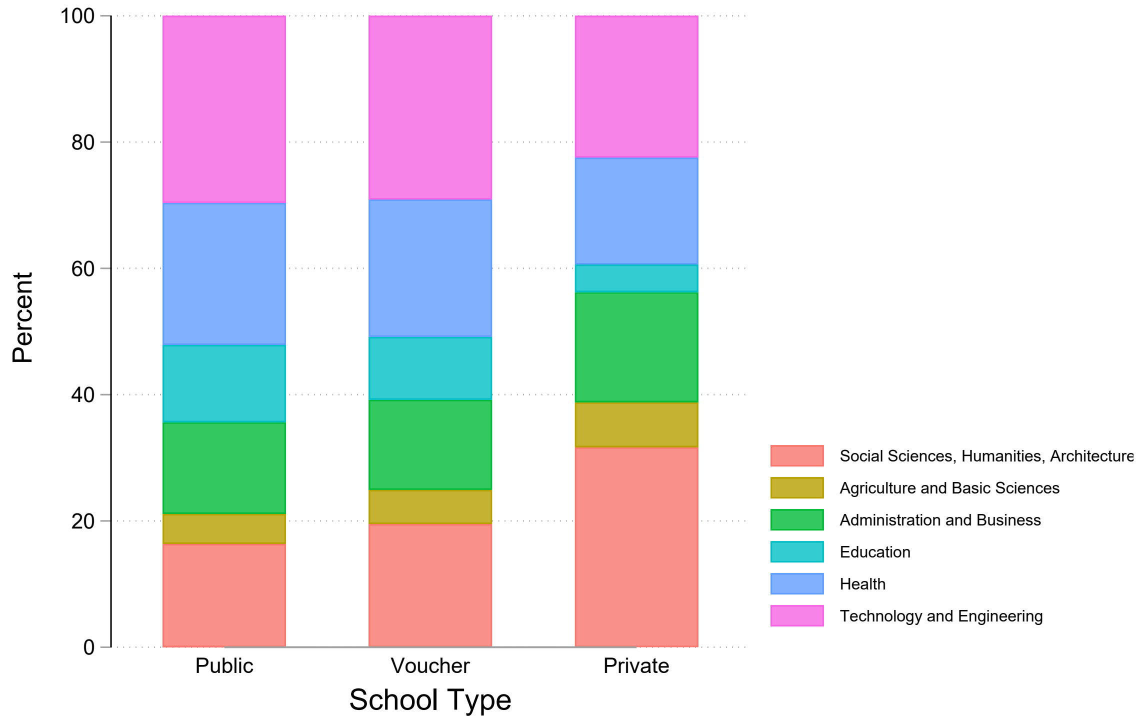


Figure A.2: Freshmen enrollment composition by fields from different school type (2017)

*Note:* Own elaboration based on administrative data from the Ministry of Education, Chile.

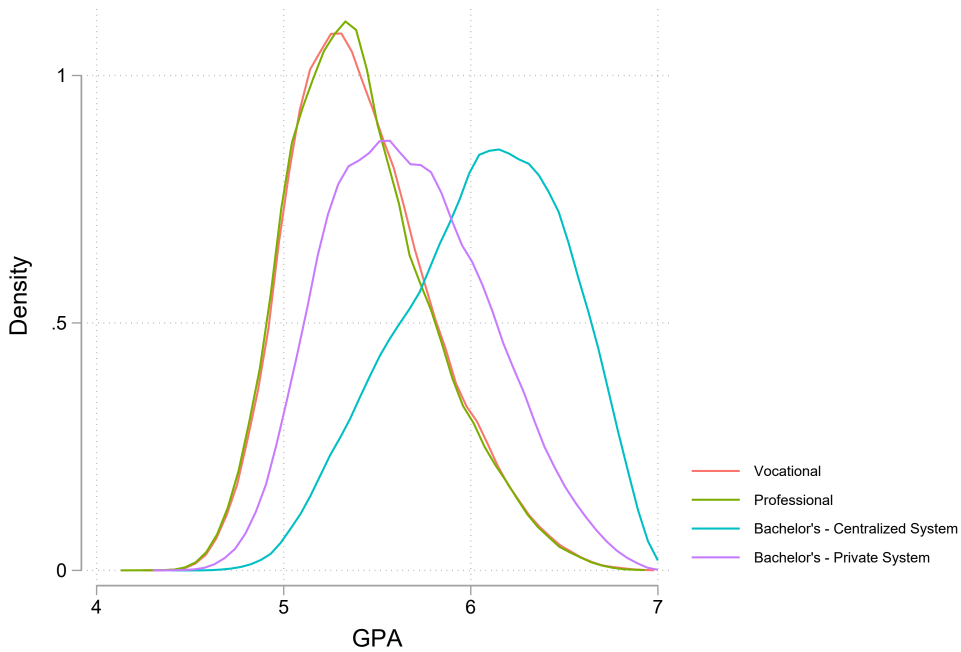


Figure A.3: GPA distribution of freshmen students by degree (2011–2017)

*Note:* Own elaboration based on administrative data from the Ministry of Education, Chile.

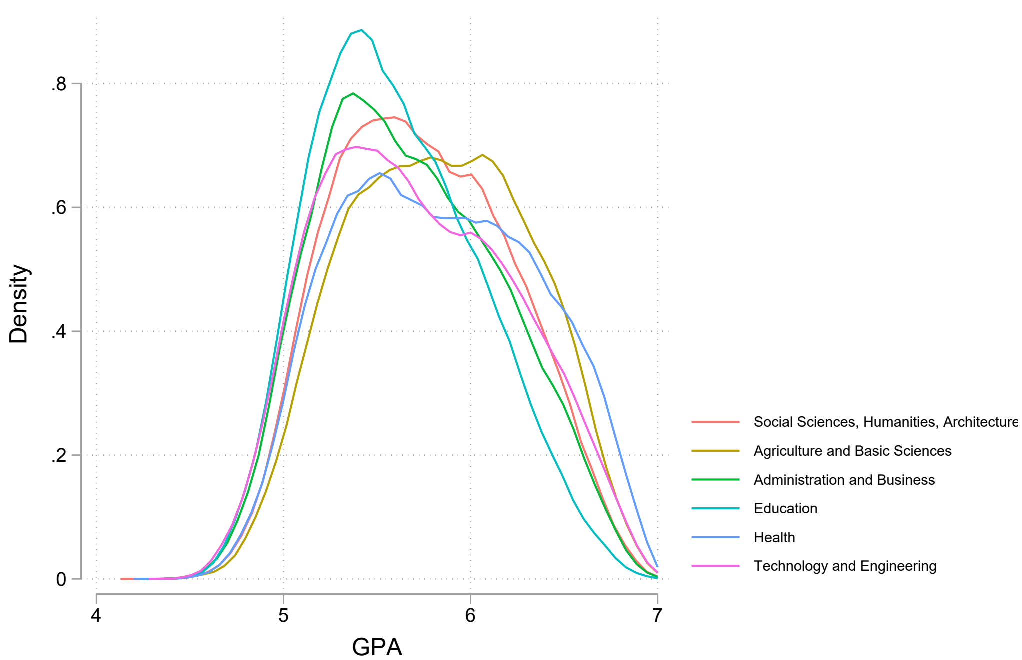


Figure A.4: GPA distribution of freshmen students by field (2011–2017)

*Note:* Own elaboration based on administrative data from the Ministry of Education, Chile.