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Are social inequalities being transmitted through higher education? A propensity-score matching analysis of private versus public university graduates using machine learning models

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## Working Paper Series

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Are social inequalities being transmitted through higher education?  
A propensity-score matching analysis of private versus public university graduates  
using machine learning models

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## **Abstract**

This study investigates differences in employment outcomes of students graduating from private versus public universities in Spain, and the resulting impact on employment outcomes. The methodology involves propensity score matching, utilising novel machine learning approaches. Machine learning algorithms can be used to calculate propensity scores and can potentially have advantages compared to conventional methods. Contrary to previous research carried out in Spain, this analysis found a wage premium for those pupils who attended a private university in the short and medium term, although these differences were relatively small. The discussion outlines the implications for intergenerational inequality, policy development, and future research that utilises machine learning algorithms.

**Keywords:** employment outcomes; intergenerational inequality; university graduates; machine learning; propensity score matching.

**JEL:** I24, I26, J62

## **Introduction**

Traditional measures of a society's intergenerational mobility compare differences in social position between parents and children, using income, professions, or other proxies (Cholli & Durlauf, 2022; Torche, 2015). Economists tend to focus on earnings and income, while sociologists tend to concentrate on occupational status and class (Torche, 2015). Social mobility is an important aspect of inequality, and the literature often distinguishes between inequality of opportunity and inequality of outcome. The former refers to inequalities that arise from individual characteristics that wrongly hinder one's possibilities to succeed in life, while the latter refers to inequalities in the distribution of resources (Breen & Jonsson, 2005). One might naturally query what role education plays in reducing (or exacerbating) inequalities of opportunities.

Another important distinction to consider is between "absolute" social mobility and "relative" social mobility. Absolute social mobility increases when new job opportunities provide higher levels of employment compensation for people from lower classes. Absolute social mobility is undoubtedly influenced by the structure of the labour market and by the economy. Conversely, relative social mobility increases when inequalities of opportunity decrease (Brown, 2013). In the context of the present analysis, relative social mobility refers to having equal access to quality higher education, therefore granting equality of opportunity in the labour market. Both absolute and relative mobility influence employment outcomes after university graduation. Intuitively, inequality of opportunities arising from elite private universities also translate to inequality of outcomes, since 'better-educated' students should have access to better-paying jobs.

Classical economic theories of education, based on rational-choice theory, consider education a great equalizer that allows societies to achieve more (relative) social mobility by equally granting education opportunities to the general population. During the 1990s, a key hypothesis driving public policy discussions related to "increasing merit-selection" (Marshall et al., 1997). This notion entailed that education would function as a means of equalization, identifying

the most "deserving" students and propelling them toward a prosperous professional trajectory, irrespective of their social background and positioning. Unfortunately, this concept has been largely discredited by research that has found “though attainment of qualifications above the basic educational level has become more common over successive birth-cohorts, differentials relating to class origins were maintained” (Marshall et al., 1997, p. 116). More recently, the dominant debate in public policy has shifted towards the notion of market logic. This idea suggests social mobility can be achieved by giving everyone the opportunity to compete in the same market (Peter, 2011). From this perspective, education is one of the pivotal ways to achieve equality of opportunity.

Recent studies suggest equal education levels do not always translate into equal opportunities” (Jerrim & Volante, 2018), and that a significant number of factors influence compensation across national contexts. For example, in 2012, a report issued by the government in the United Kingdom (UK) indicated that high-paying professions were increasingly being dominated by individuals who grew up in families with above-average income (UK Cabinet Office, 2012). Relatedly, school choice provisions which allow students to attend schools other than a national public offering were (and are) championed as a way to provide more control over one’s education and greater opportunities to succeed. Yet, the research is clear that school choice provisions for compulsory aged students is often associated with more socially segregated student populations (Volante et al., 2019; 2021). One might naturally wonder if the latter holds for higher education settings as well.

In the following sections, relevant literature concerning higher education and social mobility will be analysed to provide useful context to the analysis. After that, this study will investigate the effects of private higher education on social mobility, by comparing employment outcomes between bachelor's graduates from private and public universities in Spain.

## **Education and Social Mobility**

Mathematical and econometric models suggest public education produces lower long-run inequality than private education (Davies et al., 2005), and that banning private supplements to education maximizes social mobility (Cremer et al., 2010). Research also suggests that “more economically unequal countries tend to spend a lower proportion of national wealth on education” and that “they have a greater proportion of children attending a private school or using out-of-school private tutors” (Jerrim & Macmillan, 2005).

With the growing trend towards privatization of education in both developed and developing countries in recent years (Levy & Zumeta, 2011), it is extremely important to analyse the effect that this trend is having on social mobility. Importantly, higher social fluidity has been clearly linked to higher economic growth (Foote & Hatt, 1953; Jenkins, et al., 2017; Guell et al., 2018) and lower class-related tensions (Houle, 2019; Leventoglu, 2014). Clearly, education can play a pivotal role in driving more equitable outcomes but can also further exacerbate existing inequalities that exist between students as future wage-earners.

## **Higher Education and Intergenerational Inequality**

As previously suggested, education and intergenerational inequality are closely connected. In the UK, for example, reducing inequalities in educational attainment has been the policy instrument of choice to try and improve overall social mobility in the country (Crawford et al., 2016). Higher (or tertiary) education plays a very important role in the overall education system. Differences in participation in higher education, university outcomes and performances, and finally, labour market outcomes, both short and long-term, have all been reported in relation to socio-economic background (Crawford et al., 2016). Intuitively, this is not surprising: richer parents have more resources to help their children to study for longer; they also have the necessary resources to allow their children to focus on their studies and complete higher education; finally, they are often better positioned to guide their children as they transition to the labour market.



Brezis and Hellier (2018) developed an intergenerational model with the aim of assessing the influence of the structure of higher education on a country's intergenerational mobility. Their focus was on a two-tier system, divided by "elite" universities and "standard" universities. In their model, elite universities are much more selective in the admission of students and possess higher quality, which is reflected in higher per-student expenditures. These authors argued that this structure of higher education "leads to permanent social stratification between the middle class and the elite, the latter being to a large extent self-reproducing" (Brezis & Hellier, 2018, p. 26). It is worth noting that the difference between elite and standard universities in their model does not always equate to differences between private and public universities. Namely, private universities are not always "elite," and their nature varies significantly across countries. The present analysis examines whether private universities in Spain have the same polarizing and stratifying effects regardless of whether they are perceived as elite or not. If this is the case, the argument for stronger and higher quality public education is even more relevant.

### **The Expansion of Private Higher Education**

Private education has been on the rise all around the world in the past 50 years. In the 1950s, private higher education institutions were either small or non-existent in most countries, with the USA being the only exception (Levy & Zumeta, 2011). According to the latest estimates, private education now accounts for about a third of global enrolment (Levy, 2018). Overall, the privatization of education is part of a more general movement towards liberalization and marketisation that has struck most sectors of the global economy after the 1960s. For the most part, this incredible and sudden growth was not planned at a public policy level, and it rather "caught governments off guard" (Levy, 2006). As Furedi (2011) puts it, "since the late 1970s, the culture of academic life has been transformed by the institutionalisation of the policies of marketisation" (p. 1). This was largely due to the prevalence of a neoliberal sentiment in the international environment: indeed, Quddus and Rashid (2000) even argued that "increasingly, societies now

regard higher education as more of a “private good” with not enough immediate and positive externalities (characteristics of a “public good”) to justify public support” (p. 489). Overall, these authors conclude that “it cannot be denied that the pendulum of opinion among people and governments worldwide has swung markedly away from the expectation that the state apparatus will deliver goods and services. Rather, it has shifted to a new faith in the efficacy of free market mechanisms to allocate resources most efficiently” (p. 490). These two statements are emblematic of the pervasive international climate of the period, strongly embedded in privatisation and in smaller interventions of the governments in the market.

The role of “demand absorption” is one of the arguments in favour of the privatisation of higher education, and several authors agree that the most important driver of the growth of private education around the world has been the excess demand that public education was not able to fulfil (James, 1993; Qureshi & Khawaja, 2021; Jiang, 2021; Oketch et al., 2010). In the case of Spain, demand for higher education has risen significantly until 1998, allowing for both public and private universities to thrive without having to worry excessively about competing for students. After a drop in demand in 1998, however, private universities became increasingly more important and influenced the public sector to move towards more competitive management practices, which culminated in the 2001 University Organization Act that freed public universities from several ties that were preventing a market-like organization (Marcos, 2005). This is also the same period in which the involvement of the private sector increased, probably in part because of its higher adaptability to competitive environments.

A second important point that is brought up in favour of privatisation is that it can provide more diversification to the market. As with most other markets, “it is often considered that diversity in higher education is best ensured by the free play of market forces” (Pedro & Amaral, 2001). This diversification of the “product” (e.g., graduates) would lead to better adaptability to the labour

market but also to more effective school systems that would better cater to students' needs and desires (Volante et al., 2021).

Private universities are also believed to have advantages in terms of employability: being more connected to the private sector by design and being more "outcome-oriented" than their public counterparts. Private higher education institutions usually allow for an easier transition to the labour market. Finally, neoliberal arguments assert that innovation is only really fostered when the free forces of the market can push economic agents to seek competitive advantages. This argument can also be applied to the education sector: privatising higher education would lead to higher rates of innovation in terms of development of new curricula, teaching methods, adoption of new technologies, and so on (Porter & Davis, 1991).

Of the many arguments provided against the expansion of private higher education, those that relate to demand absorption and diversification are perhaps the most compelling. Carnoy (2011) summarises the problem very succinctly:

*"If increasing differentiation of spending among higher education institutions is the dominant trend in the developing countries, even as higher education enrolment expands, the overall rate of return to completing university can continue to hold constant or even rise (mainly from declining earnings to high school completers and those who do not complete university), but the absolute return (not the rate of return) would rise differentially for those who attend declining cost/student public universities and those who attend higher cost first- tier public universities and the private elite universities." (p. 45)*

From this perspective, the average rate of returns for the higher education system of a country can hide potentially disrupting imbalances between those that graduate from "lower level" universities and those who attended elite institutions. Having dramatically different rates of returns can lead to dramatically unequal distributions of income, even if the distribution of education per se is equal. Essentially, the rising tide does not lift all boats equally.

Some of the most successful universities of the world according to the annual QS Rankings are private. These high-level institutions can educate the best students and therefore create the new elite. A report published by the Times Higher Education (Alma Mater Index, 2017) ranked universities according to how many qualifications they had awarded to CEOs in the Fortune 500 companies. The first university in this ranking was Harvard University (private) with 29 degrees awarded to 26 CEOs, and the second was Stanford University (also private) with 14 degrees awarded to 12 CEOs. The fact that these universities have tuition fees that would be prohibitive for most people is troubling.

### **Higher Education and Employment Outcomes**

Graduate-tracking surveys are an important tool to understand the role of private higher education. This type of data is extremely useful to follow the performance of graduates in the labour market and therefore to assess the general situation of tertiary education in a country. Graduate-tracking surveys, however, are fairly sparse in the existing literature. Only a few countries possess longitudinal surveys to follow graduates' performance, and some institutions only utilise cross-sectional information gathered every few years (Frawley & Harvey (2015). In the case of Spain, there have only been a few analyses on the transition from higher education to first employment (Cordón-Lagares et al., 2022; Canal Domínguez & Rodríguez Gutiérrez, 2020). Domínguez and Gutiérrez (2020) found no evidence of an advantage for private university graduates, except for a small positive effect in the short-term job search. Similarly, Fachelli et al. (2014) found that the Spanish university system softens class differences, but they did not distinguish between private and public higher education.

Romero and del Rey (2004) analysed private and public universities in Europe. Contrary to what might hold true in the United States (US), where private institutions are generally better than the public ones, they found that in Europe private universities “optimally choose to provide an educational quality lower than the one provided publicly” (Romero & del Rey, 2004, p. 3). They

explain this result in relation to two key points: public higher education in Europe is able to act as a monopoly, keeping prices low and admission standards high; consequently, private universities only become attractive to those that could not be admitted in the public ones and that can afford to pay the higher tuition fees. By itself, this result would signal positive news for the transmission of inequalities through private institutions: namely, if the public institutions are better, we should see an increase in intergenerational mobility as tuition fees no longer serve as the determinant of the quality of education.

However, subsequent empirical research has not been as encouraging. An initial example comes from Herrmann and Nagel (2022), who compared early careers of graduates from private and public universities in Germany. Using the National Education Panel Study (NEPS), a longitudinal dataset, they performed a Bayesian regression analysis and found that private students do have a moderate wage premium on their first job, amounting to an average of €175 per month. Considering that public higher education in Germany is completely free, they expressed concern that “private education can increase the dependency between socioeconomic background and educational opportunities” (p. 139).

Additional evidence on this topic comes from Poland. For example, Jasiński et al. (2018) used the more recent Polish Graduate Tracking System (cross-sectional) to study early careers of higher education graduates. They also looked at differences between public and private institutions: even though private universities are considered less prestigious in Poland, graduates from private institutions still fared better than their peers from public ones, in terms of earnings, employment rates, and time spent looking for a job. According to their findings, private-university graduates enjoy a wage premium of about 5,7%.

Similarly, in Italy, Brunello and Cappellari (2008) ran regressions on data from the National Statistical Office (ISTAT) on professional insertion of graduates and found considerable variation between private and public institutions: attending a private university resulted in a nearly 18%

increase in employment-weighted earnings three years after graduation. Similarly, Triventi and Trivellato (2012) used the same nationally representative dataset, but instead they applied propensity score matching to assess three different hypotheses: first, that there is no difference between graduates from private versus public institutions; second, that there is a difference, but that it does not directly depend on the type of institution and it is a compositional effect of various factors; lastly, that there is a difference that depends on the type of university attended. Propensity score matching allowed these researchers to isolate the specific effect of the type of institution after controlling for other possible factors that may influence early employment outcomes. Indeed, their results showed virtually no difference in hourly wages, and only compositional effects on short-term employment prospects and occupational level. Knowing that the economic returns are essentially the same independently from the type of institution attended, the authors put forward the hypothesis that parents send their children to private universities for non-monetary rewards such as finding an “appropriate” spouse for them, prestige, and access to “better” (richer) networks. In this view, social inequalities are still passed on through higher education. Lastly, Anelli (2020) took advantage of the admission process of a highly selective private university to perform a regression discontinuity design to assess the returns of this elite university. His focus was narrower than the previous two studies but is still relevant given the quality of the information gathered. The author found that the “elite premium” for the university analysed is considerably higher than the average Italian university premium.

To summarize, Romero and del Rey’s framework (2004) argued that private universities in Europe should generally be of lower educational quality. Using Spence’s signalling theory (1973), this should mean that employers recognize the lower educational quality of these institutions, and the market value of their degrees should be lower. However, it is interesting to note that even with largely different social and institutional contexts, the fact that private universities have higher economic returns seems to hold throughout Europe. This result is quite surprising, especially in

countries like Germany where public higher education is free and provides high quality degrees (Herrmann & Nagel, 2022). Therefore, there must be an underlying reason other than educational quality that makes private universities stronger “signals” for employers. For example, private institutions could have closer ties to the labour market, making the transition easier for their graduates. They could also provide better networking opportunities, both in terms of job opportunities and in terms of social class opportunities, as hypothesized by Triventi and Trivellato (2012). There could also be an element of “prestige” associated with private universities, for example for historical reasons, which do not necessarily translate into better educational quality. However, given the highly heterogeneous nature of the education system in the European Union, these hypotheses are difficult to generalize.

### **Present Study**

The present study examines the employment outcomes that accrue to Spanish university students attending public versus private institutions. Given that the history of education in Spain is long and complex, we focus on the most recent reforms which impacted university structures. In particular, the University Reform Law of 1983 allowed universities to become much more autonomous, following the principles of the new Constitution (Flecha García, 2011). Although private institutions follow the same guidelines as public ones, they are subject to less stringent regulations: for example, their wages are not set by the central government, they have no restriction on the structure and size of their labour force and on the time dedicated by academics to teaching and research (de la Torre et al., 2017). Today, the Spanish Higher Education system consists of 87 universities, of which 50 are public and 37 are private. In the 1980s and 1990s, the expansion of the university system was mainly driven by public universities, both in terms of students enrolled and in terms of new institutions. The increase in supply of private higher education occurred mostly from the beginning of the 2000s, causing social segmentation of university education (Martínez García et al., 2021).

According to the Ministry of Education of Spain (2023), in 2022 there were 1,318,863 students enrolled in public universities and 372,084 in private ones. Although private universities account for 43% of the national universities, students enrolled in the private system are only 22% of the total national student population. Interestingly, estimates suggest that the share of independent private higher education in Europe overall is at 12% (Levy 2012). Levy also noted that the estimation varied significantly by country, with peaks at 71.7% for Cyprus, for example. Furthermore, according to the OECD Education at a Glance (2022), the share of 25- to 34-year-olds with tertiary attainment in Spain was of 49% in 2021, compared to the 47% of the OECD average.

The present analysis largely follows the econometric structure of previous studies on this subject (Anelli, 2020; Cordon-Lagares et al., 2022; Fachelli et al., 2014; Triventi & Trivellato, 2012; Canal Domínguez & Rodríguez Gutiérrez, 2020), but focuses more closely on the construct of intergenerational inequality. A straightforward research question guides the current analysis: do graduates of private universities in Spain have better employment outcomes than their peers from public universities? If a wage premium does exist for students attending private institutions, it could be problematic for social mobility: private higher education would become a means for wealthier families to perpetrate their social class through institutional education.

Our analysis follows UNESCO's definition of private institutions:

*“An institution is classified as private if it is controlled and managed by a non-governmental organization (e.g., a church, trade union or business enterprise), or if its governing board consists mostly of members not selected by a public agency. In general, the ultimate management control over an institution rests with who has the power to determine the general activity of the school and appoint the managing officers. The extent to which an institution receives its funding from public or private sources does not determine the classification status of the institution.” (UNESCO Institute for Statistics, 2014, p. 106)*

The Spanish dataset analysed contains information about employment status right after graduation and also after 5 years, providing further insight into both short-term and medium-term employment



outcomes. Additional “technical” sub-questions focus on the methodological part of this analysis, with the objective to identify whether machine learning algorithms can improve the results or not, and which was the best model in this case. Our initial hypothesis, informed by the existing literature review, was that privately educated graduates do have an advantage in employment outcomes, both in the short and medium term, and that this advantage arises solely from having graduated from a private university. We assessed this hypothesis by applying a propensity score matching design, using different models to ensure robustness, and controlling for background variables such as gender, age, and type of degree.

Finally, it is worth noting that there are multiple theories that can be used to model the job market and in particular the transition from university to the workforce. The most widespread one is Human Capital Theory, of which Paulsen and Toutkoushian (2008) provide a useful summary. In this framework, higher education is seen as a way to enhance students’ human capital – their specific set of knowledge, competencies, and skills – which will in turn increase their productivity and employability. A central tenant of this theory is the assumed rationality of all economic agents: students engage in a cost-effective analysis of the potential benefits deriving from higher education and weigh them against the costs of such education and the foregone wages that they could earn in that same time. Employers, on the other hand, aim to hire candidates with the highest possible human capital.

However, signalling theory is more interesting for the sake of the current analysis. Signalling theory was first proposed by Spence (1973) as an explanation of the interactions between job seekers and employers, especially considering education. Spence refers to signals as “those observable characteristics attached to the individual that are subject to manipulation by him” (p. 357), education being one the most important examples. Since employers do not have perfect information about the productivity of candidates, they can use these signals to create expectations about the possible performance of job seekers. The research questions proposed earlier are based on

the hypothesis that private universities – at least in Spain – provide stronger signals to employers, who in turn expect more from their graduates and therefore offer higher wages.

## **Methodology**

### **Dataset**

The current analysis used the Survey on Professional Insertion of University Graduates (*Encuesta de inserción laboral de titulados universitarios*) dataset, from the Spanish National Statistics Institute (*Instituto Nacional de Estadística – INE*). This data was collected via direct interviews merged with administrative data between July and December 2019 and refers to university graduates who completed their degrees in the academic year 2013-2014 (Instituto Nacional de Estadística, 2019). The present analysis focused on bachelor's degree holders, but future research could also consider the employment outcomes of master's students, to see whether the results observed with undergraduate degree holders remains consistent or changes.

The overall sample was nationally representative and consists of approximately 31,500 Bachelor graduates, which represent 233,626 graduates in the population. The survey was particularly comprehensive, as it contained 7 different modules on demographic background, educational information, mobility during studies, and labour market history, for a total of 299 variables.

### **Propensity Score Matching (PSM)**

Given the large size of the dataset and keeping in mind that the purpose of the analysis is to examine employment outcome differences arising from attending a private university, the methodology applied utilised propensity score matching, following an approach similar to the one applied by Triventi and Trivellato (2012).

Propensity score matching is a quasi-experimental method used to compare two different groups, to assess the impact of a “treatment”. In this case, the treatment is “attending a private

higher education institution.” Usually, groups that take on a treatment are not easily comparable due to issues of self-selection: students attending a private university are more likely to be from a family in the upper income class, for example. These comparability issues often make it difficult to understand if the differences in the outcome variables of interest are due to the treatment or due to other factors that made the two groups non-comparable from the onset. This is where propensity scores (PS) become fundamental to create two comparable groups. To further reduce possible differences in the treatment and control groups, the sample analysed was reduced to those students that have only completed one bachelor’s degree, which reduced the number of observations to 9326.

When applying PSM there is an important assumption that needs to be taken into consideration. PSM is applied in situations where randomisation of the treatment and control groups is not possible, and therefore it can only rely on observed variables. This is called Conditional Independence Assumption (CIA), which essentially states that “selection is solely based on observable characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed by the researcher” (Caliendo & Kopeinig, 2005, p. 4). This makes PSM a very data-intensive technique: one needs as many background variables as possible when calculating the propensity scores, to ensure that there are no unobserved characteristics that are creating bias in the estimated results (Bryson et al., 2002).

### **Covariate Selection**

The choice of the set of covariates that were used to compute propensity scores is a critical first step. There are a few conditions that determine whether variables should be included or not. Only those that influence simultaneously the treatment decision (graduating from a private university), and the outcome (first wage after graduation) should be considered (Caliendo & Kopeinig, 2005). Furthermore, these variables should not be influenced by the treatment, and should therefore be fixed over time or measured before “participation” (Caliendo & Kopeinig, 2005).

The selection of the covariates in the present analysis is not as straightforward due to the nature of the treatment. Treatment could either be considered as “attending a private university” or as “graduating from a private university.” In the first case, only pre-enrolment variables could be considered when calculating the propensity scores. This would make the selection more parsimonious, and it would avoid including variables that can be influenced by the treatment. However, it could also fail to make the two groups comparable enough by not considering variables that are measured during the studies and that strongly influence the outcome. Triventi and Trivellato (2012) found that both interpretations reach satisfactory classification power, and therefore for the sake of the present analysis, post-enrolment covariates were included to make sure that the two groups were as comparable as possible. The selected covariates are summarized in Table 1 below. They are all categorical.

<INSERT TABLE 1 HERE>

The selection of the covariates followed previous literature and economic theory on the determinants of university choice (for the treatment) and of wage level (for the outcome). Most papers analysing the determinants of choosing a private university over a public one have focused on students’ preferences and on the characteristics of the private universities (Shah et al., 2013; Kargić & Poturak, 2013; Anam, 2019; İlğan et al., 2018), not on demographic and background characteristics of the students themselves. However, previous analyses on the choice of private school attendance in primary and secondary education did find strong associations between income and home background and private school attendance (Rutkowski et al., 2012; Long & Toma, 1988). Therefore, all available variables relating to students’ backgrounds were included in the covariates, including gender, students’ nationality and parents’ country of birth, and parents’ education – which is used to proxy students’ socio-economic background (Torche, 2015).

The determinants of wages were also considered. The inclusion of age as a covariate and restricting the analysis to students with one degree is meant to include the classical determinants of

wage of the Mincer equation (1974): experience and education. Experience is also proxied by including previous jobs (variables *Traineeship during studies* and *Paid job during studies*). Balcar (2012) provides a useful literature review. of supply-side wage determinants – not all of them are relevant for the present study, and most of them were already considered as part of the students’ background. Out of Balcar’s review, the one important addition that was made to the set of covariates is the field of study, which could account for important wage differences. Whether or not a student has carried out part of his/her studies abroad was also considered in the covariates, since a few studies have reported a wage premium for students that have studied abroad (Netz & Cordua, 2021; Favero & Fucci, 2017; Irondo, 2020).

A few additional factors should be mentioned as they could be relevant for the present study but are not included in the available data. Sexual orientation would have been interesting to include alongside gender as it could influence the outcome variables, however it is unlikely that it could be an important determinant of treatment in this case, therefore it should not bias the results. On the other hand, the absence of literacy, numeracy, or IQ scores in the covariates has the potential to bring some bias in the results: other than being relevant determinants of wage level, they could also influence school choice. The same logic applies to soft skills, but these are even more difficult to measure, and they could also be highly correlated to the “intelligence measures” (Balcar, 2014). Lastly, knowledge of the labour market and personal network should be kept in mind as they could be part of the explanation of better employment outcomes for private university graduates. These missing covariates could possibly lead to overestimating the treatment effect of attending private higher education and should be considered when analysing the results.

Not having access to some of these variables, especially an ability measure of upper secondary school performance, could be problematic for the present study and it makes it difficult to fully prove the Conditional Independence Assumption. In any case, despite the absence of aforementioned factors in the dataset, the present analysis was able to account for most issues noted

in the existing literature. Indeed, the final list of covariates is similar to one of the previous studies that looked at differences between graduating from a private or a public university in Spain (see Canal Domínguez & Rodríguez Gutiérrez, 2020). However, the novelty of the current analysis comes from the inclusion of parent characteristics as a proxy for family socio-economic status, in order to also account for intergenerational transmission of wealth. This aspect was also included by Triventi and Trivellato (2012).

### **Handling of Missing Data**

Malla et al. (2018) observed that most papers using propensity scores (62% in their case) use complete-case analyses to handle missing data, meaning that the algorithms only used the observations for which there was no missing data on any of the relevant variables. In these cases, the analysis can be unbiased if one can argue that the missing values are “missing at random,” which means that “there might be systematic differences between the missing and the outcomes, but these can be entirely explained by other observed variables” (Bhaskaran & Smeeth, 2014). Therefore, we describe missing values in depth to explain why the dataset is not biased. Figure 1 below shows the distribution of missing values in the selected variables.

<INSERT FIGURE 1 HERE>

The only covariates with missing values are the ones accounting for parents’ background, so figure 2 provides a visualization of the correlations between the missing values in these variables. As expected, the missing values of the two parents seem to be correlated, for example when the education of the father is missing, it is very likely that the education of the mother is also missing (row 2, column 3). Despite this, missing values seem to be equally distributed between control and treatment group (variable *private*) and between the two outcome variables, therefore they should not constitute a significant threat to the estimation of the treatment effect. Of the outcome variables, the first wage (*PR\_SUELDO*) contained only a few missing values which do not seem to show any pattern with other missing values. On the other hand, the variable for the current wage

(*TR\_SUELDO*) is concerning, as the missing values are about 18% of the total observations.

Missing data in the two outcome variables also seem to be correlated.

These considerations offer plausible arguments to deduce that the missing values are “missing at random” (MAR). Furthermore, the distribution of the missing values does not show any particular anomaly that could drastically bias the outcome of the analysis. Therefore, any bias arising from missing values should be acceptably low. Following the majority of the literature on propensity scores (Malla et al., 2018), the present analysis made use of a complete case analysis. This approach also has the advantage of considerably reducing complexity, which allowed us to focus on more relevant methodological issues in the estimation of the propensity scores. After accounting for complete cases, the number of observations was reduced from 9326 to 6729.

<INSERT FIGURE 2 HERE>

### **Survey Weights in Propensity Score Matching**

There are two main moments in which survey weights could be used: when computing propensity scores, and when estimating the outcome effects. Zanutto (2006) argued that, since propensity scores are only used to match treated and non-treated groups in the sample and not to make inferences at the population level, survey weights are only necessary when estimating the treatment effect. Dugoff et al. (2014) carried out a literature review on studies that used propensity score analyses in the context of health services research. After simulating different models, they concluded that the best-performing models were the ones that use weights in both propensity scores and outcomes.

Ridgeway et al. (2015) suggested that the most robust strategy is to use sampling weights in the propensity score model, and then multiply propensity scores and weights to use them as weights in the outcome analysis. Relatedly, Austin et al. (2018) found the estimation of propensity scores with or without sampling weights were mixed, with no method being clearly preferable to others. However, they suggested using survey weights in the estimation of the treatment effect. Finally,

Lenis et. al (2019) also found that incorporating survey weights in the estimation of the propensity scores did not affect the performance of the matching estimators. They also suggested using survey weights in the outcome analysis and in assessing the balance of the covariates after matching.

Overall, there is no clear “right” method that emerges from the literature on this topic. However, those who make use of survey weights in propensity score matching seem to generally agree incorporating sampling weights into the estimation of the treatment effect to calculate the *population average treatment effect on the treated*. Therefore, this analysis followed these guidelines, and only made use of sampling weights for the final estimation models.

### **Propensity Scores**

As previously suggested, propensity scores are “the conditional probability of assignment to a particular treatment given a vector of observed covariates” (Rosenbaum & Rubin, 1983). Essentially, one can calculate the probability that someone will attend a private school by using a set of background variables that can affect their chances of going to a private university. The main point of calculating propensity scores is *prediction*, not *causation*. In other words, the algorithms used to predict the propensity scores are not concerned with finding a causal link between the covariates and the treatment; rather the aim is to predict the treatment as well as possible to create comparable groups. Because of this, machine learning algorithms can be used to calculate propensity scores and can potentially have advantages compared to conventional methods like Probit or Logit regressions. For example, they could help in choosing better covariates; allow for more functional flexibility, in the sense that they could more easily detect non-linearities; and finally, increase the precision of the estimate (Goller et al., 2020).

Previous literature has attempted to evaluate whether machine learning (ML) methods could be useful in improving PSM, but the results are mixed. Goller et al. (2020) found that Lasso algorithms perform as well as Probit only when a sufficient number of observations is reached, and Random Forest had issues in balancing score estimators and removing selection bias when the share



of treated was low. Essentially, they found that the choice of the best algorithm depends on the specific structure of the dataset and on the relations between variables, and it is difficult to know this a priori. An extensive literature review from Ferri-García and Rueda (2020) found that ML algorithms performance depends on the scenario but is generally acceptable and has potential to improve the results of a conventional logistic or probit model. Lee et al. (2010), after examining the performance of classification and regression trees (CART) and Random Forest algorithms on simulated data, recommended these two machine learning techniques for propensity score estimation. In the current analysis, we used and compared the following methods to predict propensity scores: Probit, Lasso, Classification Trees, and Random Forest.

### ***Probit***

For the first iteration, the propensity scores were calculated with a simple Probit model, the most common method used currently in economics. The functional specification of the covariates (e.g., logs, interactions, exponentials) was intentionally kept to a simple linear function, to more easily check if there are differences with the other non-parametric ML methods that can detect non-linearities automatically, like Random Forest. To apply this first method, the MatchIt package in R was used, specifying the “probit” link function to estimate propensity scores.

### ***Lasso***

The second method used to calculate propensity scores was the *least absolute shrinkage and selection operator* (Lasso), introduced by Tibshirani (1996). This model works as a normal OLS regression but adds a tuning parameter that “shrinks” the coefficients to select only the most impactful ones for the prediction. This method has the advantage to be good at managing a larger number of covariates, as it automatically excludes the ones that have little to no effect on the prediction, and it could therefore improve a normal Probit model. In this analysis, the Lasso method was applied to a logistic regression. Again, the application of this method was done through the

MatchIt package in R, which also has the option to use a Lasso algorithm to estimate propensity scores.

### ***Classification Trees***

The third method was a (binary) classification tree. Classification trees are machine learning algorithms that identify patterns among the available covariates to predict different outcomes. Starting from the whole sample, the binary classification tree splits the datasets into more homogeneous subsets according to an indicator and a threshold (called node). The process recursively continues for each sub-sample or child node until splitting is no longer possible (Duttagupta & Cashin, 2008).

A previous simulation study found that classification trees are a useful alternative to estimating propensity scores, however appropriate settings of the cost complexity parameter for pruning need to be reached in order to avoid producing trees that are too small and have low discrimination for the exposure to treatment (Setoguchi et al., 2008). In this particular case, the package used to implement the algorithm is the *party* package in R, with the *ctree* command (Hothorn, Hornik, & Zeileis, 2006), which creates conditional inference trees. According to the *party* manual (Hothorn et al., 2023), the following steps are used:

“1) Test the global null hypothesis of independence between any of the input variables and the response (which may be multivariate as well). Stop if this hypothesis cannot be rejected. Otherwise select the input variable with strongest association to the response. This association is measured by a p-value corresponding to a test for the partial null hypothesis of a single input variable and the response. 2) Implement a binary split in the selected input variable. 3) Recursively repeat steps 1) and 2).”

### ***Random Forests***

The last method used to estimate propensity scores was a “random forest.” A random forest is a non-parametric, non-linear, ensemble classification algorithm consisting of multiple classification trees. Each tree casts a unit vote, and the classification that gets the most votes is the

result (Breiman, 2001). Figures 3 and 4 are useful visualizations of classification trees and random forests. Random forests have been found to be potentially superior to the usual logit regression (Cham, 2013; Lee et al., 2010). In this case the forest was built out of 1000 conditional inference trees, using the same *party* package used in the previous step, but with the command *cforest* (Hothorn, Buehlmann, Dudoit, Molinaro, & Van Der Laan, 2006; Strobl et al., 2007; Strobl et al., 2008). Random forests are usually found to be superior to classification trees, but they are also a lot more computationally demanding. Therefore, both classification trees and random forests are used and compared in the analysis.

<INSERT FIGURE 3 HERE>

<INSERT FIGURE 4 HERE>

### **Performance Metrics of the Different Algorithms**

To understand which algorithm performed best, several performance metrics were analysed. The first one is the Mean Squared Error (MSE), which is the average of the squared difference between predicted values and actual values. The closer the MSE is to zero, the more accurate the model. MSE is an absolute measure that depends on the scale of the outcome variables, so in this case it is still useful for comparison since all models refer to the same outcomes. The second one is the R-squared measure, which indicates the percentage of variation of the outcome variable (the treatment) explained by the model. This measure can only assume values between 0 and 1, with 1 meaning that the variation of the outcome variable is completely explained by the independent variables of the model, and 0 meaning that no variation of the outcome variable is explained by the model. Lastly, we also utilised one additional measure to assess the balance of the covariates: the Standardised Mean Difference (SMD), which is also the most widely used metric in the literature (Zhang et al., 2019). Drawing from Zhang et al. (2019), the formula was represented by the following:

$$SMD = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{S_1^2 + S_2^2}{2}}}$$

where  $\overline{X}_1$  and  $\overline{X}_2$  are the sample mean for treated and control groups;  $S_1^2$  and  $S_2^2$  are the sample variance for the treated and control group. Using this approach, the means of the covariates become standardized and comparable. Usually, an SMD lower than 0.1 indicates balance between covariates.

### Matching Methods

Given that individuals with similar propensity scores have comparable backgrounds, one needs to match these individuals and find out if there are differences in the selected outcome variables. In the present analysis, two matching methods were used to improve robustness and to ensure the covariates were properly balanced. The first one was Nearest Neighbour matching (NN), which is the most used method in PSM. NN selects the unit in the control group whose propensity score is closest to the treated unit in question (Dehejia & Wahba, 2002). The second matching method was Optimal Pair Matching, which is essentially a variation of Nearest Neighbour Matching. In Optimal Pair Matching, one treated unit is matched to one control unit as in NN, but in this case the algorithm minimises the sum of the absolute pair distances in the sample (Hansen & Klopfer, 2006).

After matching, variations in outcomes can be entirely ascribed to the treatment variable, as long as two more properties are fulfilled. First, treated units do not always have a comparable control unit. This is why comparisons can only be made within the so-called *common support* region, which is the range in which treated units and comparison units have similar propensity scores. Any observation outside of this common support region was dropped from the analysis. Second, the *balancing property* of propensity scores must also be satisfied: individuals with the

same score should also have, on average, similar values of their background variables after being matched (Vanderberghe & Robin, 2004).

## **Results**

### **Propensity Scores**

Two main aspects of the distribution of propensity scores were assessed. The first was to ensure the common support region was wide enough to provide good comparability. The second was that the propensity scores have similar distributions across the two groups, to ensure balance (Garrido, et al., 2014). Figure 5 below shows the distribution of the propensity scores calculated with each model. This graph should normally show a higher distribution of the treatment units towards the higher propensity scores, meaning that the algorithm used to estimate them did detect differences between the two groups. However, it is also important that the algorithm did not perfectly predict treatment since that would not allow us to create comparable pairs. The Probit, Classification Tree, and Random Forest models performed well in predicting higher propensity scores for the group that graduated from private universities. The Lasso model, on the other hand, had more trouble in separating the two groups. The Lasso model is also the one that predicted the lowest propensity scores, possibly indicating low accuracy. All models have quite extensive overlap between treatment and control group, meaning that the common support region is sufficiently wide to allow for comparison in all of them.

<INSERT FIGURE 5 HERE>

Considering the shape of the distribution, the Probit and Random Forest models possessed the smoothest curves, meaning that the propensity scores are more evenly distributed across observations. This allows for better matching, since the propensity scores of matched pairs of students who graduated from private and public universities are more likely to be similar. The distribution of the Lasso model is skewed to the right for both treatment and control, although the treatment group has a slightly higher density towards the higher propensity scores. This type of

distribution could be the consequence of low explanatory power of the model and could lead to biased results in estimating the treatment effects, since the propensity scores are not necessarily a good measure to ensure comparability in this model. The distribution of the Classification Tree is a result of how the model itself works. The spikes in the distribution correspond to the terminal nodes of the tree, which are all connected to a specific propensity score. Therefore, even if the curves are not smooth in this case, the observations in each terminal node are very likely to be comparable and the matching should be reliable.

Finally, Table 2 reports the R-squared and MSE measures for each model. These measures are reported here for the sake of the discussion on the methodology, as normally they would not be of particular interest for assessing the usefulness of the propensity scores. However, they can still be of interest in the present context, since an important aim of this study was to evaluate the overall performance of the different algorithms. The best-performing model according to these measures is the Random Forest model, with the highest R-squared and lowest MSE. On the opposite end, the Lasso model had the poorest performance in terms of both R-squared and MSE. In all cases, however, the R-squared is fairly low, which could be a signal for low explanatory power of the covariates selected and might undermine the Conditional Independence Assumption.

<INSERT TABLE 2 HERE>

## **Matching and Balance**

For the sake of easier interpretability, graphs are reported below that display the results of the two matching methods. Figures 6 and 7 report the Standardized Mean Difference (SMD) between the groups for each category of each covariate, before matching – in red – and after matching – in blue. The dotted line represents the 0.1 limit, below which the covariates are considered comparable. If all covariates have SMDs below 0.1 (or above -0.1), then the matching has successfully balanced the two groups. The variable “distance” at the top refers to the propensity scores. They also need to be balanced for the sample to be considered balanced.

As indicated in the graphs, Nearest Neighbour Matching does a much better job overall at balancing the covariates, independently of the method used to calculate the propensity scores. Furthermore, not all propensity scores estimations could be used to balance the sample. Specifically, the Probit-based propensity scores were successful at balancing the covariates in both Nearest Neighbour and Optimal Matching. The propensity scores based on the Classification Tree model were balanced through Nearest Neighbour, but not with Optimal Matching. Random Forest and Lasso models could not be balanced in either method, but it is worth noting that the Lasso model shows consistently worse results, while Random Forest is very close to balancing all covariates.

<INSERT FIGURE 6 HERE>

<INSERT FIGURE 7 HERE>

### **Treatment Effects**

The outcome variables considered were PR\_SUELDO and TR\_SUELDO, which are the first wage after graduation and the wage after 5 years. Both these variables are categorical, and therefore they were recoded as continuous, assuming the highest value of each category (i.e., 999€ for the category “Between 700 and 999”). This was done to simplify the interpretation of the results. The downside of working with categorical variables in this context is that some accuracy is lost: the mean wage of this dataset is not the mean of all exact wages, but the mean of aggregated values (the categories of the variable). Therefore, the final estimated difference between private and public university graduates cannot be taken as an exact value, but rather as a close approximation.

Table 3 and 4 report the difference between the means of the two groups after being balanced with the propensity scores and weighted with the survey design. In other words, it is the population average treatment effect on the treated. The difference between the groups is computed as *mean of private – mean of public*, therefore positive ATTs indicate higher means for the treatment group. Standard errors and p-values are also reported, according to each of the propensity

score models. Table 3 refers to the differences in the first wage after graduation, while Table 4 considers the wage 5 years after graduation.

<INSERT TABLE 3 HERE>

<INSERT TABLE 4 HERE>

Almost all treatment effects are highly statistically significant, with p-values below 1% and with only a couple of exceptions that are still significant at 5%. However, the previously assessed balance of the covariates should be carefully considered when interpreting these results. The only models that successfully balanced all covariates were the Probit model, with both matching methods, and the Classification Tree with Nearest Neighbour matching. Therefore, only the results of these three are worthy of further interpretation, since the other methods failed to create comparable pairs across students who graduated from public and private universities and are likely to be biased. It is also worth noting that the results are overall consistent in terms of estimation, standard errors, and statistical significance, with only a few exceptions.

## **Discussion**

### **Technical Issues**

This section will discuss the results related to the methodology itself, in order to try and answer the two technical research questions:

*Technical Research Question 1:* “Do machine learning models perform better than traditional probit models in a propensity-score matching?”

*Technical Research Question 2:* “Which machine learning model works best in this scenario?”

Overall, the best-performing model was the “normal” Probit model. This model had several advantages over the others. Even with the relatively high number of categories that had to be considered, reaching balance in all covariates was extremely simple, independently of the matching



method used. It could be argued that the present case was relatively “lucky,” since a simple linear model with no interactions or higher orders was sufficient to properly balance all categories. Either way, probit models are in general computationally inexpensive and extremely simple to implement, and that is why they are used in most papers alongside logit models.

As already mentioned earlier in the justification of the methodology, machine learning methods have the potential to allow for better computation of the covariates, which in theory could have also translated into better balancing during matching. However, it was also evident from the literature that this potential advantage was, indeed, only a potential: results in the application of machine learning methods were mixed in the context of propensity score matching. It seems that the specific settings and context of this research did not allow machine learning methods to work as well as they could, and they were therefore outperformed by a simpler Probit model. There are a few aspects that might have caused this relatively poor performance. The most important one is likely the fact that machine learning methods thrive when they have access to high amount of data to work with. In this case, almost 7000 observations might have not been enough to reach optimal results. Secondly, as already mentioned earlier, classification trees and random forest are useful to identify non-linear relationships. However, in the present setting it seems that this feature of the algorithms was not needed, since a simple linear probit model balanced the covariates better than all other models.

On one hand, the Random Forest and the Classification Tree algorithms did outperform the Probit model (see Table 2), as one would expect from much more complex models that can also take into consideration non-linear relations. The Random Forest R-squared is double the one of the Classification Tree, and triple the one of the Probit model, revealing a much stronger predictive capability. However, in the context of propensity scores, the aim is not perfect prediction. One only needs enough predictive power to create a good distribution of propensity scores across the treated and control group, which will later allow the creation of balanced and comparable groups. In this

setting, the Probit model was the one that achieved the best compromise between prediction and comparability, while also keeping computational needs low.

In conclusion, it is hard to answer the first technical research question with an absolute yes or no. In this context, machine learning algorithms did not help in reaching more reliable results. However, since it is difficult to know a priori whether these alternative algorithms will work better than the traditional ones, it still makes sense to try and use them, for the sake of trial and error. As per the second technical research question, the Classification Tree model and especially the Random Forest model did reach acceptable results, even though they did not fully balance the covariates. It seems that these two models have potential as alternatives to the Probit model to calculate propensity scores. With different settings and datasets, they might even outperform it, especially when dealing with high volumes of data and more complex propensity score specifications.

## **Main Study Findings**

Finally, this section will discuss the actual results of the analysis, therefore answering the two main research questions outlined at the beginning of this study:

*Main Research Question:* “Are there differences between the first wage of graduates of public and private universities in Spain?”

*Corollary Research Question:* “Are there differences between the wage of graduates of public and private universities in Spain after 5 years?”

Table 3 summarises the results to answer the first research question. All estimated population treatment effects on the treatment group are statistically significant, most of them at 1%. As mentioned earlier, the interpretation of the results should focus on the three models that achieved balance of the covariates, but it is still of interest that the results are very consistent across different methods. The only clear outlier is the ATT derived from Lasso and optimal matching, but this is

also the method that achieved the worst covariate balance so it should be disregarded. From these results, it can be deduced that students that graduated from a private university in Spain earn more in their first job than their peers who graduated from a public university. In particular, on average their wage premium is around €90, which corresponds to around a 7% increase compared to public university graduates. Therefore, the first null hypothesis is rejected: there is a wage premium arising from attending a private university in the short term, although this is not particularly large.

Table 4 reports the results related to the second research question. Here the population ATTs vary more compared to the consistent results of the first research question, even if one focuses only on the methods that achieved covariate balance. However, they are all consistently significant at 1%. From this, it can be confidently said that students that graduated from a private university in Spain earn more than their peers that graduated from a public university 5 years after graduation. In this case it is more difficult to say with certainty how big the wage premium is. However, it can be said that it varies between 108€ and 180€, which is the variation of the ATTs of the balanced models. This corresponds to a wage a premium estimated between 5% and 10%.

It is now natural to ask why this could be the case. Unfortunately, given the difficulties in meeting the CIA requirements for this study, the difference in wages cannot be entirely attributed to the simple fact of “attending a private university,” although it does surely play an important role. As noted earlier in the literature review, there does not seem to be a higher perception of private universities in Spain, so prestige should not be a critical factor influencing employment outcomes. However, there are still some hypotheses that could be advanced. As mentioned during the discussion of the covariates, the treatment “attending private education” could still be a proxy for some information that was missing in the dataset, like soft and hard skills, networking opportunities, or knowledge of the labour market. Crawford and Vignoles (2014) also note that families who allocate resources to private education tend to also invest in various enriching

experiences for their children, such as tutoring, music and art lessons, as well as travel, potentially cultivating supplementary skills enhancing their CVs and benefiting their future careers.

In any case, according to the findings of the present analysis, graduates from private universities seem not only to enjoy a short-term advantage in the labour market, but this advantage appears still consistently present in the medium term, 5 years after graduation. These conclusions converge with most of the literature analysed earlier, which found a wage premium for students of private universities, although the estimate is somewhat smaller compared to other European countries. What is more interesting, however, is that the previous paper that analysed the same outcomes in Spain did not find differences across private and public university graduates. Domínguez and Gutiérrez (2020) only found a very small, essentially irrelevant, difference between contribution bases 5 years after graduation of private and public university graduates, equal to 1.5%. And, at most 18% of this difference could be attributed to the effect of the private university. Considering that the context of their analysis is very similar, this difference deserves a deeper discussion.

There are a few reasons that could explain this difference in the two findings. The first one is simply that “times changed.” The paper from Domínguez and Gutiérrez refers to graduates of the academic year 2009-2010, while the present analysis refers to the year 2013-2014. This could certainly be the case; however, it seems unlikely that the labour market and the importance of private universities could have changed so much in such a short span of time. A second, more likely reason, is the differences in the methodology. To account for self-selection bias, Domínguez and Gutiérrez used the two-staged method proposed by Heckman (1979) and added the inverse of Mill’s ratio to the equations estimated, while the present paper made use of propensity-score matching. Heckman’s method is used to address selection bias in the form of missing data, whereas the current PSM analysis is based only on complete cases, which could lead to some overestimation. However, there is also a sample difference that should be considered: Domínguez and Gutiérrez used the

whole sample available and considered other degrees obtained as a regressor, while this analysis used observations for those individuals that only had one bachelor's degree. Furthermore, the two outcome variables used in the current analysis did not exist in the previous dataset, and the authors had to estimate the salaries of the graduates from their contribution base, which was only available in quintiles. Although *PR\_SUELDO* and *TR\_SUELDO* are still categorical variables, their precision is very likely to be higher than an estimation. As per the choice of the covariates, Domínguez and Gutiérrez considered more covariates that could not have been justifiable in the context of PSM, (and also should not be needed) but they also did not consider the parents' backgrounds. Lastly, their paper does not mention the use of survey weights, so it is difficult to assume if and how those were used in the statistical analysis. The authors do claim their findings to be nationally representative, however.

To sum up, this analysis has some valuable features compared to the previous one. In particular, a more novel approach that included machine learning algorithms, albeit with some drawbacks, was provided. Nevertheless, due to data availability, meeting the CIA requirements at the basis of PSM was problematic, and so further research is needed to establish the rate of returns of private universities in Spain in both the medium and long-term. The latter necessitates robust longitudinal data sets that can also account for a wide range of variables known to influence employment earnings, like upper secondary school results and family wealth.

## **Conclusions**

As previously noted, additional research is needed to assess whether attending a private university provides an advantage in the labour market or not, and whether this advantage arises from the better education of the private sector or from external factors that are connected to and channelled through a privately obtained university degree. The present analysis sheds some doubt on previous findings and hopefully encourages more investigation both in Spain and within other countries. Although it is difficult to establish a general rule for the role of private higher education

in furthering intergenerational inequality, continued cross-cultural research will provide a firmer basis for understanding the complex interplay of various personal and institutional factors. Finally, this study also shows that machine learning models have the potential to improve results in future research, and that it is not particularly difficult to implement them.

The present findings underscore how the wage premium of private universities is relatively small, but it does hold over time. Thus, graduates of private universities enjoy higher wages at least until the medium term, and this has important implications for inequality. It could be argued that since private university graduates paid higher costs during their education, the actual rates of returns from public and private universities are very similar. This would imply that the higher wages are actually used to pay back the higher tuition fees, and in the end, there would not be much difference between public and private university graduates once these costs are included in the equation. However, if tuition fees are entirely borne by the parents, private university graduates simply begin their work life with higher salaries. This would mean that wealthier families have the means to jump-start their children's careers through a nationally accredited institution: private higher education. Collectively, these results underscore how inequality persists through generations, and that private university attendance contributes to the intergenerational accumulation of wealth.

Certainly, some may argue that private higher education has had an important role in filling the gaps when public systems could not keep up with the massification of tertiary education. However, these achievements seem to have been reached at the expense of increasing inequality in higher education. To name one study, Chetty et al. (2020), in an analysis of income segregation across colleges in the US, concluded that changing how students are allocated to colleges based on parental income could reduce intergenerational income persistence by about 25%.

Perhaps the most robust conclusion is that private higher education should not exist in the forms we see today. As noted in Article 26(1) of the Universal Declaration of Human Rights:

*Everyone has the right to education. Education shall be free, at least in the elementary and fundamental stages. Elementary education shall be compulsory. Technical and professional education shall be made generally available and higher education shall be equally accessible to all on the basis of merit.*

Emphasis here should be put on equal access to higher education on the basis of merit. Higher education should not exist as a tool for class reproduction, but to achieve better intergenerational mobility. Of course, private universities are not the only problem that contributes to the rise of inequality. But if higher education is an important determinant of employment outcomes, then it should also be important to ensure a more meritocratic system, more detached from parental income and education.

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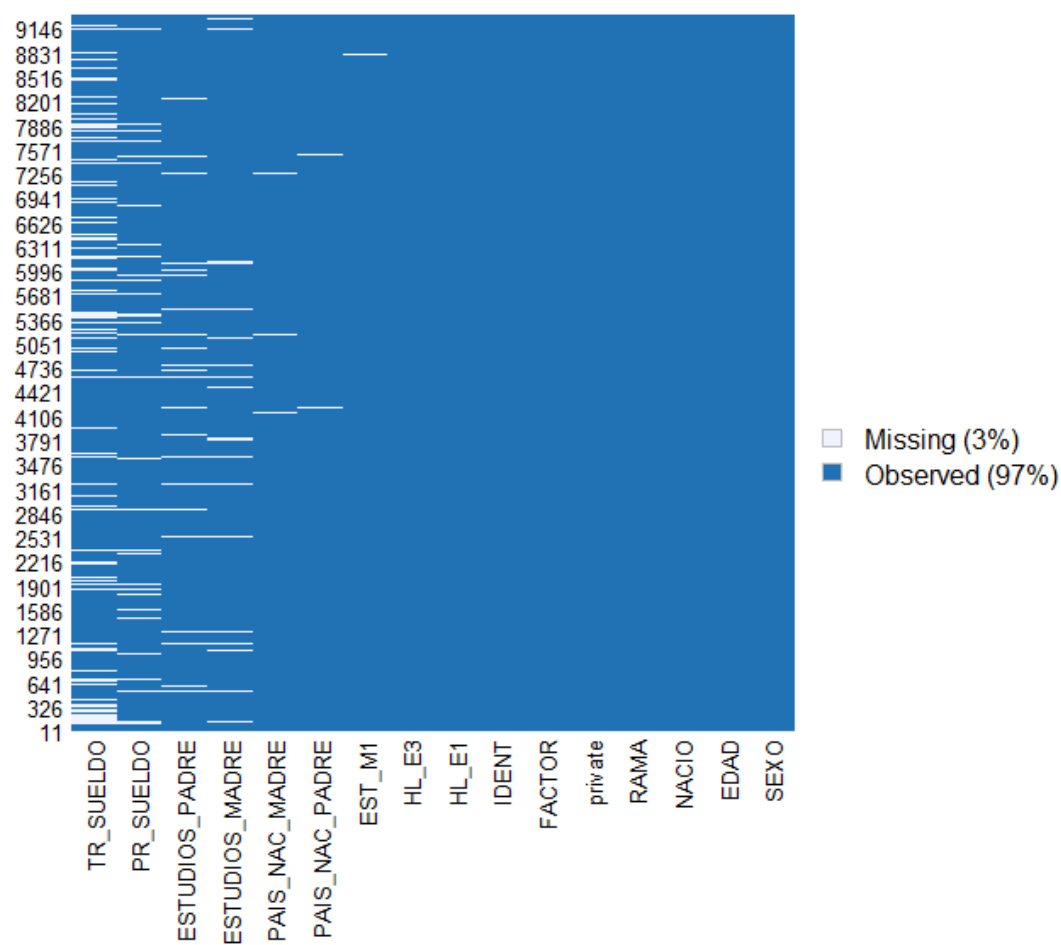
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**Figure 1: Missingness map of the relevant variables.**



Note: Y axis represents the number of observations for each variable. The white lines correspond to missing observations.



**Figure 2: Missing matrix of the relevant covariates. *Note:* Columns represent the distribution of all values of the variables (blue), rows account for the missing values only (grey).**





**Figure 3: An example of a binary classification tree. Taken from Santos et al. (2018).**

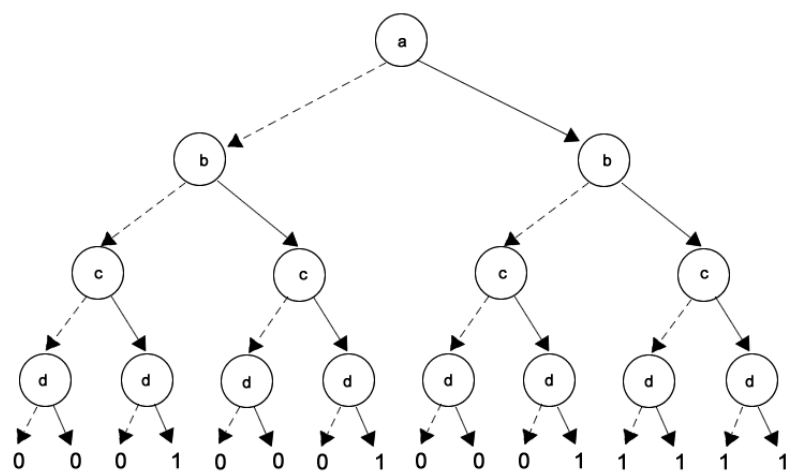
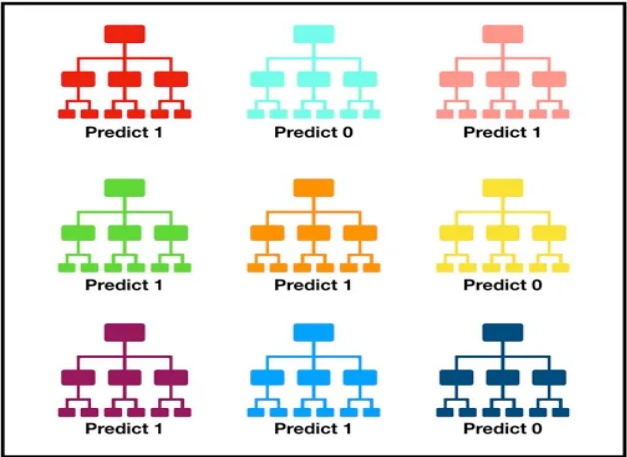
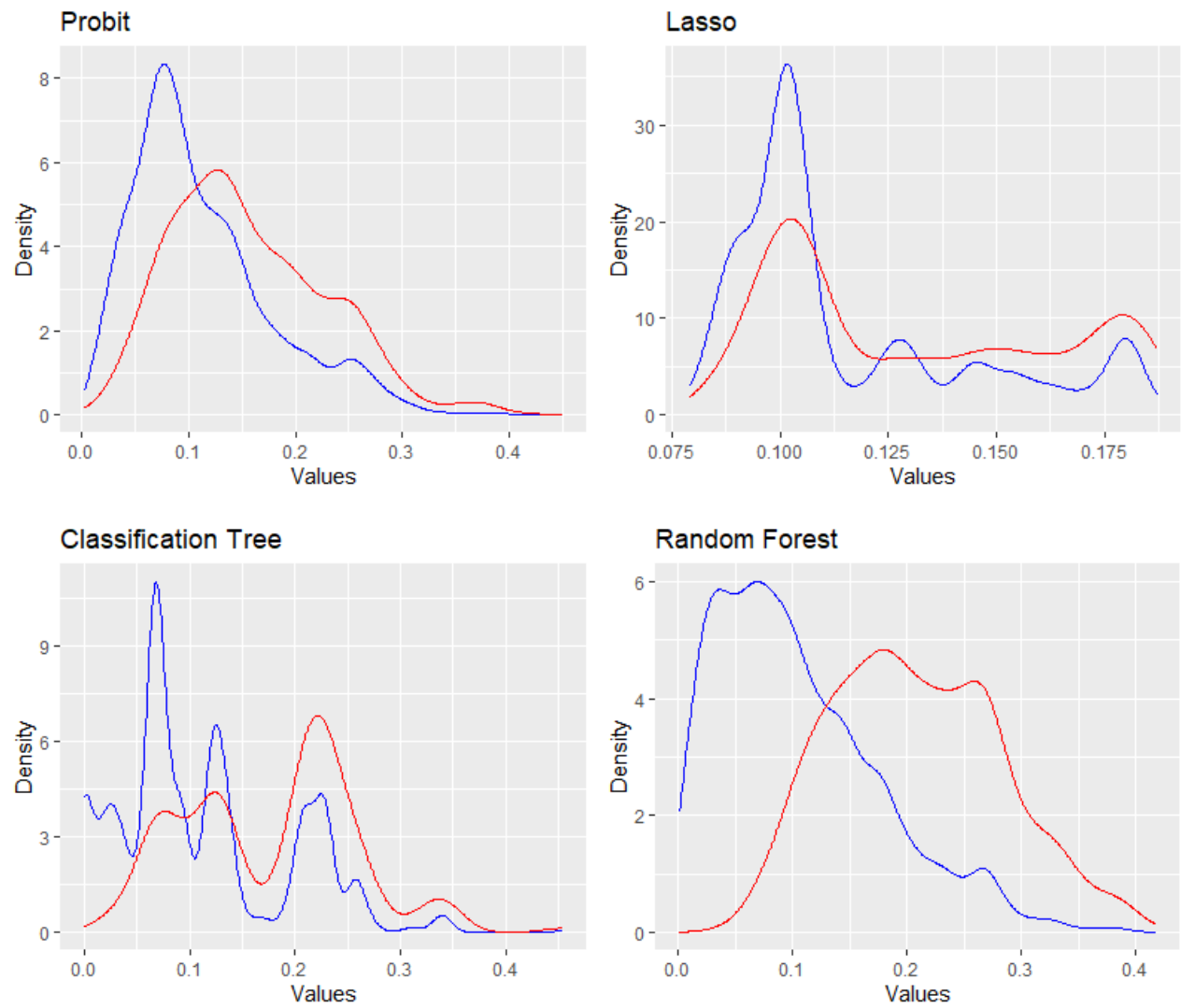


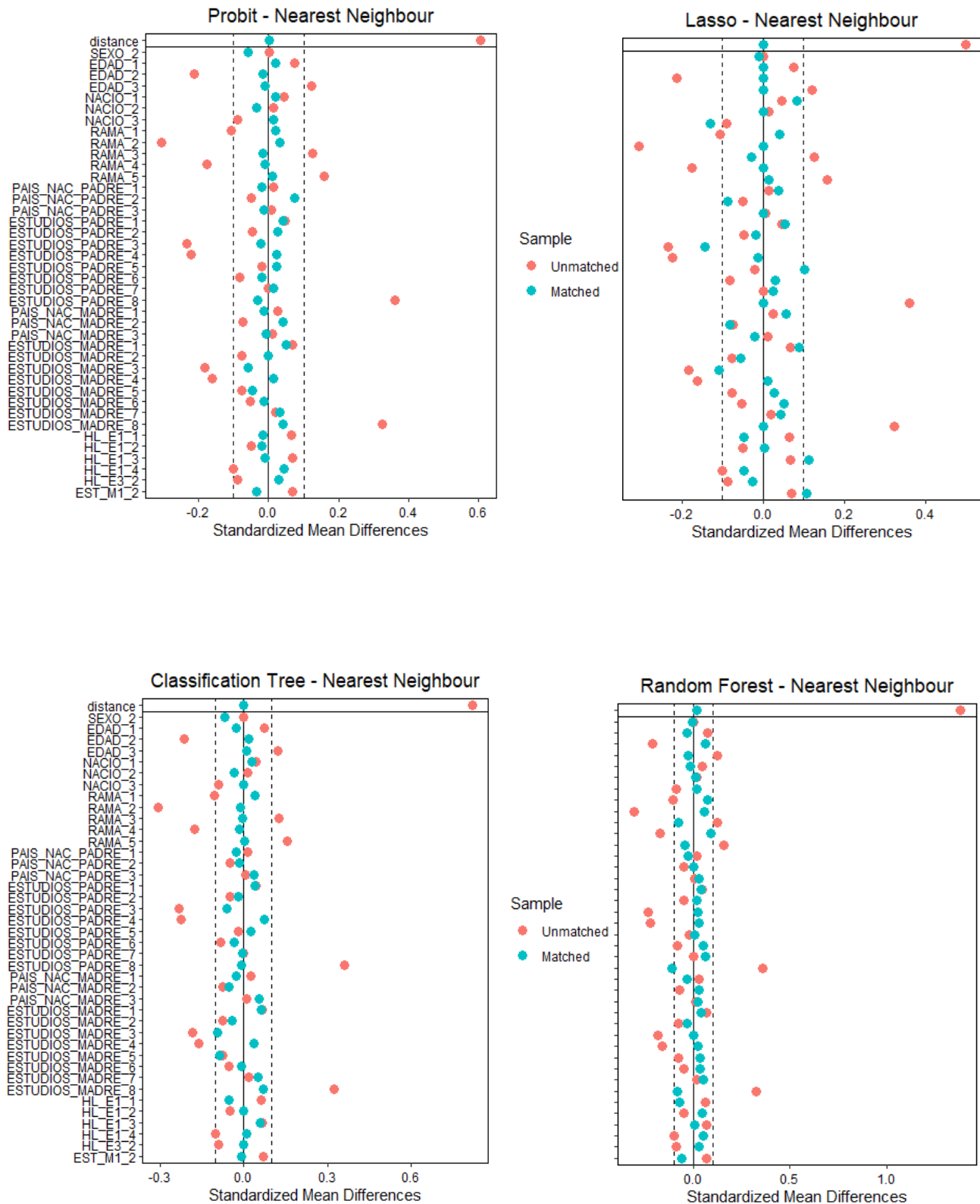
Figure 4: Visualization of a random forest. Taken from Yiu (2019).



**Figure 5: Propensity scores distributions (Kernel density). Red line is for private universities, blue is for public ones.**

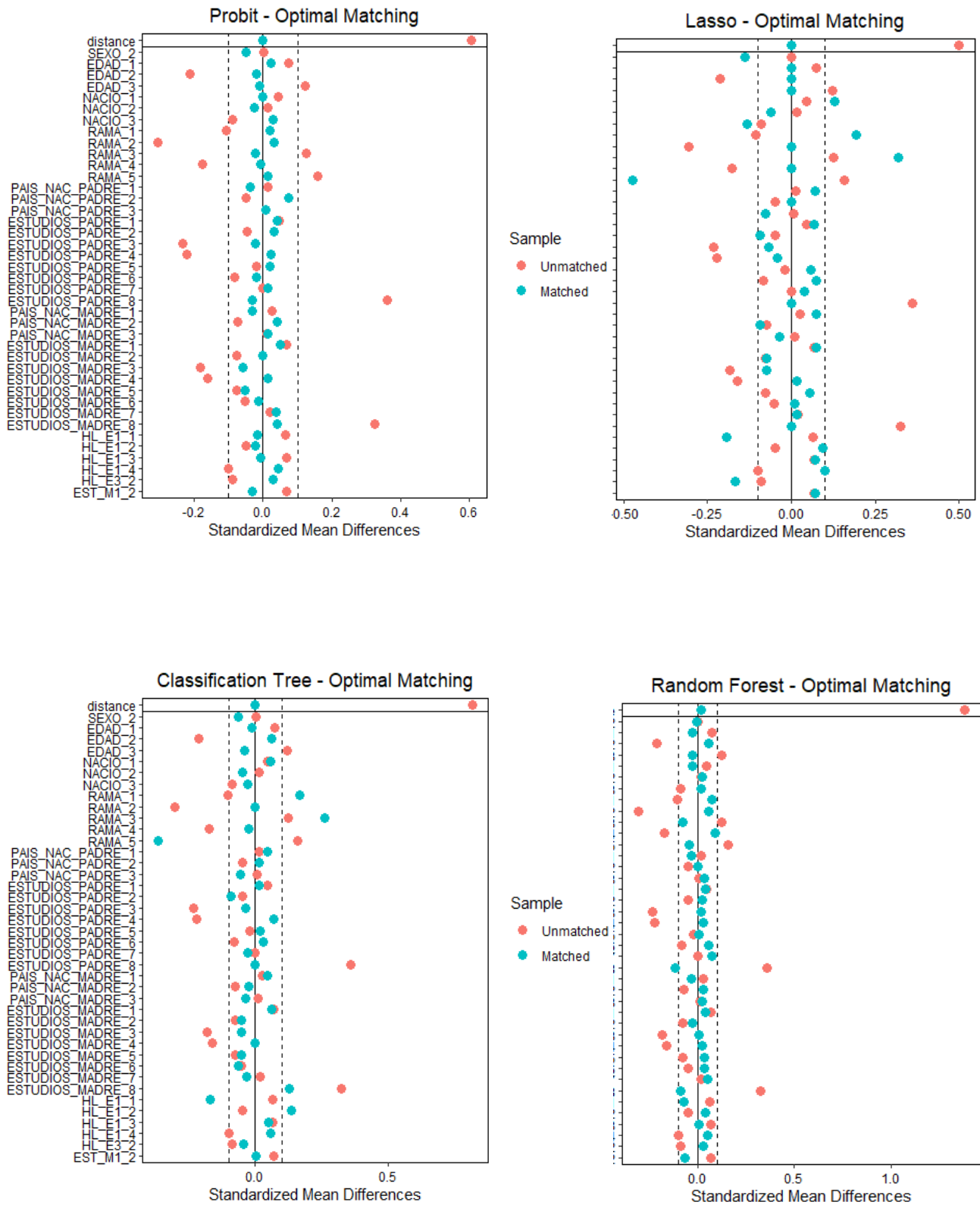


**Figure 6: Balancing of covariates for each model, Nearest Neighbour Matching.** *Note:* refer to Table 1 for value labels.



Note: Standardized Mean Difference shown for each category of each covariate, before and after matching. The dotted line represents the 0.1 threshold, below which the variable is considered balanced.

**Figure 7: Balancing of covariates for each model, Optimal Matching.** *Note:* refer to Table 1 for value labels.



Note: Standardized Mean Difference shown for each category of each covariate, before and after matching. The dotted line represents the 0.1 threshold, below which the variable is considered balanced.

**Table 1: Summary statistics for selected covariates (%), original name in parenthesis. Source: author's calculations on INE (2019).**

	Public	Private		Public	Private
<i>Gender</i>			<i>Father's country of birth</i>		
Male	46.0%	44.1%	Spain	94.3%	93.8%
Female	54.0%	55.9%	Other EU country	1.8%	1.2%
<i>Age</i>			Other non-EU country	3.9%	5.0%
Less than 30 years old	51.7%	55.9%	<i>Mother's country of birth</i>		
Between 30 and 34	31.8%	21.2%	Spain	94.1%	94.8%
Older than 35	16.5%	22.9%	Other EU country	1.9%	1.4%
<i>Nationality</i>			Other non-EU country	4.0%	3.7%
Spanish	96.1%	96.5%	<i>Mother's Studies</i>		
Spanish and another one	0.9%	1.6%	Can't read or write	0.3%	0.8%
Other Nationality	3.0%	1.9%	Incomplete primary education (less than 5 years of school)	4.7%	3.3%
<i>Field of Knowledge</i>			Primary Education	17.9%	11.8%
Arts and Humanities	4.7%	2.5%	First stage of Secondary Education, with or without diploma	20.3%	16.1%
Sciences	3.0%	0.4%	High School Studies (Bachillerato LOGSE, BUP, COU, Preu)	13.6%	11.4%
Social and Juridical Sciences	48.2%	53.4%	Intermediate vocational education or equivalent	10.2%	7.8%
Engineering and Architecture	28.9%	20.0%	Higher professional education or equivalent	5.8%	6.2%
Health Sciences	15.2%	23.7%	University Studies or equivalent	27.3%	42.5%
<i>Father's Studies</i>			<i>Traineeship during studies</i>		
Can't read or write	0.4%	0.8%	Yes, part of the curriculum	48.7%	51.9%
Incomplete primary education (less than 5 years of school)	4.9%	3.6%	Yes, outside of curriculum	14.1%	10.5%
Primary Education	18.5%	11.3%	Yes, both types	13.3%	15.9%
First stage of Secondary Education, with or without diploma	18.4%	12.4%	No	23.9%	12.7%
High School Studies (Bachillerato LOGSE, BUP, COU, Preu)	12.7%	11.8%	<i>Paid job during studies</i>		
Intermediate vocational education or equivalent	9.0%	7.2%	Yes	43.0%	44.7%
Higher professional education or equivalent	7.2%	6.2%	No	57.0%	55.3%
University Studies or equivalent	29.1%	46.7%			
<i>Studied abroad during Bachelor</i>					
Yes	18.2%	16.7%			
No	81.8%	83.3%			

**Table 2: Accuracy measures of the models used to calculate the propensity scores.**

<b>Model</b>	<b>R-Squared</b>	<b>Mean Squared Error</b>
Probit	0.042	0.099
Lasso	0.022	0.102
Classification Tree	0.066	0.097
Random Forest	0.143	0.089

**Table 3: ATT for first wage after graduation (outcome variable *PR\_SUELDO*). Note: models that achieved covariate balance are marked with \*; \*\* on p-values marks statistical significance at 5%, \*\*\* at 1%.**

<b>Model</b>	<b>Population ATT</b>	<b>Standard Error</b>	<b>P-values</b>
<i>Nearest Neighbour</i>			
Probit*	91.5	35.7	0.0103**
Lasso	93.7	32.4	0.0038***
Classification Tree*	87.7	33.3	0.0085***
Random Forest	93.5	34.7	0.007***
<i>Optimal Matching</i>			
Probit*	92.8	35.3	0.0087***
Lasso	105.0	37.0	0.0047***
Classification Tree	91.2	37.5	0.0149**
Random Forest	89.7	36.2	0.0132**

Note: the table shows the monthly earning advantage (the difference in earning) in Euro of graduates from private universities compared to public universities by methods for estimating the propensity score and matching method (earnings of students from private universities – earnings of students from public universities).



**Table 4: ATT for wage 5 years after graduation (outcome variable *TR\_SUELDO*). Note: models that achieved covariate balance are marked with \*; \*\* on p-values marks statistical significance at 5%, \*\*\* at 1%.**

<b>Model</b>	<b>Population ATT</b>	<b>Standard Error</b>	<b>P-values</b>
<i>Nearest Neighbour</i>			
Probit*	180	40.2	<0.001***
Lasso	133	39.8	<0.001***
Classification Tree*	108	39	0.0058***
Random Forest	162	41.6	<0.001***
<i>Optimal Matching</i>			
Probit*	169	40.4	<0.001***
Lasso	192	43.8	<0.001***
Classification Tree	189	41.1	<0.001***
Random Forest	119	41.5	0.0040***

Note: the table shows the monthly earning advantage (the difference in earning) in Euro of graduates from private universities compared to public universities by methods for estimating the propensity score and matching method (earnings of students from private universities – earnings of students from public universities).

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