Quality and selection in regulated professions*

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Abstract

Entry into many occupations is regulated to screen out the least able candidates, but available evidence suggests that this objective is rarely achieved. Using microdata covering the universe of Italian law school graduates (2007-2013), we show that this result is largely due to the strong intergenerational transmission within regulated professions. We find that having relatives already active in the profession significantly increases the probability of passing the entry exam and boosts earnings, particularly for those who performed poorly in law school.

Keywords: Occupational regulation, licensing, intergenerational mobility.
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1 Introduction

Entry in many occupations is regulated with the objective of protecting consumers by selecting only the most able producers into the market (Bryson and Kleiner, 2010; Friedman and Kuznets, 1945; Kleiner, 2000; Kleiner and Krueger, 2013). However, the available empirical evidence suggests that in most cases occupational regulation fails to achieve such a goal (Anderson, Brown, Kerwin, and Rees, 2020; Bryson and Kleiner, 2019; Kleiner, 2017). The robustness of this finding across different professions and institutional contexts is surprising, as occupational regulations are explicitly designed to produce positive selection, and solid theoretical considerations suggest they should work (Leland, 1979; Maurizi, 1974; Shapiro, 1986; Stigler, 1971).[1] Nonetheless, the literature has devoted little attention to understanding the reasons for the generalised failure of occupational regulations.

In this paper, we study entry into the legal profession in Italy and we investigate the potential mechanism that can explain why occupational licensing so often fails at selecting the best professionals. We use data obtained from university administrative records covering the universe of all Italian law school graduates between 2007 and 2013 merged with the lists of all licensed lawyers, allowing us to know which graduates eventually enter the market of legal services. In addition, all graduates are interviewed at the end of their university program as well as one, three, and five years after graduation. From these surveys, we obtain information on family background, apprenticeship, and earnings.

Our empirical analysis proceeds in two steps. First, we document that law school graduates with relatives who are already operating in the profession are more likely to become licensed lawyers. Furthermore, the percentage of connected graduates – i.e. those with some lawyers relatives – who enter the profession does not increase significantly with their GPA in law school. For unconnected graduates, instead, GPA in law school matters a lot for the probability of entering the profession, and only those with the highest grades display entry rates similar to their connected counterparts. These results imply that connected lawyers are much less positively selected along the distribution of GPA than unconnected lawyers.

There are two alternative interpretations of this finding. First, connected law school graduates might be more skilled than their unconnected colleagues, because they learn useful occupation-specific abilities at home not captured by GPA. The second interpretation is that family connections facilitate entry into the profession for reasons beyond occupational ability (e.g. favoritism). Although our data do not allow us to identify precisely the relative importance of each channel, we present several pieces of evidence suggesting that mechanisms other than human capital accumulation at home are the main force at play in our setting.

In the second part of the paper, we explore the mechanism underlying the process of selection into the profession. We investigate whether the disproportionate inflow of low-GPA connected individuals into the legal profession occurs during the apprenticeship stage, at the entry exam stage, or is driven by connections increasing expected earnings in the profession. We postulate that family connections can influence both the probability of passing the exam that is required to enter the profession and expected earnings in the market of legal services. Law school graduates make forward-looking occupational choices, hence both the probability of passing the exam and expected earnings matter for selection. By exploiting the random allocation of exam commissions to exam locations, our data allow us to estimate the role of connections separately in these two processes. We use the resulting estimates to simulate se-

[1] Anderson et al. (2020), discussed below, is the only paper that finds positive effects of regulation on quality.

lection into the profession under different scenarios about the role of connections. We find that eliminating the effect of connections in the entry exam would result in a decrease of 4 percentage points in the predicted share of lawyers with GPA in lowest decile and a corresponding increase of 1 percentage point in the top decile, improving the selection into the profession along the distribution of GPA.

Our analysis suggests that the interplay of poorly designed licensing regulation and the intergenerational transmission of occupations can undermine the potential of licensing to generate the positive selection it is designed to create. This is an important result for policy design, as occupational licensing affects about 20% of workers in the European Union and up to 30% in the United States (Kleiner and Krueger, 2013; Koumenta and Pagliero, 2018).

The main contribution of this paper is to provide a rationale for the failure of occupational licensing documented in so many countries and for so many professions. Although our results are obviously specific to our setting, we believe that they are general enough to be informative about selection into occupations where entry standards may favour nepotistic practices. This is certainly the case for the traditional regulated liberal professions, where long apprenticeship periods, the involvement of incumbents in the entry process, and restrictions to prices and commercial practices are common across many occupations and countries and are likely to favour connected entrants (Paterson, Fink, and Ogus, 2003; Pellizzari and Pica, 2010; Pellizzari, Basso, Catania, Labartino, Malacrino, and Monti, 2011; UK Office of Fair Trade, 2001).[2]

We are not the first to look into the relationship between occupational regulation and the quality or output of producers. Carroll and Gaston (1981) in their exploratory analysis had already concluded that *"[..] there is [..] evidence from several professions and trades that indicates that restrictive licensing may lower received service quality. We know of no contrary findings[..]."*. More recently, Kleiner, Marier, Park, and Wing (2016) could not find any detectable improvement in the quality of health services when licensing regulations for nurses became stricter. Similarly, Kleiner and Kudrle (2000) show that stricter licensing requirements for dentists result in higher prices with no significant improvement in quality.[3] Barrios (2018) exploits changes in the licensing requirements for accountants to find that *"[...] restrictive licensing laws reduced the supply [...] and increased rents to the profession without drastically improving quality [...]"*. Haas-Wilson (1986) and Kugler and Sauer (2005) show similar results for optometrists and physicians, respectively.

An important profession that has attracted a lot of attention is teachers, and once again there does not seem to be clear positive effects of regulation on quality. Angrist and Guryan (2008) investigate the introduction of state-mandated teacher testing in the US and find positive effects on wages but no effect on quality, measured by teacher qualifications. Larsen, Ju, Kapor, and Yu (2020) examine the effect of stricter licensing requirements for teachers in the US and find an increase in the left tail of the quality distribution.

Anderson et al. (2020) is perhaps the only study to document a clear positive effect on quality. They examine the staggered introduction of licensing requirements for midwives across US

[2]In addition, in countries with selective tertiary education systems, such as the US, college admission is a crucial step in the selection process and it has been widely documented to favour connected candidates over unconnected ones, often regardless of quality (Broscheid and Teske, 2003; Cannings, Montmarquette, and Mahseredjian, 1996; Chetty, Friedman, Hendren, Jones, and Porter, 2018; Chetty, Friedman, Saez, Turner, and Yagan, 2020).

[3]Wanchek (2010) and Wing, Langelier, Continelli, and Battrell (2005) also investigate occupational regulations for dentists but do not focus on quality.

States between 1900 and 1940 and find significant reductions in maternal and infant mortality.[4]

A recent significant advancement in this literature is Kleiner and Soltas (2023), who develop a sufficient statistics approach to assess the overall welfare cost or benefit of occupational licensing. They apply their methodology to a variety of occupations exploiting variations in regulations across US states and finding an overall welfare loss, suggesting that even if there were quality effects, they are more than offset by the welfare loss due to higher prices and lower supply.

This paper is also tightly connected to the literature on the intergenerational transmission of occupations. Lentz and Laband (1989) and Laband and Lentz (1992) had already documented strong intergenerational persistence of professions for doctors and lawyers in the US, and rationalised this evidence with either nepotism or transmission of human capital within the family. Dunn and Holtz-Eakin (2000) and Bjorklund, Roine, and Waldenström (2012) further find similar results for general self-employment and capitalist dynasties, and Corak and Piraino (2011) even document that parents and children are often employed by the same employers. More directly related to our work, a recent literature documents sizeable intergenerational correlations of professional affiliations in Italy (Aina and Nicoletti, 2018; Bamieh and Cintolesi, 2021; Mocetti, 2016; Mocetti and Roma, 2021; Mocetti, Roma, and Rubolino, 2022; Raitano and Vona, 2021). Compared to these papers, we link the intergenerational transmission of occupations to the effectiveness of licensing regulations by directly addressing the selection and quality of professionals.

Many other papers have looked at occupational licensing in a variety of professions, but without focusing specifically on quality. Most of these studies document an increase in costs for consumers and profits or rents for incumbents. This is the case for driving schools in France (Avrillier, Hivert, and Kramarz, 2010), lawyers (Pagliero, 2010, 2011), barbers (Thornton and Weintraub, 1979; Timmons and Thornton, 2010), and radiologists (Timmons and Thornton, 2008) in the US.

The rest of the paper is organized as follows. Section 2 describes the institutional setup of the legal profession in Italy. Section 3 presents our main data sources and explains how we combine them. In Section 4 we provide empirical evidence about the selection process into the legal profession, with a specific focus on the role of law school GPA, family connections and their interactions. In Section 5 we develop and estimate an empirical model of the selection process and simulate various counterfactual scenarios. Section 6 contains a battery of robustness checks. Section 7 concludes.

2 Institutional Background

The regulation of the legal profession in Italy is similar to many other countries. A government-issued license is required to offer legal services to clients and represent them in court. Only graduates from law schools, offered by either public or private universities, can obtain the license conditional on completing 18 months of compulsory practice and passing an entry exam.

[4]Deyo, Hoarty, Norris, and Timmons (2020) also look at quality, but rather indirectly by studying the implications on crime and health of licensing massage therapists.

The entry exam

The exam takes place in the courts of appeal, the second layer of the Italian judiciary system.[5] There are 26 such courts in the country, approximately one per region, with the most populated regions having more than one. For simplicity, we will hereafter refer to courts of appeal as districts. The exam takes place once per year and consists of two parts. First, candidates sit a written exam that lasts three consecutive days. On the first day, they must write an opinion on a civil case, on the second day on a penal case, and on the third day, they write a judiciary act (e.g. court summon, complaint, succession, etc.). The dates and the texts of the exam are the same throughout the country, but each district has its own grading commission. Candidates sit the exam in the district where they did their apprenticeship.

Key to the possibility of estimating the role of connections separately on the probability of passing the exam and on earnings is that the written tests are graded anonymously by the commission of a randomly assigned district. The randomisation is performed by the Ministry of Justice and is clustered within 5 groups of districts with similar sizes. The randomization is also designed to avoid pairing, namely two commissions grading each other. As an example, in 2019 the group of largest districts, comprising Rome, Naples and Milan, had Naples grading Rome, Rome grading Milan, and Milan grading Naples. The outcome of the randomisation process is made public at or after the start of the written exams.[6]

Every year several thousand candidates attempt the written exam: on average, over 30,000 candidates participated every year during the period of our analysis. Hence, the grading process is long, usually lasting around 6 months. The written exam takes place at the same time for all districts, normally at the beginning of December. The results are published during the summer and successful candidates are then admitted to the oral exam. The interviews happen in alphabetical order, starting with a letter that is randomly drawn by each district. The oral examinations are scheduled independently in each district and start as soon as the results of the written exams are available. The interview usually takes about one hour and candidates are immediately notified about the outcome. In most districts the interview calendar spans from September to December and, eventually, the entire process is completed just before a new round of written exams begins.

Given the 18 months of practice and the length of the examination process, young lawyers obtain their license approximately 2.5-3 years after graduation, unless they fail the exam (either the written or the oral part), in which case the process may take substantially longer. The entry exam can be retaken any number of times.[7] Figure 1 summarizes the entry process into the profession, from the moment of graduation to the final occupational outcome. Candidates who fail the exam can either retake or choose to move into a different occupation, often as legal consultants in private firms.

The local bar associations

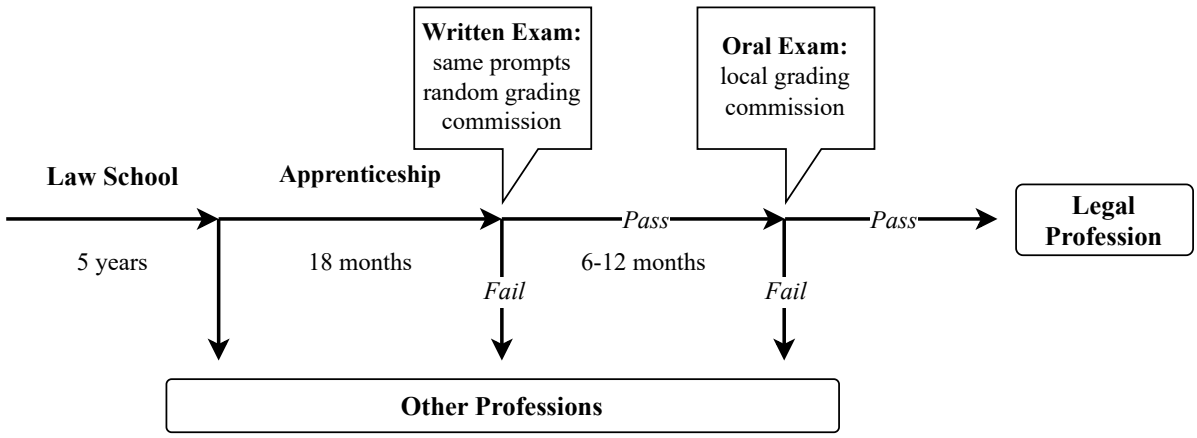
Candidates who successfully pass both the written and oral exams can then register with the local bar associations and operate in the corresponding local market. There exists one bar for

[5]Beside the organisation of the lawyer entry examination, courts of appeal are mainly responsible for appeals against judgments issued by the ordinary courts, the first layer of the system.

[6]For example, in 2019 the written exam took place on December 10-11-12 and the grading commissions were announced on December 10. In 2018 the written exam took place on December 11-12-13 and the grading commissions were announced on December 21.

[7]The completion of the 18-month training period is valid only for 5 years.

Figure 1: Timeline of the licensing process for Italian lawyers



each ordinary court, the lower level of the judiciary system, corresponding approximately to administrative provinces. Hence, there are multiple bars (on average about 5) in each district. In total, there currently are 139 local bar associations that are responsible for enforcing the professional code of conduct and organising training for their associates. Lawyers are only allowed to represent clients in the ordinary and appeal courts outside their local bar if they pair with a local lawyer, but they can freely choose to transfer to any bar in the country at any time of their career. Registered lawyers can only work as self-employed professionals and cannot be dependent employees in the private sector (exceptions are possible in the public sector).

The local bar associations play an important role also in the organisation of the entry exam as they nominate three of the five components of the local exam commission. The other two members are a judge (usually retired) and a university professor and they are nominated by the Ministry of Justice. The president of the commission must be chosen among the three lawyers. The local commissions are responsible for the logistics of both the written and the oral examinations, they mark the written exams of the candidates of the randomly assigned district and they carry out the oral interviews of the local candidates who passed the written exam.

A central commission with the same composition is created by the Ministry of Justice and it is responsible for preparing the written exam questions, defining grading criteria, and overseeing the entire examination process. All commissions change every year.

3 Data and descriptives

We combine various data sources to follow several cohorts of Italian law school graduates over the first 5 years of their careers. The starting point is an administrative dataset covering (almost) the entire universe of university graduates in Italy.[8] The dataset is constructed and maintained by AlmaLaurea, a consortium of Italian universities sharing their administrative records for research purposes and offering placement services to both graduates and employers.

[8] All 50 public universities offering law degrees are included. Five of the nine private universities offering law degrees are included.

In addition to maintaining the administrative data, the consortium also runs a series of regular surveys of all graduates. A first survey takes place right before they graduate and collects information about the students' backgrounds, opinions about the university experience, and expectations about their professional careers. Then, students are interviewed again one, three, and five years after graduation to collect information about their labour market status. Almost all students fill in the survey at graduation, which is required to obtain their diplomas. The response rates of the other surveys are very high: on average around 80% at one year, 75% at three years, and 70% five years after graduation. For this study, we focus on students who graduated from law school between 2007 and 2013.[9]

Administrative records include high school type and marks, the university the students graduated from, GPA, graduation grades, age and gender. Important survey information comprises employment status and wages, parental education and parental occupation, scholarships, experiences abroad, proficiency in foreign languages and computer skills.

To identify graduates who eventually enter the legal profession, we match the main dataset with the official registers of licensed lawyers in the entire country. Local bar associations are responsible for publishing and maintaining the lists of licensed professionals in their jurisdictions and most of the associations make them available on their websites. We have collected all the registers from November 2017 to January 2018 and we observe the names, surnames and unique tax identification numbers of all the associates. We use this information to match our main dataset of law school graduates with the lists of licensed lawyers, allowing us to identify those who eventually entered the legal profession, when and where.[10]

This information might suffer from some inaccuracy. For example, some individuals might register and then unregister shortly after if they choose to leave the profession.[11] Given the high cost of entering the profession, we expect this to happen rarely. The opposite source of error is also possible, namely individuals who become lawyers more than 5 years after graduation and are not recorded as licensed professionals in our data. We also expect this to happen rarely, essentially only for candidates who fail the exam several times or who try a different career path first.

We further complement our data with measures of connection with the profession based on surnames. For all graduates, both those who eventually work as lawyers and those who do not, we compute how frequently their surnames appear in the local register (or in others). We assign the local district corresponding to the location of the university from which they graduate for both lawyers and non-lawyers.[12]

Of course, this is an imperfect measure of connectedness. There can be family ties not sharing the same surname, like one's mother and her relatives, and, conversely, individuals sharing the same surname may not be connected to one another. We know from the literature

[9]Before 2007, the follow-up surveys were only administered to those who graduated in the summer session (that is, about one-third of graduates) and data about only 49 out of the 76 participating universities was available, whereas the 5-year post-graduation surveys for students who graduated after 2013 have not yet been released at the time of analysis.

[10]The matching has been performed for us by AlmaLaurea and we only have access to the matched anonymised version of the final dataset, which we can only access on the consortium's premises.

[11]It is also unclear whether it would be correct to classify them as lawyers. Ideally, we would like to consider them as successful candidates when we look at the likelihood of passing the exam, but change their status to non-lawyers when we look at their earnings.

[12]We have also experimented with an alternative definition which assigns to lawyers the district where we observe them registered. The results are largely unaffected.

that, given the usual Western conventions for surname transmission (and Italy is no exception), the second source of error is likely to be very small because the vast majority of individuals hold surnames that are highly infrequent. Hence, the probability that any two individuals with the same surname are linked by some family tie is extremely high (Güell, Pellizzari, Pica, and Mora, 2018).[13] It remains possible, however, that we fail to capture some connections because they do not share the same surname. In Section 6.1, we simulate various scenarios of mismeasurement to show that, under most assumptions, the degree of error must be extremely large to overturn our main findings, at least qualitatively.

In addition, we also observe the professional coordinates of each lawyer from public registers – postal addresses, emails and phone/fax numbers – allowing us to identify those who are likely working in the same law firm. More specifically, we assume that any two lawyers reporting the same phone number or fax address or postal address work in the same firm.[14] We use this information to compute the size of the law firms that appear in our data (recall that from the professional registers we observe all active professionals) and also to identify young connected lawyers who work in the same firms as their connections.

Finally, we collect information on the distribution of surnames in each district from tax records. Specifically, we compute the number of times each surname appears in the tax records of each district and we use this information to control for the incidence of each surname in the underlying population.[15]

In our empirical analysis, we estimate several equations and, due to missing values and survey non-response, the number of observations available for each of them varies. For comparability purposes, in our main analysis, we restrict the sample only to the observations that can be used for all equations, but in Section 6.3 we replicate all our estimates to show that the results are largely unaffected by this sample selection.

Table 1 reports some basic descriptive statistics for the 24,260 individuals in this common sample, broken down by those who eventually enter the legal profession and those who do not. Law school attracts over 60% female students and a little majority of them eventually end up not practising as licensed professionals. The descriptive statistics suggest some minor positive selection on academic ability into the legal profession, both looking at high school and university grades.[16] Over half of the graduates have some connection with the profession and the incidence of connections is substantially higher among those who eventually enter the profession. These students are also slightly more likely to come from educated and affluent families,

[13] Güell et al. (2018) compute that in Italy the probability of two people taken at random being family members, conditional on having the same surname, is 0.1838, which is about 2000 times higher than the unconditional probability.

[14] Multiple firms may have the same postal address if they are located in the same building. We manually checked (by searching their websites) the largest resulting studios to confirm that indeed the coordinates refer to a single firm. Many younger lawyers do not provide fax numbers and 9.97% of those who provide a phone number give a mobile line. In the end, we are able to retrieve addresses for 240,727 out of 240,957 registered lawyers (99.9%), telephone numbers for 220,438 lawyers (91.5%), and fax numbers for 192,609 lawyers (79.9%). We use the more precise information on landline phones, fax and email to validate matching based on postal addresses, and we conclude that misclassification is a minor problem.

[15] We extract this information from the same data used in Güell et al. (2018). The population appearing in the tax records is not exactly identical to the total population, but Güell et al. (2018) show that it is a reasonable approximation, especially regarding the adult population.

[16] To account for differences in grading standards, we have standardised GPA to have mean zero and standard deviation equal to one within each university. High school final grades are instead standardised across the entire sample because they are attributed via a common national exam.

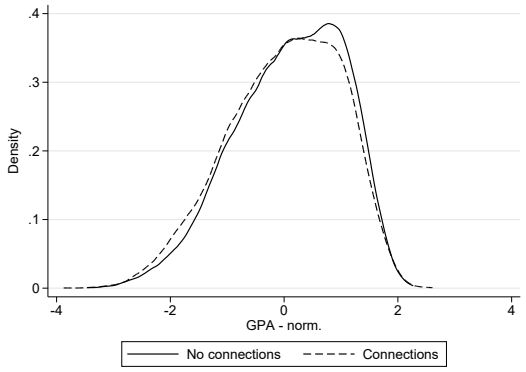
Table 1: Descriptive statistics

	Full sample	Lawyers[a]	Non-lawyers[a]
1=female	0.63	0.62	0.64
	(0.482)	(0.485)	(0.479)
High school grade[b]	-0.00	0.03	-0.02
	(1.000)	(0.984)	(1.014)
GPA[c]	0.00	0.02	-0.02
	(0.999)	(0.977)	(1.003)
1=connected[d]	0.58	0.62	0.53
	(0.494)	(0.485)	(0.499)
Number of connections[e]	4.14	4.54	3.76
	(12.26)	(13.16)	(11.36)
1=graduate parent(s)[f]	0.38	0.40	0.37
	(0.486)	(0.489)	(0.483)
1=parent(s) in high-ranked occup.[g]	0.44	0.46	0.41
	(0.496)	(0.498)	(0.492)
1=apprenticeship[h]	0.88	1.00	0.77
	(0.323)	(0)	(0.419)
Log earnings[i]	5.82	5.96	5.69
	(2.600)	(2.266)	(2.868)
Observations	24260	11629	12631

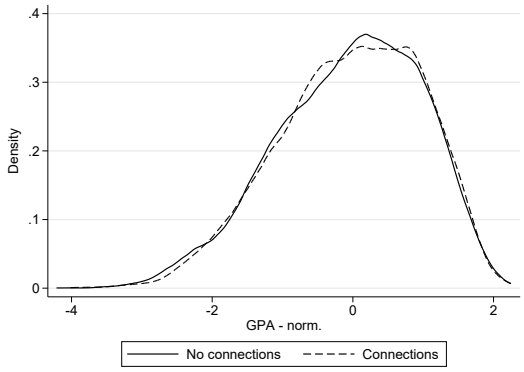
[a] Graduates who appear or not in some local register of lawyers in 2017/2018.
[b] Standardised over the sample.
[c] Grade point average for all graded exams taken over the five-year law school program, weighted by academic credits and standardised within university.
[d] At least one person (25y+ older) with the same surname appears in the local register at the (expected) time of sitting the bar exam.
[e] Number of persons (25y+ older) with the same surname appearing in the local register at the (expected) time of sitting the bar exam.
[f] At least one parent with a university degree.
[g] At least one parent employed as a professional, entrepreneur, or executive manager.
[h] Graduates who self-reported having started a legal apprenticeship in at least one post-graduation survey (one, three and five years after graduation) or who are registered as apprentices in the official lawyer registry.
[i] Self-reported earnings five years after graduation (in Euros 2015).

Figure 2: GPA distribution (standardized) by connected status

(a) Lawyers



(b) Non-Lawyers



which we measure with parental education and occupation. The data suggests that most law school graduates attempt to enter the legal profession: 88% of them start the apprenticeship and eventually 77% of those who do not become licensed lawyers report having started an apprenticeship. Earnings five years after graduation are already significantly higher for lawyers than non-lawyers by about 10% of a standard deviation.[17] Finally, Figure 2 shows the grade distribution separately for connected and unconnected graduates, separately by whether they become lawyers. The two distributions largely overlap and there is no suggestion that connected lawyers perform better than nonconnected lawyers at university. If anything, the distribution of GPA for nonconnected lawyers seems to first-order stochastic dominate the distribution of GPA for connected lawyers.

4 Selection into the legal profession

In this section, we investigate the process of selection into the legal profession with a particular focus on the role of GPA in law school and family connections. We begin by presenting some descriptive evidence.

Figure 3 plots the share of law school graduates in our sample by decile of the distribution of GPA. This plot shows that some positive selection on academic ability does take place, but it is quite limited. About 46% of graduates in the first and second deciles access the profession and this share barely reaches 50% at the very top of the distribution.

Figure 4 shows instead the share of connected individuals in our sample, broken down both by deciles of GPA and by the groups of those who eventually become licensed lawyers and those who do not. Several notable facts emerge from this figure. Family connections are much more frequent among lawyers than non-lawyers throughout the distribution of GPA, but the difference is much larger at the bottom. Among the least able graduates, almost 70% of those who eventually enter the legal profession have some family member who is already a licensed lawyer. For those who end up in a different occupation, this figure is about 52%. At the top of the distribution of GPA, the difference is around 6 percentage points (56% versus 50%). The

[17] In our data, earnings are reported in intervals and we assign to each respondent the mid-point of the interval they indicated.

Figure 3: Law school graduate-to-lawyer conversion rates by GPA decile

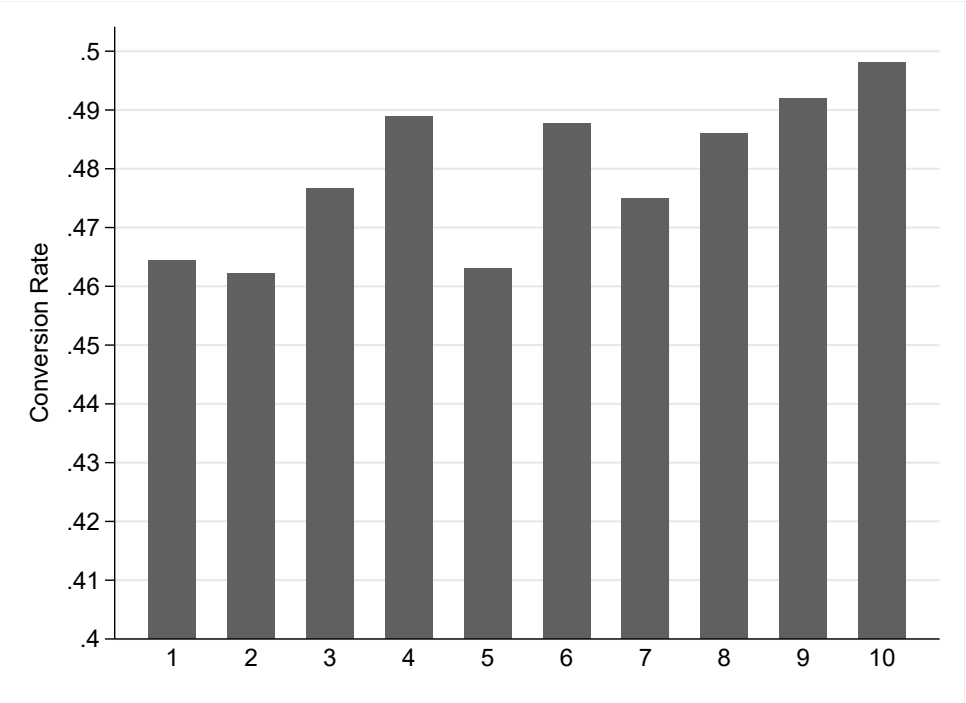
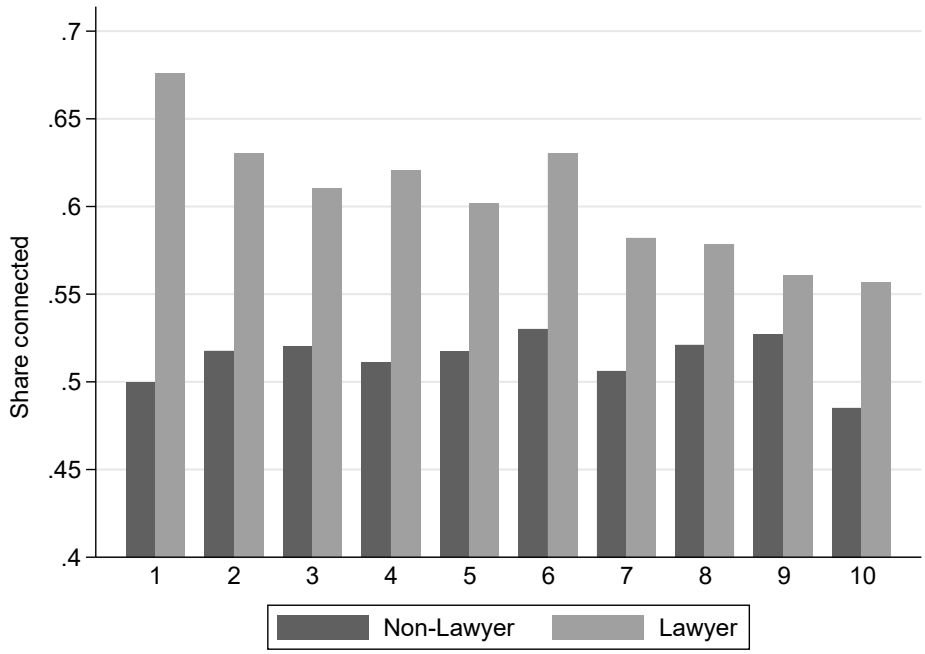


Figure 4: Share of connected individuals by occupation and GPA deciles



share of connected lawyers declines markedly with GPA, whereas it appears to be rather flat for non-lawyers.

Taken together, Figure 3 and Figure 4 suggest that family connections might interfere with the selection process and explain, at least in part, the mild positive selection on GPA that we detect in the raw data.

We now analyse the selection process more in detail and estimate the following probit model:

$$P(L_i = 1|Z_i) = \Phi\{\theta_0 + \theta_1 GPA_i + \theta_2 C_i + \theta_3 (GPA_i \times C_i) + \theta_4 X_i\} \quad (1)$$

where L_i is a dummy equal to 1 if individual i eventually appears in one of the lawyers' registers within 5 years since graduation, GPA_i is the (normalised) GPA in law school and C_i is a dummy indicator that takes value 1 for those who have family members who are already in the legal profession. X_i is a set of controls that includes the high-school leaving grade, parental education (a dummy for having at least one parent with college education), parental occupation (a dummy for at least one parent employed as professional, manager or entrepreneur), gender, age at graduation and dummies for graduation years, district of origin, district of the written exam grading and university.[18] We assign to all individuals the exam grading district that was paired with the district associated with their university 3 years after graduation, which is the earliest year when they could sit the written test. Following conventional notation, $\Phi(\cdot)$ is the cumulative density of the standard normal distribution and we use Z_i to indicate the full set of explanatory variables.

The estimated coefficients are reported in Table 2. Consistent with the evidence in Figures 3 and 4, the results indicate that both GPA and connections are positively associated with the probability of entering the legal profession. However, their interaction has a negative coefficient, suggesting that connections favour especially those with lower GPA, or that GPA matters only for the non-connected. Female graduates are less likely to become lawyers whereas it seems helpful to have parents in good jobs. There are two slightly surprising results in Table 2. The first is the negative coefficient of the high school grade suggesting that, conditional on GPA, the best high school graduates choose not to be professional lawyers. The second is the small and insignificant effect of parental education, which can perhaps be rationalised by the fact that these results are conditional on academic performance.

To better understand the importance and the magnitude of the effects reported in Table 2, Figure 5 shows the differences in the predicted probabilities of entering the legal profession for connected and unconnected candidates by deciles of the distribution of GPA.

The figure shows that connected candidates are systematically more likely to become licensed lawyers, especially at low levels of GPA where the difference is approximately 8 percentage points (over an average of about 54%). Since GPA matters the most for unconnected candidates, the gap in the probability of entering the legal profession narrows as one moves up along the distribution of GPA and it becomes insignificant only from the eighth decile onward. The linearity of the estimates reported in Figure 5 is imposed by the linear interaction used in the probit model of equation (1) but the main findings are robust to alternative less parametric specifications.

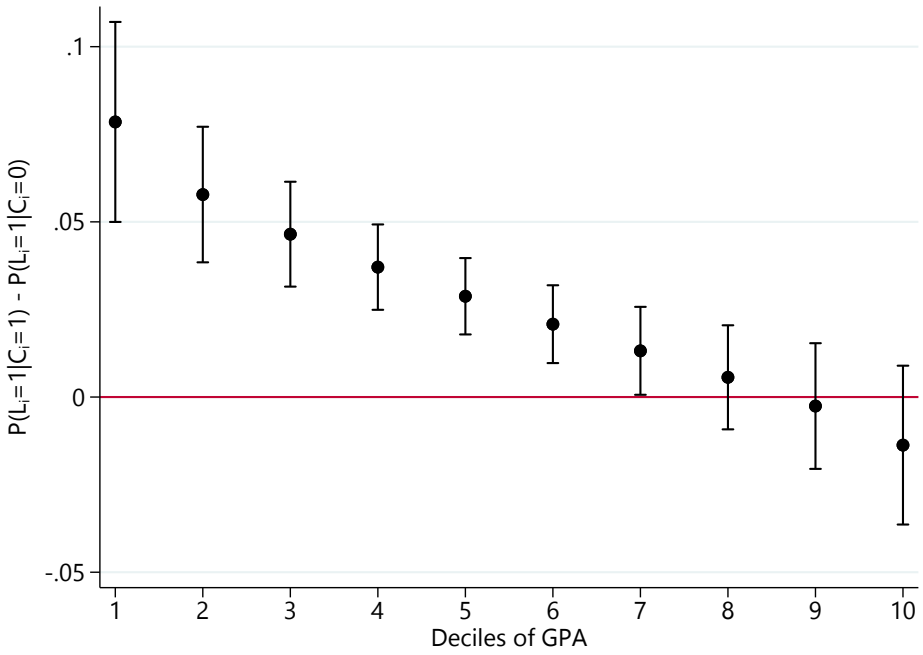
[18] The occupational definition follows a relatively standard definition of social groups that is also adopted by the Italian National Statistical Institute (ISTAT, 2017).

Table 2: Selection into the legal profession

Dep. Variable	$P(L_i = 1\|Z_i)$
GPA[a]	0.073***
	(0.015)
1=connections[b]	0.122***
	(0.024)
GPA $\times$ [1=connections]	-0.081***
	(0.018)
High school grade[c]	-0.032***
	(0.010)
1=female	-0.067***
	(0.018)
1=graduate parent[d]	-0.030
	(0.020)
1=parent(s) in high-ranked occup.[e]	0.081***
	(0.019)
Observations	24,260
Mean of dep. variable	0.544

[a] Average grade in all exams at the law school. Standardised within each university.
[b] 1=some connections; 0=no connections.
[c] Standardised over the sample.
[d] At least one parent with a university degree.
[e] At least one parent employed as professional, entrepreneur or manager.
Additional controls include fixed effects for university, district of origin and exam grading district, year of graduation, and age at graduation. Bootstrapped standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 5: Differences in the probability of entering the legal profession by GPA and connections



Note: Predictions based on estimates Table 2. The vertical bars represent 95% confidence intervals.

4.1 Human capital or favoritism?

The results in Table 2 and Figure 5 suggest that connected graduates are more likely to enter the legal profession than non-connected ones and that this difference is particularly pronounced at lower levels of GPA.

It is natural to think of two possible explanations for this pattern. First, human capital accumulation within the family might lead connected graduates to learn additional occupation-specific skills from their parents or relatives and eventually outperform low-GPA non-connected candidates at the entry exam. Second, connected candidates may benefit from some form of favouritism during one or more stages of the selection process. For example, established senior lawyers may lobby or put pressure on colleagues who sit in the exam commissions to facilitate entry into the profession by young members of their families who might otherwise be unlikely to pass the exam.

Of course, human capital and favouritism might be operating at the same time and our data do not allow us to precisely identify their relative importance. However, in this section, we present several pieces of empirical evidence which all seem to suggest that human capital is unlikely to be the most important channel in our setting.

We start with the results in Table 3, where we show that connected law school graduates do not seem to perform better than their unconnected peers during their university careers. The table reports results from a simple OLS regression with GPA as a dependent variable and our indicator of connections as the main explanatory variable. The regression also includes our standard set of controls. The results clearly show the lack of any meaningful and statistically significant association between GPA and connectedness with the legal profession. In our simplest specification (column 1), the estimated coefficient on the dummy indicator of connectedness is equal to -0.016 (1.6% of a standard deviation, given the standardisation of GPA) with a standard error of 0.014, implying that a standard one-sided test assigns a probability of 86.1% to the coefficient taking any non-positive value.

The following columns investigate potential nonlinearities. Column 2 categorises connections into three broad groups: no connections (the baseline), few connections (1 to 3), and many connections (4 or more). Columns 3 and 4 further look at the linear number of connections and its square. None of these specifications points towards a positive effect of connectedness on GPA. If anything, these results indicate that law school graduates with older relatives in the profession tend to have slightly lower GPA, although the estimated coefficients do not reach conventional levels of statistical significance.

For completeness, Table 3 reports the coefficients of a few control variables and they appear to be consistent with simple intuition. GPA is positively associated with high school grades and with parental education and female students do better than male students.

One may argue that having a relative in the profession may help develop skills that might not be captured by performance in university exams. To address this concern, we replicate the analysis from Table 3 using other skill-related indicators that we observe in our data—knowledge of foreign languages, computer skills, participation in volunteering activities, and previous study abroad experiences (Table B1 in the Appendix). We do not find any meaningful significant differences between connected and unconnected graduates for any of these variables.

The next set of empirical results investigates the relationship between ability, connectedness, and firm size—an indicator of firm quality.

So far, we have shown that the accumulation of occupation-specific human capital during

Table 3: Occupation-specific human capital

Dep. variable= GPA[a]	(1)	(2)	(3)	(4)
1=connections[b]	-0.016	-	-	-
	(0.014)			
1= few connections[c]	-	-0.014	-	-
		(0.014)		
1= many connections[c]	-	-0.029	-	-
		(0.020)		
Number of connections	-	-	-0.001*	-0.001
			(0.001)	(0.001)
Number of connections^2	-	-	-	-0.000
				(0.000)
High school grade[d]	0.403***	0.403***	0.403***	0.403***
	(0.006)	(0.006)	(0.006)	(0.006)
1=female	0.098***	0.098***	0.098***	0.098***
	(0.011)	(0.011)	(0.011)	(0.011)
1=graduate parent[e]	0.111***	0.112***	0.111***	0.111***
	(0.012)	(0.012)	(0.012)	(0.012)
1=parent(s) in high-ranked occup.[f]	0.041***	0.041***	0.040***	0.040***
	(0.012)	(0.012)	(0.011)	(0.011)
Observations	24,260	24,260	24,260	24,260

[a] Standardised within university.
[b] 1=some connections; 0=no connections
[c] few = 1-3 ; many = 4+
[d] Standardised over the entire sample
[e] At least one parent with university degree.
[f] At least one parent employed as professional, entrepreneur or manager.
All regressions include fixed effects for university, district, year of graduation, log size of district, log name frequency in district, and age at graduation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

formal training does not differ between connected and unconnected individuals.[19] Of course, it remains possible that connected individuals accumulate more occupation-specific human capital at later stages, perhaps due to access to better training opportunities in higher-quality firms during the apprenticeship period.

An important feature of our main findings in the previous section (Table 2 and Figure 5) is that connections increase the probability of selection into the legal profession mostly at the bottom of the distribution of GPA. For a mechanism based on human capital accumulation in the family to explain this pattern, there must be some sort of substitutability between the human capital accumulated during university and the learning that takes place at later stages. In Appendix 7 we derive this result more formally in a simple model of professional human capital formation that allows accumulation to take place in multiple steps, such as in law school and during the apprenticeship or in the family.

The most commonly used models of human capital formation are fundamentally based on the idea of complementarities between the various stages of the accumulation process and the bulk of the existing empirical evidence seems to support this view (see Elango, García, Heckman, and Hojman (2015) for a review). Nevertheless, substitutability remains theoretically possible and we want to explore its potential in explaining our main findings.

In Figure 6 we provide a first piece of empirical evidence to examine the possibility that connected lawyers with lower GPA may have better learning opportunities during their apprenticeship. We do so by looking at measures of the quality of the law firms where connected and unconnected individuals do their apprenticeships. We construct such measures using an auxiliary dataset covering the population of all lawyers and apprentices of one Italian region, Veneto. In this dataset, we observe both incomes and the law firm in which the lawyers and the apprentices are employed. We also observe surnames and other basic demographic information.[20] We use this dataset to estimate law firm fixed effects from a regression of lawyers' earnings.[21] We interpret these fixed effects as measures of the quality of the law firms and we match them to the apprentices doing their training in these law firms. Notice that we cannot perform this exercise on our main dataset because we do not observe apprentices' law firms. Using the data from Veneto, we can then check whether connected apprentices sort into firms with higher fixed effects compared to similar unconnected apprentices.

Figure 6 overlays the distributions of the firm fixed-effects for connected and unconnected apprentices and shows that the two overlap substantially. This result is at odds with the idea that connected apprentices train at better firms.

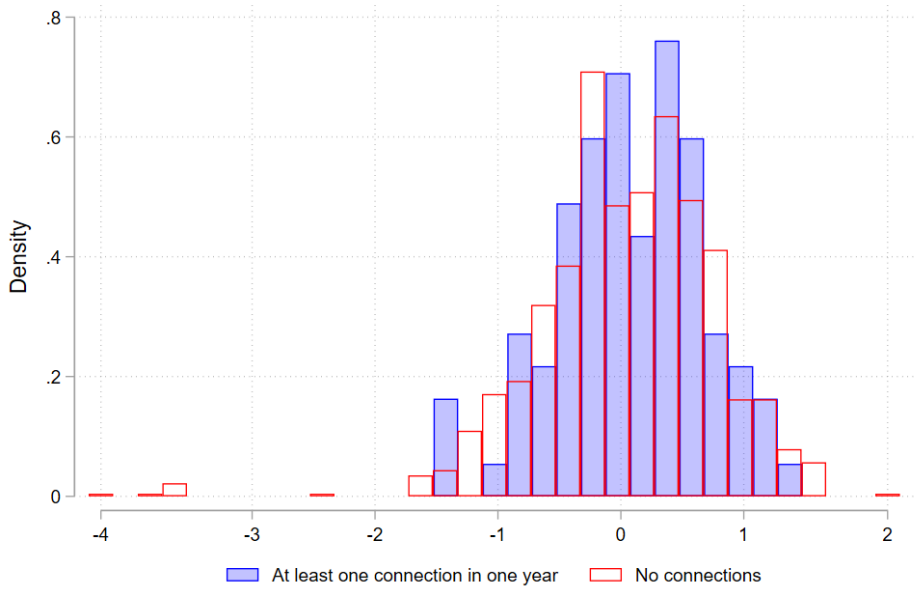
The Veneto data do not include GPA, so we cannot explore differences in firm fixed effects along the distribution of GPA. Thus, in Figure 7 we return to our main data and use firm size – which we observe – as a measure of firm quality, and investigate how it correlates with

[19] Lentz and Laband (1989) find similar evidence for medical doctors in the US.

[20] Veneto registers, excluding that of Venice, were collected in the context of a previous project focusing on this region (see Pellizzari and Pica (2010)). Unlike the data used in this paper, in Veneto we only observe lawyers and apprentices and we have no information on law graduates who choose a different occupation. Hence, we cannot study selection into the legal profession with that dataset.

[21] To estimate firms fixed effects, we restrict the analysis to licensed lawyers (i.e., we exclude apprentices, who should have zero earnings from legal practice) and regress (log) income on a gender dummy, a connection dummy, experience dummies, age dummies, region of birth dummies, the total number of surnames within each register/year, the total number of surnames within each province, year dummies and firms fixed effects. In this ancillary dataset, we do not have information on individual GPA, which implies that the firm fixed effect also captures the ability of the lawyers employed in the firm. We do not find this problematic for this specific exercise.

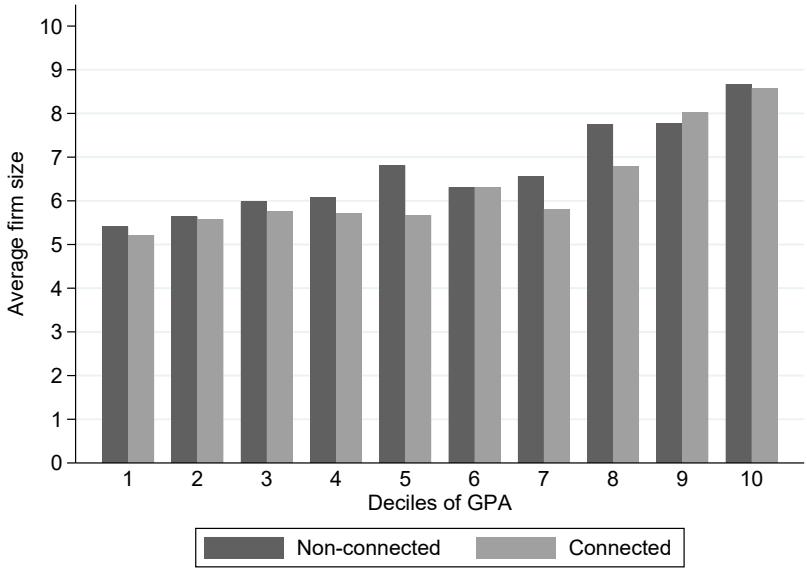
Figure 6: Distribution of law-firm fixed effects by connected and unconnected apprentices



Note: Firm fixed effects are produced from a regression of (log) income on firm dummies for the population of lawyers of the Veneto region. The additional controls included in the regressions are a gender dummy, a connection dummy, experience dummies, age dummies, region of birth dummies, total number of surnames within register/year, total number of surnames within the province and year dummies. Apprentices are excluded when calculating the fixed effects; lawyers from Venice are not part of the dataset (Pellizzari and Pica, 2010).

GPA. Using firm size as a measure of firm quality has a long tradition in labour and industrial economics (see, for example, Bartelsman, Haltiwanger, and Scarpetta (2013); Berlingieri, Calligaris, and Criscuolo (2018); Schmidt and Zimmermann (1991)) and, consistent with this literature, we find a substantial firm-size premium in earnings in our data.[22]

Figure 7: Average law-firm size by connectedness and GPA



If larger firms are also better and more productive, one would expect the best professionals to work there. Figure 7 shows the average firm size of connected and unconnected lawyers by deciles of GPA, and it clearly indicates that professionals with higher GPA tend to work in larger firms, regardless of connections. This is another result that appears to counter the idea that connected lawyers with low GPA have high professional ability. If this were the case, one would expect them to work in larger firms more than unconnected colleagues, both those with low and high GPA. This is clearly not the evidence shown in Figure 7.

Overall, the results in this section seem to be more consistent with the interpretation of our main findings based on some form of favoritism rather than human capital accumulation within professional dynasties.

5 An empirical model of selection into the legal profession

In this section, we further investigate the mechanisms by which connectedness can influence the process of selection into the legal profession. We do so by developing and estimating an empirical model where connections can affect both the probability of passing the bar exam and earnings in the profession. Agents are forward-looking and make occupational choices on the basis of expected future earnings.

[22] In unreported regressions, we find that the earnings of those working in law firms with more than 8 colleagues (top 25%) earn 75% more than those who are self-employed. Results are available from the authors upon request.

In Section 5.2 we use the model to simulate the selection process under different assumptions about the role of connections. We find that, if connections did not influence the likelihood of passing the bar exam, licensed lawyers would be much more positively selected on their GPA.

The model consists of a sequential process, mimicking the scheme in Figure 1. First, agents make occupational choices, namely whether they want to try to enter the regulated legal profession or not.[23] Those who choose the legal profession must do an apprenticeship and pass the entry exam, whereas the others can immediately start producing earnings in another non-regulated occupation. Agents who choose the legal apprenticeship but fail the entry exam work in some other non-regulated occupation, whereas those who successfully pass become lawyers and generate earnings from professional practice.

Agents are forward-looking, so the model is best described starting from the earnings equations and going backwards to the choice of doing an apprentice.

Earnings. We describe earnings using the following switching regression model:

$$Y_i = \begin{cases} \alpha_0^L + \alpha_1^L GPA_i + \alpha_2^L C_i + \alpha_3^L (GPA_i \times C_i) + \alpha_4^L \tilde{X}_i + u_i^L & \text{if working as a Lawyer} \\ \alpha_0^N + \alpha_1^N GPA_i + \alpha_2^N C_i + \alpha_3^N (GPA_i \times C_i) + \alpha_4^N \tilde{X}_i + u_i^0 & \text{if working as a Non-lawyer} \end{cases} \tag{2}$$

Y_i is the log of the monthly earnings that individual i self-reported in the 5-year post-graduation survey. To avoid dropping individuals with zero earnings, which is not uncommon for self-employed professionals, we simply add one to all records.[24]. As in equation (1), GPA_i is the GPA in law school and C_i is a dummy indicator of connectedness.

The switching between the two earnings equations is governed by equation (1) and identification is obtained by excluding the dummies of the grading district of the written exam from the set of controls $\tilde{X}_i$. Recall that the grading district is randomly assigned and it seems reasonable to assume that it only affects the probability of passing the bar exam and eventually becoming a lawyer and does not affect earnings directly. Figure B1 in Appendix B plots the estimated district fixed effects and shows that they correlate strongly with the probability of passing the bar exam.

The bar exam. We assume that agents pass the bar exam if their performance is above a certain threshold, which we allow to vary by district:

$$p(GPA_i, C_i, \tilde{X}_i) + \epsilon_i \geq t(R_r, C_i) \tag{3}$$

$p(GPA_i, C_i, X_i)$ is the deterministic component of performance, which may depend on both GPA_i and connections C_i, and ϵ_i is a random term that captures shocks that are realised at the exam (e.g. luck, fatigue, anxiety, etc.). $t(R_r, C_i)$ is the passing threshold, which we allow to depend both on the grading standard of the district R_r and connections. Notice that in this specification, connections can affect both performance (human capital) and the passing threshold. The grading standard of the district varies both cross-sectionally and over time due to the random assignment of districts marking the written exams.

Assuming linearity of both $p(\cdot)$ and $r(\cdot)$ and normality of ϵ_i, we can rewrite the probability of passing the exam as the following probit model:

$$P(L_i = 1 | T_i = 1, Z_i) = \Phi\{\theta_0^L + \theta_1^L GPA_i + \theta_2^L C_i + \theta_3^L (GPA_i \times C_i) + \theta_4^L X_i\} \tag{4}$$

[23] We are not interested in the choice of attending law school.

[24] y_i^L and y_i^0 are meant to measure the monetary returns from alternative occupational choices and we do not model explicitly the process of finding employment.

where T_i is a dummy indicator for agents who have completed their apprenticeship (and can take the bar exam) and the set of control variables X_i includes the marking district fixed effects, as in equation (1). The only difference between equation (1) and equation (4) is that the probability described by the latter is conditional on the apprenticeship ($T_i = 1$), thus it refers more precisely to the probability of passing the bar exam rather than the probability of entering the profession (which would be the product of the probability of completing the apprenticeship (equation (6) below) and passing the exam (equation (4)).

Apprenticeship. At graduation, agents choose whether to do a legal apprenticeship taking into account the probability of passing the exam and expected future earnings, in the legal profession or in other occupations. For simplicity, we assume that apprentices are not compensated.[25] Then, agent i chooses to do an apprenticeship and eventually sit the exam if expected future earnings in the legal profession, discounted by the probability of passing the bar exam, are larger than expected future earnings in other occupations:[26]

$$P(L_i = 1|T_i = 1, Z_i)(y_i^L - y_i^N) + v_i \geq K \tag{5}$$

where y_i^L and y_i^N are expected earnings in the legal profession and in other occupations, respectively.[27] v_i is an idiosyncratic preference component and K is the cost of the apprenticeship. We could further model K as forgone earnings plus additional direct costs of the apprenticeship but this would unnecessarily complicate the specification, so we leave it as a fixed parameter.

Assuming normality of v_i and with estimates of the parameters of equations (2) and (4), we can compute the probability in equation (5), up to the constant K. We fix the constant K by simply estimating the following reduced-form version of equation (5):

$$P(T_i = 1|Z_i) = \Phi\{\theta_0^T + \theta_1^T GPA_i + \theta_2^T C_i + \theta_3^T (GPA_i \times C_i) + \theta_4^T X_i\} \tag{6}$$

5.1 Estimation results

In this section, we present the estimates of the equations in the model, namely the probit models for the probability of doing the legal apprenticeship (equation (6)) and the probability of passing the bar exam (equation (4)) and the switching earnings regressions (equation (2)).

Table 4 shows the estimates of the two probits. The estimation samples for equations (6) and (4) are different. The likelihood of starting an apprenticeship is estimated on all graduates, whereas the estimation of the probability of passing the bar exam is restricted to the sample of those who actually sit the exam. Unfortunately, we do not have direct information about whether someone actually sits the exam, but we can approximate it quite precisely with those who did an apprenticeship. This is the only group of individuals who can take the exam and, given the length of the apprenticeship, it is unlikely that someone in this group does not take it.

Table 4 shows that GPA matters for both passing the exam and deciding to undertake the apprenticeship period, while connections matter only for the former. The interaction of these two terms is negative and significant only in the probability of passing the bar exam. This suggests that GPA is more important for unconnected candidates than connected ones. To further investigate this important issue and get a sense of the magnitudes, Figure 8 shows the differences in

[25] There is no legal requirement to compensate apprentices and, in practice, few of them receive a salary.

[26] We assume that the idiosyncratic components of earnings (u_i^L, u_i^N) in equation (2) are realized only upon entering the labour market and that their conditional means are zero.

[27] From equation (2), we can define $y_i^L = \alpha_0^L + \alpha_1^L GPA_i + \alpha_2^L C_i + \alpha_3^L (GPA_i \times C_i) + \alpha_4^L \tilde{X}_i$ and $y_i^N = \alpha_0^N + \alpha_1^N GPA_i + \alpha_2^N C_i + \alpha_3^N (GPA_i \times C_i) + \alpha_4^N \tilde{X}_i$.

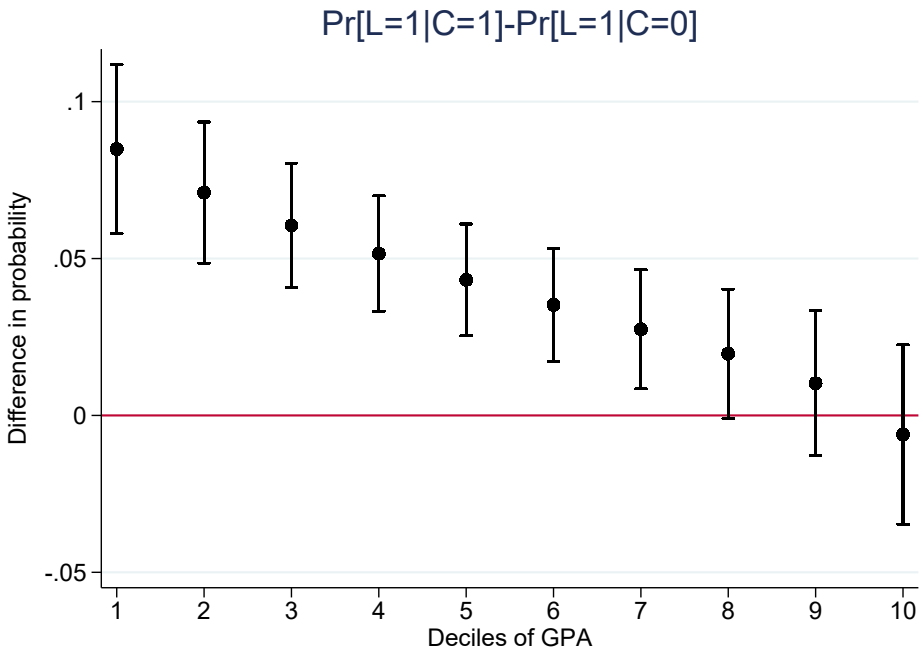
Table 4: Probabilities of apprenticeship and exam

	Probability of	
	doing an apprenticeship	passing the exam
	$P(T_i = 1\|Z_i)$	$P(L_i = 1\|T_i = 1, Z_i)$
GPA[a]	0.139***	0.041**
	(0.018)	(0.016)
1=connections[b]	0.051	0.126***
	(0.031)	(0.026)
GPA × [1=connections]	-0.026	-0.079***
	(0.022)	(0.019)
High school grade[c]	-0.073***	-0.015
	(0.013)	(0.011)
1=female	0.066***	-0.091***
	(0.024)	(0.017)
1=graduate parent[d]	0.036	-0.041**
	(0.026)	(0.021)
1=parent(s) in high-ranked occup.[e]	0.094***	0.065***
	(0.026)	(0.020)
grading district FE[f]	No	Yes
Observations	24,256	21,394
Mean of dep. variable	0.882	0.544

[a] Average grade in all exams at the law school. Standardised within each university.
[b] 1=some connections; 0=no connections.
[c] Standardised over the sample.
[d] At least one parent with university degree.
[e] At least one parent employed as professional, entrepreneur or manager.
[f] Fixed effects for the exam grading district.
All regressions include fixed effects for university, and year of graduation, and age at graduation. Probit coefficients are reported. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the predicted probabilities of passing the bar exam for connected and unconnected candidates by deciles of the distribution of GPA. The pattern in this figure is almost identical to Figure 5, suggesting that connections matter mostly in the probability of passing the bar exam and not so much in the choice of doing the apprenticeship.

Figure 8: Difference in predicted pass rates by GPA and connections



Note: Predictions based on estimates Table 4, column 2. The vertical bars represent 95% confidence intervals.

Connected candidates are systematically more likely to pass the exam, especially at low levels of GPA where the difference is of almost 10 percentage points. Interestingly, GPA matters the most for unconnected candidates and very little for connected ones. As GPA increases, the gap between unconnected and connected candidates narrows until it finally disappears from the eighth decile onward.

Table 5 reports the results of the estimation of the switching regressions for earnings in the legal profession and in others. Recall (i) that the dependent variable is the log of monthly earnings 5 years after graduation; (ii) that identification is obtained assuming that the randomly selected grading district matters only for passing the exam and not for earnings, and (iii) that the second step regressions include the inverse Mills ratio.

We find that a higher GPA commands higher earnings in all occupations, but more so in the legal profession. This is perfectly consistent with the idea that GPA in law school captures abilities that are more valuable in the legal profession than elsewhere. Notice also that high school grades are more important for non-legal earnings, presumably because this variable captures the returns to a broader set of skills in the absence of a measure of occupation-specific ability. Consistent with a large body of empirical evidence, we also find sizeable gender gaps in earnings (Azmat and Ferrer, 2017).

Table 5: Lawyer and non-lawyer earnings

	Lawyer earnings y_i^L	Non-lawyer earnings y_i^0
GPA[a]	0.237**	0.133***
	(0.039)	(0.046)
1=connections[b]	0.173***	-0.096
	(0.057)	(0.084)
GPA $\times$ [1=connections]	-0.122**	0.026
	(0.045)	(0.056)
High school grade[c]	0.063***	0.088***
	(0.024)	(0.031)
1=female	-0.627***	-0.658***
	(0.044)	(0.057)
1=graduate parent[d]	0.045	0.031
	(0.043)	(0.054)
χ^2 of exclusion restrictions	58.17	
Observations	24,260	24,260
Mean of dep. variable	5.960	5.691
Predicted earnings[f]	6.305	5.144
	(0.185)	(0.405)

[a] Average grade in all exams at the law school. Standardised within each university.
[b] 1=some connections; 0=no connections.
[c] Standardised over the sample.
[d] At least one parent with university degree.
[e] Fixed effects for the exam grading district.
[f] Earnings predicted at the sample average values of all explanatory variables.
All regressions include fixed effects for university, district and year of graduation and controls for age at graduation. Bootstrapped standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Having relatives in the profession is also associated with higher earnings, but only for those working as licensed lawyers. In addition, the interaction of GPA and connectedness is negative for lawyers (and non-significant for non-lawyers). The χ^2 test indicates that the randomly assigned grading district matters substantially for the probability of passing the exam.

Notice that the switching regression of Table 5 also identifies the causal effect of being a lawyer on earnings by comparing law school graduates who pass or do not pass the bar exam because they are randomly assigned to a marginally more or less lenient marking commission.[28]

The predicted earnings reported at the bottom of Table 5 show that lawyers earn substantially more than non-lawyers – approximately 2.19 times more in the first few years of their career. Although this figure may seem large, it is consistent with the findings of Bamieh, Cintolesi, and Pagliero (2024), who use a regression discontinuity design to identify the effect of passing the bar exam and report that, over a long period of almost 20 years, lawyer salaries are 2.5 times higher than those of non-lawyer law graduates. We add to their evidence by showing that this finding is robust to alternative identification assumptions.[29]

To get a better sense of the magnitudes of the effects implied by the estimates in Table 5, Figure 9 shows the predicted difference in log earnings in the legal profession between connected and unconnected lawyers along the distribution of GPA. In the bottom decile of the distribution, connected lawyers earn 40% more than their unconnected colleagues and it is only towards the very top of the distribution that this difference becomes statistically insignificant.

One possible interpretation of this effect is that unconnected lawyers, especially at the beginning of their careers, find it difficult to attract clients. Having relatives who can share their portfolios of clients might represent a significant advantage. This interpretation is also consistent with the strict regulations concerning professional practice. In Italy, like in many other countries in continental Europe, professional associations impose codes of conduct that regulate commercial practices, among other things. For example, it is often prohibited to approach clients who are already served by another professional and, until recently, commercial advertising was considered to be contrary to the "dignity of the profession". In addition, the code of conduct indicates price floors.[30] Being unable to lower prices and advertise their services, young lawyers find it extremely difficult to attract clients.

Of course, an alternative interpretation of this result is that connected lawyers with low GPA, have higher occupation-specific human capital along dimensions that are not captured by GPA. In Section 4.1, we have already presented various pieces of evidence suggesting that such an alternative explanation likely plays a relatively minor role in our setting.

5.2 Simulations

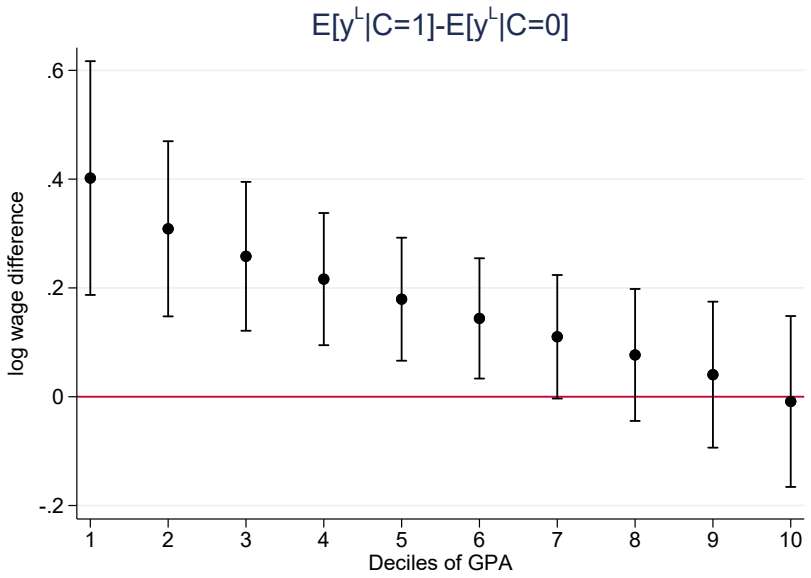
Using the estimates of our model, we can perform counterfactual exercises. We are particularly interested in understanding the role of connections in the selection process into the legal pro-

[28] An alternative method to obtain the same causal effect consists of pooling the observations of lawyers and non-lawyers in the same regression, with log earnings as the dependent variable and a dummy for lawyers among the explanatory variables (all other controls can stay the same). Our approach is more flexible than the traditional 2SLS, insofar as it allows the coefficients on all control variables to be different for lawyers and non-lawyers but it relies on additional distributional assumptions about the residuals of the two equations, that need to be normal.

[29] Recall that earnings are reported in intervals in our data and we cannot distinguish the zeros from small positive values, which presumably explains the relatively low absolute values of our predicted earnings.

[30] Some of these regulations were recently reformed in Italy, but they remain strongly present in the daily practice of the profession (Orsini and Pellizzari, 2012).

Figure 9: Predicted (log) wage differences between connected and unconnected lawyers by GPA



Notes: Predictions based on the estimates of Table 5, column 1. The vertical bars represent 95% confidence intervals.

fession. In our model there exist two potential channels through which family ties could influence the process of occupational choice. First, connected candidates are apparently facilitated in passing the bar exam. Figure 5 suggests that the effect of connections on the probability of passing the exam is stronger at lower levels of GPA, thus potentially generating negative selection or, at least, mitigating positive selection along this dimension. Second, connected individuals earn higher earnings than other colleagues and, once again, the effect is stronger at the bottom of the distribution of GPA. To the extent that individuals are forward-looking, we expect also this second channel to generate negative selection on academic ability.

We use the estimates presented in the previous section to simulate the probability of becoming a lawyer based on equations (3) and (5), i.e. the probability of passing the bar exam and the forward-looking probability of choosing to undertake the legal apprenticeship.

Eventually, we simulate the probability of being a lawyer as follows:

$$\widehat{P}(L_i = 1|Z_i) = \widehat{P}(L_i = 1|T_i = 1, Z_i) \times \Phi\left[\widehat{P}(L_i = 1|T_i = 1, Z_i)(\widehat{y}_i^L - \widehat{y}_i^N) - \widehat{\theta}_0^T\right] \quad (7)$$

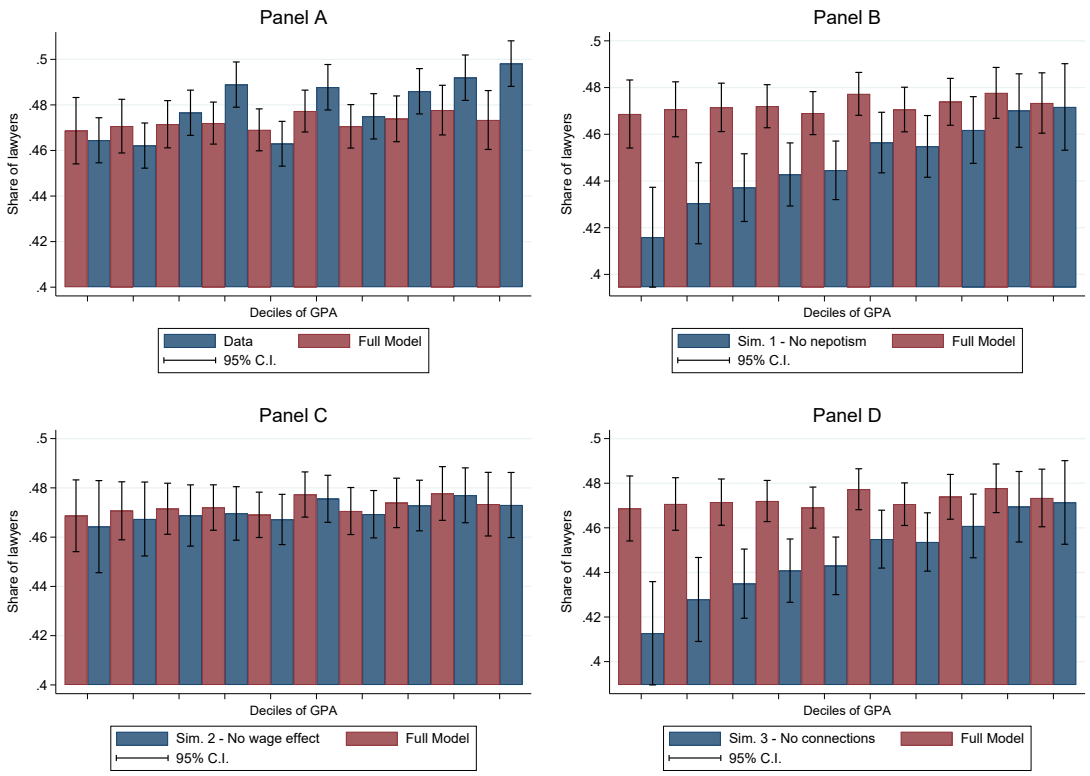
where $\widehat{P}(L_i = 1|T_i = 1, Z_i)$ is the predicted probability of passing the bar exam obtained using equation (4) and its estimated coefficients (see Table 4), $\widehat{y}_i^L$ and $\widehat{y}_i^N$ are the predicted earnings produced using equations (2) and the corresponding estimates from Table 5. $\widehat{\theta}_0^T$ is the constant of the reduced-form probit for the apprenticeship in equation (6).

We replicate these simulated probabilities multiple times under different assumptions and the results are summarised in Figure 10. First, for completeness, we present the comparison between the data and our model. The results, summarised in Panel A, show the average sim-

ulated probability of being a lawyer with the share of lawyers in the raw data, breaking down the results by deciles of the distribution of GPA. Although the model predicts slightly lower incidence of lawyers at the bottom of the distribution and slightly higher at the top, the overall fit is quite good and we can replicate the small degree of positive selection that is observed in the data. In fact, the confidence intervals of the model predictions overlap with those of the data for all deciles.[31]

The following panels replicate the simulations of the selection probabilities under different scenarios and compare results with the predictions of the original model, i.e. those reported in the first panel.

Figure 10: Counterfactual simulations exercises



Notes: The Figure reports the results of the counterfactual simulation exercises described in Section 5.2. Panel A reports the baseline results of the empirical model. Panel B reports the results of the simulations with no connections at the exam stage. Panel C reports the results of the simulations with no connections at the earnings stage. Panel D reports the results of the simulations with no connections at any stage. The confidence intervals have been generated replicating the calculations on both the raw data and the model over 1.000 bootstrapped samples.

Panel B shows results produced by eliminating the influence of family connections from

[31]The confidence intervals have been generated replicating the calculations on both the raw data and the model over 1,000 bootstrapped samples. We also checked that the model predicts well other relevant outcomes, such as earnings or the probability of doing the apprenticeship. Results are available upon request.

the probability of passing the bar exam, but not from the earnings process.[32] Results show that, when family connections do not influence the results of the entry exam, a substantial degree of positive selection on GPA emerges, especially due to fewer individuals with low GPA entering the profession. The simulation shows that, compared to the original model, the predicted share of lawyers declines by over 4 percentage points (from 0.45 to 0.41) in the lowest decile of GPA, whereas it increases by one percentage point at the top.

In Panel C, we repeat the simulation exercise, but this time we eliminate the effect of family connections from the earnings process and we maintain it in the exam.[33] Contrary to the previous analysis, the predicted shares of lawyers by deciles are now similar to the original model, suggesting that the effect of family connections on earnings has limited influence on the selection process.

Finally, in Panel D we consider a scenario in which family connections have no influence, neither on earnings nor on the exam. Consistently with the previous simulations, we find that positive selection is now much stronger than in the original model and the results are numerically very similar to those in Panel B.

Taken together, these simulations point to the fact that without connections there would be significantly fewer lawyers with low GPA, while high-GPA lawyers would not be penalized. In addition, eliminating connections would also slightly reduce the overall pass rate, hence the overall number of licensed lawyers. The average simulated pass rate declines from 47.2% in the model with connections to 44.8% when connections are completely eliminated.[34] Overall, without connections there would be fewer lawyers on the market with comparatively higher GPA, and the main channel through which connections impact the probability of becoming a lawyer is through the probability of passing the exam.[35]

Given the results presented in Section 4.1, we believe that the most likely interpretation of these findings is related to nepotistic practices in the entry exam. Presumably, this happens due to two factors: (i) the important role of incumbent lawyers in the process and (ii) the partial anonymity of the examination (in our specific case, this is due to the oral interview). In many systems of occupational regulation around the world, especially with regard to liberal professions, either one or the other or both of these factors are present and our results could easily generalise to most of these settings. The evidence we gathered about accessing the legal profession in the main advanced economies confirm that the entry process broadly follow a three-step procedure almost everywhere: a tertiary degree, a compulsory apprenticeship, and a state-administered exam, which is seldom completely anonymous (see Appendix C for additional details).

6 Robustness checks

In this Section, we present several robustness checks to complement our main analysis. Section 6.1 investigates the implications of measurement error in family connections. In Section 6.2, we study how our results change when we take into account that wage growth in the legal

[32] We set $\theta_2^L = \theta_3^L = 0$ in equation (4) and re-simulate the probabilities in equation (7).

[33] We set $\alpha_2^j = \alpha_3^j = 0$ for $j = \{L, N\}$ in equation (2) and re-simulate the probabilities in equation (7).

[34] Simulations with a fixed pass rate (either overall or by district) show very similar results in terms in selection.

[35] Alternative simulation exercises in which all individuals are corrected either by the most lenient or the strictest district show that selection varies as expected.

profession might be different than in other occupations. Finally, in Section 6.3 we replicate our main findings using the largest possible number of observations for each equation instead of using the same sample in all of them, as we do in Section 5.1.

6.1 Measurement error in connectedness

We measure family connections with family names and it is rather obvious that such a measure is subject to error. The direction of the error is difficult to predict. On the one hand, we might be missing some relevant family ties who do not share the same surname as the individuals in our sample. Given that Italy adopts the relatively standard practice of giving children the surname of the father, our measure clearly misses relatives coming from the maternal arm of the family. On the other direction, there can also be individuals who share the same surname and are nevertheless not linked to each other by any kinship connection. This is especially true for frequent surnames. However, we know from previous studies that only a very small share of the population holds very frequent surnames and, for the very vast majority of cases sharing the same surname is associated with a very high probability of being related to each other via some family link (Güell, Mora, and Telmer, 2015; Güell et al., 2018).

Some datasets contain information on direct parent-children connections (Chetty, Hendren, Kline, and Saez, 2014; Raitano and Vona, 2021). This is not the case in our data. Notice, however, that it is difficult to say whether, for the purposes of this paper, our surname-based measure of connections is better or worse than one relying on exact parent-child links. Using surnames is subject to the mis-classification errors discussed above, but it allows capturing family ties beyond mothers and fathers, like grandparents or uncles/aunts, who might also influence one's occupational career.

Unfortunately, there is little we can do with our data to identify or reduce the error in our indicator of family connections. Hence, we take a different approach and, instead of trying to reduce mis-measurement, we artificially increase it and we look at how much more error would be necessary to make our main results go away.

For brevity, we only focus on two outcomes, namely the probability of passing the bar exam and earnings, and we re-estimate the corresponding equations using an indicator of family connections where a given share of observations are randomly re-coded.[36]

Table 6 reports the results of this exercise for the probability of passing the bar exam. For comparison purposes, the first column simply reports our main results from equation (1) (compare with Table 2). In column 2, we replicate the same estimation, but we randomly recode 1% of the connected individuals as unconnected and we randomly take an equal number of unconnected individuals recoding them as connected.[37] The following columns perform the same exercise with higher shares of random re-classification. Of course the magnitude of the estimates changes across columns, but we find reassuring that our main results on GPA, connections and their interaction are qualitatively robust and tend to disappear only when we reclassify large shares of individuals, i.e., more than 30%.

In Table 7 we reproduce the same exercise for the earnings equation (2). For brevity, we

[36] Results for the other equations confirm the findings in this section and can be obtained upon request.

[37] We also experimented with other forms of recoding, such as recoding a given share of the connected and of the unconnected, and results are consistent with what we report in this section. An advantage of our specific choice of the exercise is that the share of connected individuals remains fixed and we can associate the differences in results exclusively to mis-measurement.

Table 6: Measurement error in connections and the probability of passing the bar exam

	Percentage of randomly re-assigned connections[a]						
	0%	1%	5%	10%	20%	30%	40%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
GPA[b]	0.073***	0.072***	0.060***	0.061***	0.053***	0.040***	0.034**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
1=connections[c]	0.122***	0.116***	0.107***	0.083***	0.059***	0.031*	0.009
	(0.024)	(0.024)	(0.022)	(0.021)	(0.019)	(0.018)	(0.017)
GPA × [1=connections]	-0.081***	-0.080***	-0.060***	-0.064***	-0.051***	-0.028*	-0.018
	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
High school grade[d]	-0.032***	-0.032***	-0.032***	-0.033***	-0.033***	-0.033***	-0.033***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
1=female	-0.067***	-0.067***	-0.067***	-0.068***	-0.068***	-0.069***	-0.070***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
1=graduate parent[e]	-0.030	-0.030	-0.029	-0.028	-0.026	-0.026	-0.025
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
1=parent high-rk occ.[f]	0.081***	0.081***	0.081***	0.082***	0.082***	0.083***	0.083***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	24,260	24,260	24,260	24,260	24,260	24,260	24,260

[a] Percentage of connected individuals who are randomly reassigned to having no connections. Each time an equal number of unconnected individuals is randomly assigned to be connected.

[b] Average grade in all exams at the law school. Standardised within each university.

[c] 1=some connections; 0=no connections.

[d] Standardised over the sample.

[e] At least one parent with a university degree.

[f] At least one parent employed as professional, entrepreneur or manager.

All specifications include fixed effects for university, district, exam grading district three years after graduation, year of graduation, and controls for age at graduation. Probit coefficients are reported. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Measurement error in connections and lawyers' earnings

	Percentage of randomly re-assigned connections[a]						
	0%	1%	5%	10%	20%	30%	40%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
GPA[b]	0.237***	0.230***	0.218***	0.219***	0.182***	0.172***	0.167***
	(0.039)	(0.039)	(0.038)	(0.038)	(0.036)	(0.035)	(0.034)
1=connections[c]	0.173***	0.174***	0.158***	0.156***	0.102**	0.043	0.016
	(0.057)	(0.056)	(0.053)	(0.049)	(0.045)	(0.042)	(0.040)
GPA × [1=connections]	-0.122***	-0.112**	-0.094**	-0.097**	-0.041	-0.026	-0.019
	(0.045)	(0.045)	(0.044)	(0.043)	(0.042)	(0.041)	(0.040)
High school grade[d]	0.063***	0.063**	0.061**	0.061**	0.061**	0.061**	0.061**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
1=female	-0.627***	-0.627***	-0.627***	-0.628***	-0.629***	-0.630***	-0.631***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
1=graduate parent[e]	0.045	0.046	0.050	0.052	0.054	0.056	0.058
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Observations	24,260	24,260	24,260	24,260	24,260	24,260	24,260

[a] Percentage of connected individuals who are randomly reassigned to having no connections. Each time an equal number of unconnected individuals is randomly assigned to being connected.

[b] Average grade in all exams at the law school. Standardised within each university.

[c] 1=some connections; 0=no connections.

[d] Standardised over the sample.

[e] At least one parent with university degree.

All specifications include fixed effects for university, district, year of graduation, and control for age. Results are obtained with a switching regression model, where the exclusion restrictions are fixed effects for the grading district and parental occupation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

only report results for earnings in the legal profession and, similarly to Table 6, we find that adding measurement error to our indicator of family connections only affects our coefficients of interest when we reclassify relatively large shares of individuals (above 20%).

Overall, we are reassured by the results in this section. Although we cannot exclude a priori that measurement error in connections affects the magnitude of our most important estimates, it seems unlikely that this bias is large enough to overturn their qualitative message.

6.2 Differential wage growth

One limitation of our data is that we observe earnings only at the very beginning of the career. More specifically, we observe self-reported earnings via the survey carried out at five years since graduation. For rational forward-looking agents, this is not the relevant measure of earnings they should use for their occupational choices. Rather, they should consider the present discounted value of the entire stream of expected future earnings.

Unfortunately, we do not have longitudinal earnings data for lawyers and for law school graduates who entered a different occupation. Nevertheless, we have collected from external sources the average annual growth rates of earnings for these two categories of individuals, broken down by gender.

For lawyers, we obtain this information from the professional social security administration (*Cassa Forsense*).[38] For non-lawyers we compute the growth rates of earnings from the official Italian Labour Force Survey (LFS), which contains information on field of study and occupation. We pool all surveys from 2009 to 2018 and we restrict the sample to graduates from law school who are not employed in a liberal profession. With this data, we estimate cross-sectional experience profiles, separately by gender and conditional on year effects.[39]

Figure 11 shows the earnings profiles implied by these growth rates and, to facilitate the comparison, we normalise initial earnings to one for all four categories. Apparently, earnings in the legal profession grow more rapidly than in other professions (but for law school graduates), but they are also more concave.

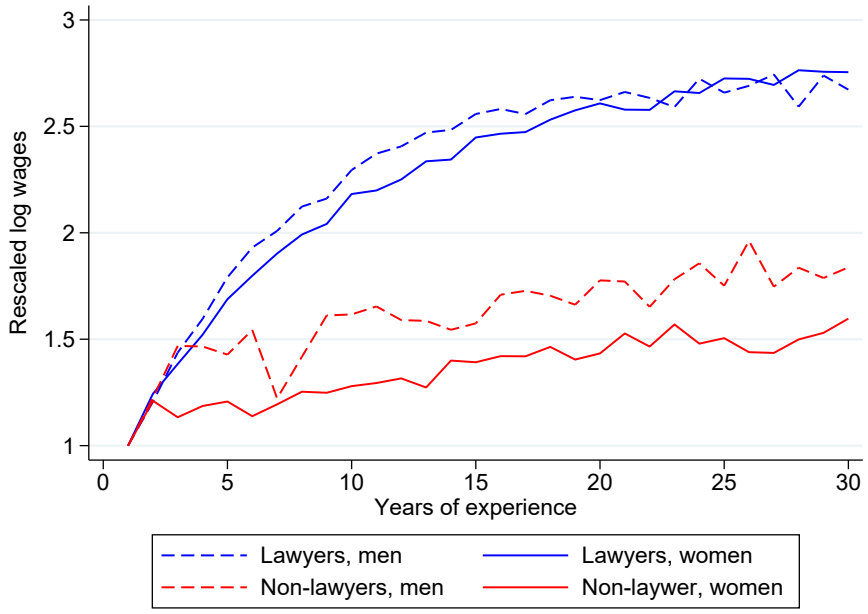
To understand the implications of the differential growth rates of earnings for our simulations, Figure 12 reproduces the simulation exercise by redefining expected (log) earnings as the full stream of discounted future earnings over 30 years of experience:

$$\widehat{E}\left[\Delta y_i | Z_i\right] = \widehat{E}\left[(y_i^L + \sum_{e=1}^{30} \gamma_{ie}^L) - (y_i^0 + \sum_{e=1}^{30} \gamma_{ie}^0) | Z_i\right] \tag{8}$$

[38] We thank Michele Raitano for providing us with these aggregate growth rates. The experience profiles are produced via a simple OLS regression with log earnings as a dependent variable and year dummies (data is available for 6 years: 1985, 1990, 1995, 2000, 2005 and 2008) and experience dummies (one per each year of experience) as explanatory variables. The regression is estimated separately for men and women. The coefficients on the experience dummies are the annual growth rates of earnings for lawyers (male and female) that we use in equation (8).

[39] Each yearly Italian LFS is a representative cross-section of the Italian population: unfortunately, it does not report the wages of self-employed individuals, including lawyers. We estimate the experience profiles in the same way they are estimated for lawyers (see footnote 38), namely via a simple OLS regression with log earnings as a dependent variable and year dummies and experience dummies (one per each year of experience) as explanatory variables. We estimate one regression for each gender and the coefficients on the experience dummies are the annual growth rates of earnings for non-lawyers that we use in equation (8).

Figure 11: Wage-experience profiles for lawyers and non-lawyers by gender



Source: Own calculations on ISTAT LFS 2009-2018 and Cassa Forense data.

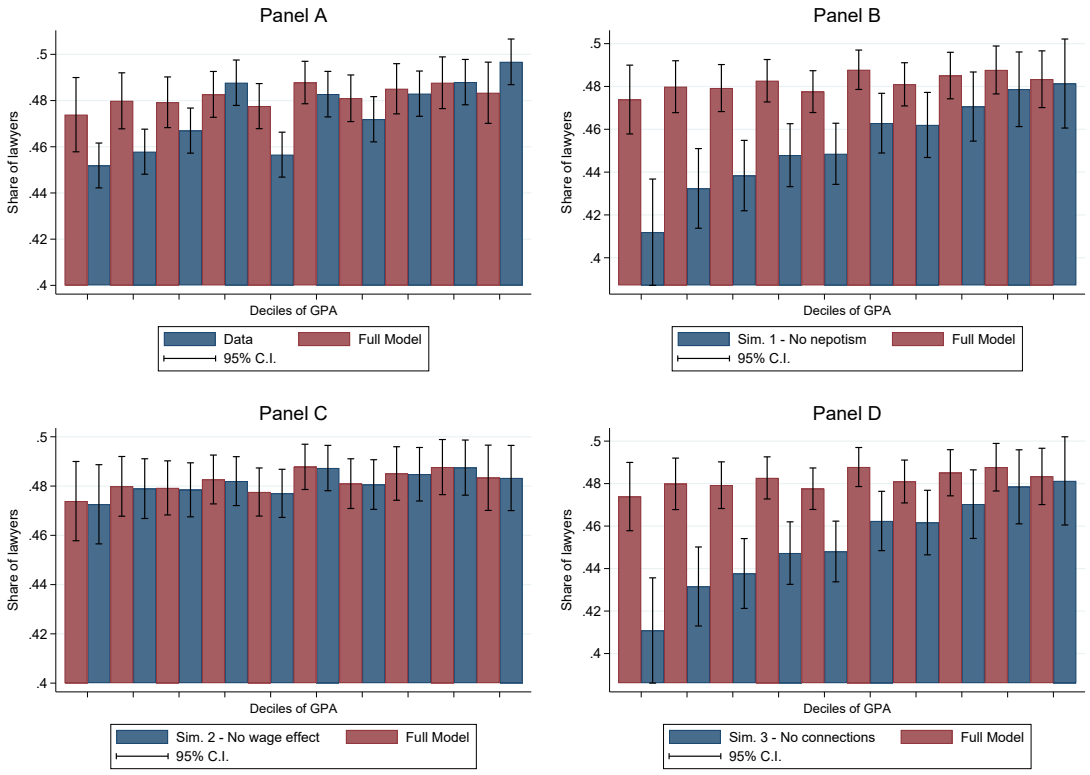
where γ_{ie}^{L} and γ_{ie}^{0} are the growth rates of earnings for lawyers and non-lawyers at experience e and the variation across individuals is restricted to gender. Obviously, we similarly redefine $\widehat{E}\left[\Delta y_i | Z_i', N_i = 0\right]$.

Results are similar to those in our main simulations of Section 5.2. Only a few minor differences are worth noticing. Consistent with the notion that individuals make forward-looking decisions, Panel A suggests that considering lifetime earnings allows the model to fit the data a little better, especially at higher deciles of GPA. Panel B now shows a slightly stronger effect of eliminating connections in the exam than in our baseline simulations. Evidently, considering longer careers makes the returns to the legal profession larger, especially for individuals with higher GPA, who already start off with higher earnings. One potential limitation is that the experience profiles might be different for connected and unconnected individuals and we, unfortunately, have no information about this. We do not expect particularly large differences outside the legal profession and it is hard to say whether the earnings of connected lawyers would grow faster or slower than those of their unconnected colleagues.

Given how we incorporated the earnings profiles in our simulation, it is not surprising to find that they do not change much the effect of eliminating the role of connections in earnings (see Panel C). In equation (8), the differential growth rates simply enter linearly and are unaffected by connections. Hence, the only reason why they might influence occupational choices is when expected returns are multiplied by the probability of passing the bar exam, which does not change in the simulation shown in Panel C.

Eventually, and as in our baseline simulation, eliminating the role of connections both in earnings and in the exam yields very similar results as when eliminating them only in the exam

Figure 12: Counterfactual simulations with wage-experience profiles



Notes: The Figure reports the results of the counterfactual simulation exercises with earnings' yearly growth rates described in Section 6.2. Panel A reports the baseline results of the empirical model. Panel B reports the results of the simulations with no connections at the exam stage. Panel C reports the results of the simulations with no connections at the earnings stage. Panel D reports the results of the simulations with no connections at any stage.

(Panel D).

6.3 Sample composition

In our main analysis of Sections 4 and 5.1, we estimate all the equations of the model using the same sample of observations with valid information on all the variables required for each and every equation. This approach allowed us to produce results that could be easily compared across equations, but it might also generate doubts about the implications of sample selection. In this section, we replicate our main estimates using the largest available sample for each equation separately.

Table 8: Occupation specific human capital with largest possible sample

Dep. variable= GPA[a]	(1)	(2)	(3)	(4)
High school grade[b]	0.405***	0.405***	0.405***	0.405***
	(0.004)	(0.004)	(0.004)	(0.004)
1=connections[c]	-0.007	-	-	-
	(0.011)			
1= few connections[d]	-	-0.005	-	-
		(0.010)		
1= many connections[d]	-	-0.020	-	-
		(0.014)		
Number of connections	-	-	-0.001***	-0.002***
			(0.000)	(0.001)
Number of connections^2	-	-	-	-0.000
				(0.000)
1=female	0.106***	0.106***	0.106***	0.106***
	(0.008)	(0.008)	(0.008)	(0.008)
1=graduate parent[e]	0.150***	0.150***	0.150***	0.150***
	(0.008)	(0.008)	(0.008)	(0.008)
Observations	46,619	46,619	46,619	46,619

[a] Average grade in all exams at the law school. Standardised within each university.
[b] Standardised over the sample.
[c] 1=some connections; 0=no connections
[d] few = 1-3 ; many = 4+
[e] At least one parent with university degree.
All regressions include fixed effects for university, district, year of graduation, log size of district, log name frequency in district, and age at graduation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8 is the equivalent of Table 3 implemented on the largest available sample of individuals for whom information on our human capital indicators (and controls) is available. Despite the large difference in sample sizes, results remain very similar, both qualitatively and quantitatively. The large difference in samples arises because, when we restrict the analysis to the common sample, we need to drop several individuals for whom we have no information on earnings and apprenticeship. These variables are gathered via the post-graduation surveys, whereas most of the information needed to produce the estimates in Table 8 comes directly

from administrative archives, where the issue of missing data is minimal.

Table 9 reproduces a similar exercise with reference to Table 4 in our main results of Section 5.1. The number of available observations is smaller than in the previous Table 8 because we now need to use information about whether the individuals have ever done a professional apprenticeship. Yet, sample size is substantially larger than in the common sample and some important differences in the estimates are present. For example, connections now appear to affect not only the probability of passing the bar exam but also the decision to undertake an apprenticeship, although the magnitude of the latter coefficient is less than half the former. Moreover, the effect of GPA on the exam is now more distinctively different between connected and unconnected individuals. Overall, our main results are confirmed.

Table 9: Probabilities of apprenticeship and exam with largest possible sample

	Probability of	
	doing an apprenticeship	passing the exam
	$P(T_i = 1\|Z_{ir})$	$P(E_i = 1\|T_i = 1, Z_{ir})$
GPA[a]	0.128***	0.004
	(0.016)	(0.013)
1=connections[b]	0.067**	0.140***
	(0.027)	(0.021)
GPA × [1=connections]	-0.034*	-0.080***
	(0.019)	(0.015)
High school grade[c]	-0.074***	-0.037***
	(0.012)	(0.009)
1=female	0.053***	-0.084***
	(0.021)	(0.016)
1=graduate parent[d]	0.035	-0.047***
	(0.023)	(0.015)
1=parent(s) in high-ranked occup.[e]	0.089***	-
	(0.022)	
Grading district FE[f]	No	Yes
Observations	38,259	34,873

[a] Average grade in all exams at the law school. Standardised within each university.
[b] 1=some connections; 0=no connections.
[c] Standardised over the sample.
[d] At least one parent with university degree.
[e] At least one parent employed as professional, entrepreneur or manager.
[f] Fixed effects for the exam grading district.
All regressions include fixed effects for university, district, year of graduation, and age at graduation. Probit coefficients are reported. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Finally, in Table 10 we look at earnings, expanding the size of the sample as much as possible for each equation. Once again, results are comparable to those reported in our main analysis (Table 5).

Table 10: Lawyer and non-lawyer earnings with largest possible sample

	Lawyer earnings y_i^L	Non-lawyer earnings y_i^0	Selection $P(L_i = 1\|Z_{ir})$
GPA[a]	0.250***	0.126***	0.054***
	(0.040)	(0.047)	(0.013)
1=connections[b]	0.192***	-0.129	0.118***
	(0.057)	(0.089)	(0.021)
GPA × [1=connections]	-0.130***	0.040	-0.087***
	(0.046)	(0.058)	(0.016)
High school grade[c]	0.058**	0.108***	-0.012
	(0.024)	(0.035)	(0.009)
1=female	-0.629***	-0.658***	-0.094***
	(0.045)	(0.056)	(0.016)
1=graduate parent[d]	0.049	0.026	-0.048***
	(0.043)	(0.054)	(0.017)
Exclusion restrictions:			
1=parent(s) in high-ranked occup.[e]	-	-	0.038***
			(0.016)
Grading district FE[f]	No	No	Yes
Observations	36,778	34,022	36,778

[a] Average grade in all exams at the law school. Normalized within each university.
[b] 1=some connections; 0=no connections.
[c] Standardised over the sample.
[d] At least one parent with university degree.
[e] At least one parent employed as professional, entrepreneur or manager.
[f] Fixed effects for the randomly assigned exam grading district.
All regressions include fixed effects for university, district, year of graduation, and age at graduation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

7 Conclusions

The available evidence indicates that occupational regulation very often fails to improve the quality of professionals and the services they provide. Whereas this finding is well established, much less is known about the reasons for such a blatant failure. Of course, not knowing the reasons why occupational regulation so often fails, it is hard to offer policy advice.

In this paper, we provide what we believe to be the first systematic analysis of the mechanism by which occupational licensing selects professionals, and we highlight where and how the system breaks down. Our results suggest that the problem lies with the strong degree of intergenerational transmission of occupations that, while being a general phenomenon, is also particularly relevant in the presence of professional licensing.

Of course, our findings are specific to the context that we analyse, namely that of licensed lawyers in Italy, and they may not easily generalise to other settings. Nevertheless, the institutional environment of the legal profession in Italy is relatively standard with respect to that of most advanced economies and extend also to other intellectual liberal professions. Beyond lawyers, these liberal professions include accountants, notaries, architects, and pharmacists, among others. Hence, we believe that our work can be very informative for a large and important set of regulated professions around the world. For example, Koumenta and Pagliero (2018) report that in the European Union, approximately one-quarter of the self-employed and a similar share of all graduates work in a regulated profession.

Our analysis offers insights that can be immediately useful for policy interventions. We show that system malfunctions are mostly concentrated in the entry exam, which assigns an important role to incumbent professionals and does not guarantee the complete anonymity of the candidates. Incumbent lawyers might have an interest in facilitating connected candidates and they might be able to do so lawfully and possibly even unconsciously. For example, by statistical discrimination, commissioners might explicitly or implicitly assume that young lawyers coming from successful dynasties of professionals are better than others. Hence, any intervention that might preserve the anonymous identity of the candidates and limit or regulate the role of incumbents could have potentially important effects on selection.

In the specific case of Italy, one could change the composition of the local commissions and avoid having lawyers of one district interviewing candidates in the same district. For example, the random allocation of districts could be extended to commissioners. A more drastic solution would be to abolish the oral exam completely.

A number of important avenues remain open for future research. Among the most important ones is the investigation of output quality. The ultimate aim of the regulation is to guarantee the quality of services that are offered on the market, whereas our analysis focuses on the quality of providers. Measuring quality is a notoriously difficult task and it is already an important achievement that we were able to measure some dimensions of input quality in this paper. Measuring output quality is even more challenging and Anderson et al. (2020) is the only paper we are aware of that addresses it. In addition, we transparently acknowledge that our measure of quality or competence is imperfect, and improving it would be a very welcome development that could lead to a better understanding of the process of professional human capital accumulation.

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Appendix A. A model of professional human capital accumulation with endogenous effort

In this Appendix section, we sketch a simple two-period model of human capital accumulation with endogenous effort. For exposition clarity, we refer to the two periods as law school and apprenticeship, although they could be interpreted also as learning in the family and at law school.

We assume that individuals (with a certain predetermined level of general human capital A) first accumulate occupation-specific human capital at law school and then during the apprenticeship. At each step, human capital accumulation requires effort and depends positively on the stock accumulated up to that step.

We assume that the production function of occupation-specific human capital at law school (that we denote as GPA) takes the following form:

$$GPA = \Phi_1 A^{\beta_1} e_1^{\beta_2}$$

where e_1 denotes the amount of endogenous effort exerted in period 1. A and Φ_1 are positive parameters. The former reflects the fact that higher general human capital favours the accumulation of occupation-specific human capital; the latter parametrizes the effectiveness of the learning process at law school, a factor which is fully captured in our empirical specification by university fixed effects.

During the apprenticeship period (period 2) there is further accumulation of occupation-specific human capital S_2. We assume that:

$$S_2 = \Phi_2 A^{\gamma_1} (GPA)^{\gamma_2} e_2^{\gamma_3} \tag{9}$$

where e_2 denotes the amount of endogenous effort exerted in period 2 and Φ_2 is a positive parameter that reflects the quality of the law firm where the apprenticeship takes place. The amount of general and occupation-specific human capital previously accumulated (i.e. A and GPA) also contributes to the process. We assume that there are decreasing returns to scale in overall effort, i.e. $\gamma_2\beta_2 + \gamma_3 < 1$.

Finally, lifetime earnings are an increasing and concave function of the total amount of occupation-specific human capital S_2:

$$w = f(S_2)$$

We assume that individuals choose effort in each period to maximize lifetime earnings and that exerting effort is costly. For simplicity, we assume that $c(e_t) = \delta_t e_t$ for $t = 1, 2$ (any increasing and convex cost function would generate similar results). As a result, the individual solves the following problem:

$$\begin{aligned} & \max_{e_1, e_2} f(S_2) - \delta_1 e_1 - \delta_2 e_2 \\ s.t. & \\ GPA &= \Phi_1 A^{\beta_1} e_1^{\beta_2} \\ S_2 &= \Phi_2 A^{\gamma_1} (GPA)^{\gamma_2} e_2^{\gamma_3} \end{aligned}$$

The first-order conditions are:

$$\beta_2\gamma_2 f'(S_2)\Phi_2 A^{(\gamma_1+\beta_1\gamma_2)}\Phi_1^{\gamma_2}\left[e_1^{\beta_2\gamma_2-1}e_2^{\gamma_3}\right] = \delta_1 \tag{10}$$

$$\gamma_3 f'(S_2)\Phi_2 A^{(\gamma_1+\beta_1\gamma_2)}\Phi_1^{\gamma_2}\left[e_1^{\beta_2\gamma_2}e_2^{\gamma_3-1}\right] = \delta_2 \tag{11}$$

Notice that the marginal productivity of effort in each period depends positively on the effort exerted in the other period. Dividing equation (10) by equation (11) we get:

$$\frac{e_2}{e_1} = \frac{\delta_1}{\delta_2}\frac{\gamma_3}{\beta_2\gamma_2} \tag{12}$$

Notice the following:

1. Neither the Φs, nor A, nor the shape of $f(\cdot)$ affect relative effort between periods. This implies that it is never the case that the individual wants to make little effort in period 1, during law school, and a lot of effort in period 2, during the apprenticeship period, because the human capital accumulation process is more effective during the apprenticeship than at law school, i.e. because $\Phi_2 > \Phi_1$. Complementarity between GPA and e_2 in the production function of human capital in equation (9) implies that the agent does want to exert effort in period 1 even if Φ_1 is low relative to Φ_2 because this raises the marginal productivity of effort in period 2.

2. What matters in shaping relative effort is the relative marginal cost (δs) and the curvature of the human capital production function. The more concave the human capital production function in a specific period, the lower effort in that period.

Substituting back equation (12) into equation (10) we get:

$$\beta_2\gamma_2 f'(S_2)\Phi_2 A^{(\gamma_1+\beta_1\gamma_2)}\Phi_1^{\gamma_2}\left[e_1^{\beta_2\gamma_2-1}e_2^{\gamma_3}\right] = \delta_1 \tag{13}$$

$$\beta_2\gamma_2 f'(S_2)\Phi_2 A^{(\gamma_1+\beta_1\gamma_2)}\Phi_1^{\gamma_2}\left[e_1^{\beta_2\gamma_2-1}\left(e_1\frac{\delta_1}{\delta_2}\frac{\gamma_3}{\beta_2\gamma_2}\right)^{\gamma_3}\right] = \delta_1 \tag{14}$$

$$\beta_2\gamma_2 f'(S_2)\Phi_2 A^{(\gamma_1+\beta_1\gamma_2)}\Phi_1^{\gamma_2}\left[e_1^{\beta_2\gamma_2-1+\gamma_3}\left(\frac{\delta_1}{\delta_2}\frac{\gamma_3}{\beta_2\gamma_2}\right)^{\gamma_3}\right] = \delta_1 \tag{15}$$

The above equation implicitly defines the optimal amount of effort in period 1.

Assuming that $f(\cdot)$ is linear we get a closed-form solution (qualitatively, results hold with any $f(\cdot)$, provided that $f(\cdot)$ is not too concave):

$$e_1^* = \left[\frac{\beta_2\gamma_2\Phi_2 A^{(\gamma_1+\beta_1\gamma_2)}\Phi_1^{\gamma_2}\left(\frac{\delta_1}{\delta_2}\frac{\gamma_3}{\beta_2\gamma_2}\right)^{\gamma_3}}{\delta_1}\right]^{\frac{1}{1-\beta_2\gamma_2-\gamma_3}} \tag{16}$$

$$e_2^* = e_1^*\frac{\delta_1}{\delta_2}\frac{\gamma_3}{\beta_2\gamma_2} \tag{17}$$

The model shows that – holding fixed general human capital and the quality of the law school – a higher expected quality of the law firm (Φ_2) raises e_1^* and therefore also the amount of occupation-specific human capital accumulated at law school (GPA). Note that the quality of

the law firm in our context captures also the ability of senior lawyers in transferring soft skills to apprentices. Thus, candidates who are connected to lawyers who can transfer them soft skills are still incentivized to exert more effort during law school to get a higher GPA.

Of course, this result relies on the assumption that the amount of occupation-specific human capital accumulated at law school and effort during the apprenticeship are complements in the production of further occupation-specific human capital. Should instead the two inputs be substitutes, this result would be overturned. However, we view complementarity as the most natural and plausible assumption.

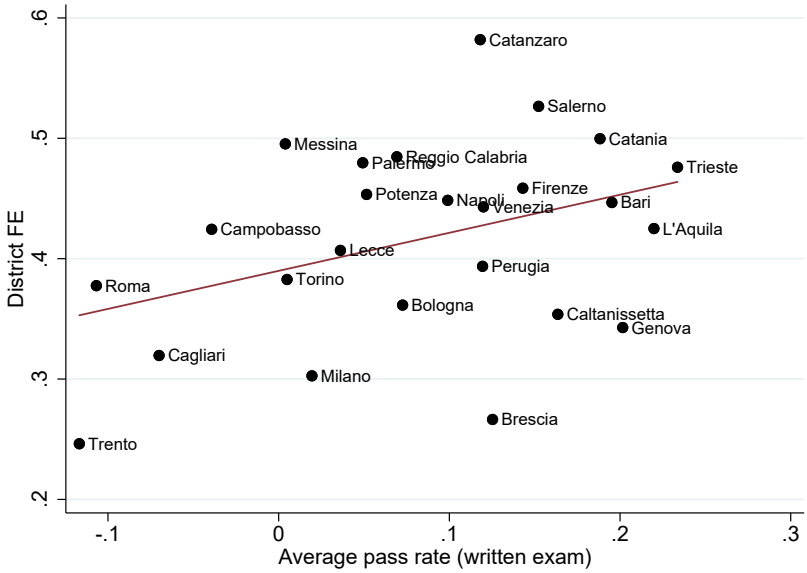
This result would be reversed, for instance, if the production function of human capital featured a high degree of substitutability between the human capital accumulated in law school and the effort exerted during the apprenticeship.[40] We believe that such a situation is highly unlikely, but it could be generated, for example, by connected individuals having access to better training firms during their apprenticeships. In this scenario, connected agents might choose to exert little effort in law school and then, thanks to their connections, recoup the lost human capital through apprenticeships in high-quality law firms. In this setting, GPA in law school might even be negatively correlated with professional ability at the end of the apprenticeship.

As a confirmation that this scenario does not square with empirical evidence, in Section 4.1 we showed that there is no evidence of connected individuals receiving additional training from high-quality lawyers during their apprenticeship.

[40]Notice that a small degree of substitutability would not suffice to undo the positive relationship between law school performance and final professional ability.

Appendix B. Additional results

Figure B1: District fixed effects and pass rates at the written exam



Note: Fixed effects for the exam grading district from Table 4, column 2.

Table B1: Additional measures of human capital

Dep. Variable	(1) Languages[a]	(2) Computer Skills[b]	(3) Volunteering[c]	(4) Study Exchange[d]
High school grade[e]	0.070***	0.018***	0.007**	0.002
	(0.003)	(0.003)	(0.003)	(0.002)
1=connections[f]	0.015*	-0.006	-0.003	0.002
	(0.008)	(0.007)	(0.009)	(0.006)
1=female	0.013**	-0.011*	0.004	-0.015***
	(0.006)	(0.005)	(0.006)	(0.005)
1=graduate parents[g]	0.086***	-0.008	0.036***	0.068***
	(0.007)	(0.006)	(0.007)	(0.005)
1=parent in high-ranked occ.[h]	0.020***	-0.020***	-0.005	0.035***
	(0.007)	(0.006)	(0.007)	(0.005)
	(0.481)	(0.435)	(0.564)	(0.339)
Observations	21,983	22,655	21,448	24,260
Mean of dep. variable	0.312	0.195	0.257	0.131

[a] Dummy equal to 1 if the respondent holds an internationally-recognized language certificate (e.g. TOEFL).
[b] Dummy equal to 1 if the respondent holds the "European Computer Driving License" (ECDL).
[c] Dummy equal to 1 if the respondent participates in volunteering activities.
[d] Dummy equal to 1 if the respondent has spent a study period abroad (e.g. Erasmus).
[e] Standardised over the sample.
[f] 1=some connections; 0=no connections
[g] At least one parent with university degree.
[h] At least one parent employed as professional, entrepreneur or manager.
All regressions include fixed effects for university, district, year of graduation, log size of district, log name frequency in district, and age at graduation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix C. International comparison

The overall structure of the licensing process for lawyers is quite similar across most industrialised countries, Italy included. Virtually everywhere aspiring lawyers need to graduate from law school, complete some compulsory vocational training and go through an exam-based admission process.[41]

The characteristics of the law degrees that give access to the vocational training are usually also highly uniform across countries. Within the European Union, agreements are in place to allow the automatic mutual recognition of degrees, and systems of minimum requirements determine the validity of degrees across a broader set of countries. In most Western countries, access to the legal profession requires the equivalent of 4 to 5 years of tertiary education. The subsequent professional apprenticeship is usually organized in collaboration between universities and the state with slight differences across countries. In most common law countries (e.g., UK, Canada, Australia), the young graduates go through a compulsory articling period, during which they train directly with senior members of the bar.[42]

In the US, graduates must enroll in a post-graduate American Bar Association (ABA) accredited law school, which includes some vocational training. Alternatively, some states accept work periods within the court system as an alternative to law school. Overall, even though a mandatory articling period is seldom required in the US, the system encourages aspiring lawyers to obtain on-field training through pro-bono programs, clerical work and supervised "Public Service Requirements" (now compulsory in certain law schools). In France, law graduates must obtain a state-administered vocational degree (*certificat d'aptitude à la profession d'avocat (CAPA)*), which normally requires attending a post-graduate law school (including both academic and vocational training), with entrance through a competitive examination. Germany requires two state-administered exams to enter the legal profession: a first one after university which allows successful candidates to qualify for two years of compulsory training period (*Referendariat*), and a second one after successful completion of the training. Israel follows a similar system, with two state-administered examinations (one after university and one after the vocational training), and one year of articling, which is accessible conditional on passing the first exam successfully. Other countries requiring a compulsory articling period after obtaining a law degree at university are Singapore (six months), Spain (two years), Poland (the duration depends on the specialization), Iran (18 months), Finland (four years), Denmark (three years), Japan (one year), India (two years).[43] All these countries then require passing a state-administered exam, which upon successful completion allows an individual to practice law.[44]

[41] One notable exception is the state of Wisconsin in the US, where individuals who obtained a degree in Law from an American Bar Association accredited school in the state may be admitted to the state bar through diploma privilege.

[42] Most common law countries require different vocational training and state-administered exams depending on whether a candidate wishes to pursue a career as a barrister or as a solicitor. Even though this difference does not exist in Italy, it does not change the admission mechanism substantially, as both careers require university training, articling, and passing a state-administered exam.

[43] Japan's vocational training takes place after sitting a nationally administered exam, which has the lowest success rate in the world, around 22%.

[44] The level at which an individual can practice may vary from country to country: in Italy, separate training and competitive examinations must be undertaken to practice as a judge or a notary. Common law countries usually distinguish between barristers and solicitors, and countries such as Poland and Hungary allow for different specializations.

The written exam is always anonymous, however many countries require some sort of oral examination (Italy, Germany), trial examination (Finland, Australia), or character and fitness requirements (US), which, by their nature, cannot be anonymous. Furthermore, most countries organize their local bar associations in a way similar to Italy, which are responsible for administering the final admission exam.

Given the information we collected, we observe that most countries broadly follow a three-step procedure to regulate access to the legal profession: a tertiary degree, a compulsory apprenticeship, and a state-administered exam, which is seldom completely anonymous. The similarity of the regulations across countries suggests that the mechanisms that we highlight in this study, notably the role of the inter-generational transmission of occupation, are likely to be present in many other contexts.