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THE IMPACT OF POTENTIAL LABOR SUPPLY ON LICENSING EXAM DIFFICULTY IN THE US MARKET FOR LAWYERS

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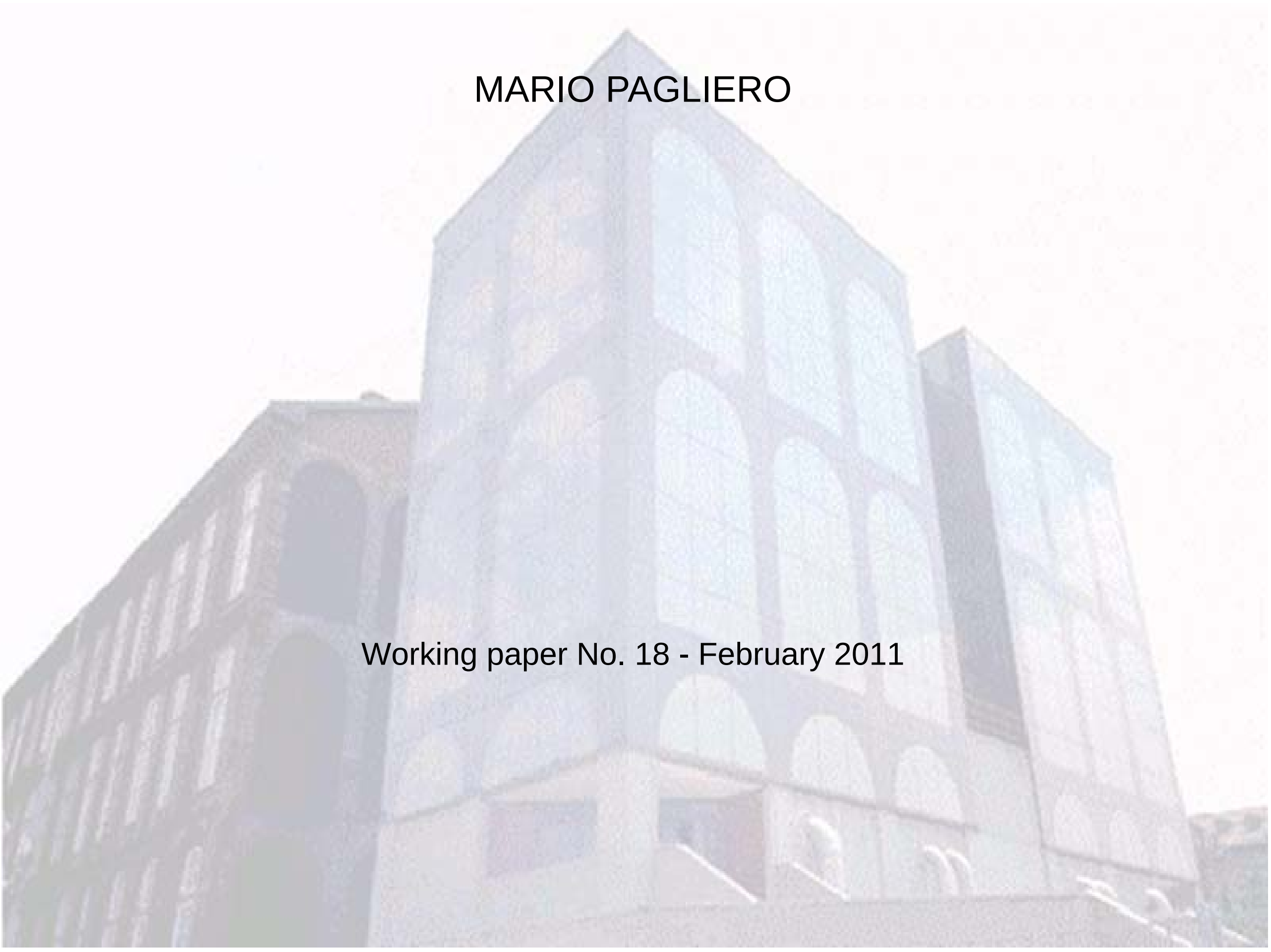

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The Impact of Potential Labor Supply on Licensing Exam Difficulty in the US Market for Lawyers

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Abstract

Entry into licensed professions requires meeting competency requirements, typically assessed through licensing examinations. In the market for lawyers, there are large differences in the difficulty of the entry examination both across states and over time. The paper explores whether the number and quality of individuals attempting to enter the profession (potential supply) affects the difficulty of the entry examination. The empirical results show that a larger potential supply leads to more difficult licensing exams and lower pass rates. This implies that licensing partially shelters the legal market from supply shocks.

JEL: L4, L5, J44, K2.

Keywords: occupational licensing, legal market, bar exam, minimum standards, entry regulation.

1 Introduction

For admission to most licensed professions, applicants must fulfill the standards set by state licensing boards. This usually means passing a licensing examination and meeting a

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number of educational, residency and moral character and fitness requirements. According to Kleiner (2000), over 800 occupations are licensed in at least one US state, including lawyers, accountants, auditors, teachers, nurses, engineers, psychologists, barbers and hairdressers. Occupational licensing directly affects 18 percent of US workers, more than those affected by either minimum wage or unionization. To enter a regulated profession, candidates have to meet the standards set by licensing boards.

To the extent that occupational licensing is replacing unions as the main labor market institution (Kreuger 2006), an understanding of the determinants of licensing restrictions is becoming increasingly important. This paper explores the possibility of a link between potential supply and the stringency of entry requirements. While the existence of such a relationship is generally accepted in the literature (a summary is provided in Section 2), there is no direct evidence as to whether potential labor supply affects entry requirements. This may be, in part, due to the difficulty in measuring the stringency of entry requirements: while licensing boards may adjust the difficulty of the exams, their behavior is not generally observable to the researcher, nor are measures of candidate quality readily available.

By focusing on the US market for lawyers and studying the grading procedures of the bar exam in detail, these challenges can be overcome. I find that accurate data is, in fact, available on bar exam difficulty and outcomes. Moreover, detailed data concerning the ability and the number of candidates and describing the two key aspects (quality and quantity) of the potential labor supply can also be procured. Another factor making this market well suited for the present study is that the structure of the bar exam remains the same in the states and years in my sample, whereas the exam difficulty and the number and quality of candidates vary significantly.

The empirical results of this paper reveal large discrepancies in exam difficulty across states. For example, when holding candidate ability constant, a change in exam difficulty from the standard in Alabama to the standard in California would imply a drop from 79% to 39% in the pass rate.[1] States with higher quality candidates or more numerous

[1] I use for comparison a normal score distribution, with a mean equal to the mean bar exam score and

candidates tend to have more difficult examinations. Also using within-state variability, I find a positive impact of the quality and number of candidates on the difficulty of the bar exam. Accounting for endogeneity (using instrumental variables) significantly reduces the impact of candidates' quality, but increases the estimated impact of the number of candidates. Overall, the paper shows that minimum entry requirements are relative standards, which respond to potential labor supply in the profession.

The magnitude of the impact of potential supply is considerable. Doubling the number of bar exam candidates implies an increase of about 8 percent in bar exam difficulty. This implies that the actual increase in lawyer supply is about half of the increase that would have happened without increases in standards. Thus, the bar exam partially shelters the legal market from supply shocks. More generally, it may dampen the impact of labor market policies targeted at increasing labor supply and may also affect diversity in the profession. The results of this paper are also relevant for the debate on the causes and consequences of occupational licensing and the applicability of competition rules in professional markets, both in the US and in the European Union (Andrews 2002; Paterson, Fink and Ogus 2003; European Commission 2004).

2 Related literature

The stringency of entry requirements is the key variable controlled by licensing boards. The stated objective of entry examinations is uniquely to protect the public from unqualified practitioners. In fact, when standards are changed, there is typically no reference to changes in market conditions. However, there is agreement among economists that minimum standards are expected to vary depending on (potential) labor supply in the profession, since their impact on social welfare and salaries in the profession crucially depends on the availability of potential entrants. Independently of the exact objective function of licensing boards, then, potential supply is a key determinant of licensing strin-

the variance equal to the mean variance in the US over the period 1981-2003. The grading procedures for the bar exam are described in Section 3.

gency.[2] However, there is surprisingly little empirical research on the subject. In practice, little is known on how and why entry requirements change.

In one of the early contributions to the literature on licensing, Maurizi (1974) finds some cross-sectional evidence of a negative correlation between the number of applicants and the pass rate on professional exams. He suggests that this correlation may be evidence of licensing boards increasing exam difficulty in response to excess supply. Although this evidence is intriguing, using pass rates as a measure of licensing strictness has clear limitations, given that they depend both on exam difficulty and candidate ability.

Leffler (1978) attempts to overcome this problem by developing a proxy for licensing difficulty in the market for physicians. Since candidates can take either a state or a national examination, the portion of candidates choosing the state exam is used to develop a proxy for state exam difficulty. Although this is a significant step forward in measuring the stringency of entry requirements, the indirect procedure makes this proxy very imprecise. Moreover, candidate ability remains unobservable, and endogeneity may seriously affect the analysis (p.182).

A related stream of literature has focused on the impact of licensing on wages and on the quality of professional services (Shepard 1978, HaasWilson 1986, Kleiner and Kudrle 2000, Kugler and Sauer 2005, Pagliero 2010), labor mobility (Pashigian 1979), the origins of licensing (Law and Kim 2004), and the impact on minorities (Law and Marks 2009). Harrington and Krynski (2002), and Harrington (2007) study the funeral industry, Federman, Harrington and Krynski (2006) the market for manicurists, and Timmons and Thornton (2008) radiologic technologists. This paper departs from this stream of literature, as it does not focus on the effects of licensing regulation, but rather on the

[2] There are two main views of licensing. According to Adam Smith (1776, I.x.c.5), the objective of licensing requirements "is to restrain the competition to a much smaller number than might otherwise be disposed to enter into the trade". According to this classic view, licensing is an inefficient institution that allows practitioners to capture monopoly rents by restricting entry (Friedman and Kuznets 1945, Stigler 1971). More recent theoretical studies have focused on the existence of asymmetric information on the quality of professionals (Akerlof 1970, Leland 1979, Shaked and Sutton 1981, Shapiro 1986). In the presence of asymmetric information, the licensing board takes into account both the quality-enhancing and competition-reducing effects of entry requirements. In this setting, if the objectives of the licensing board correspond to social welfare, licensing may be socially beneficial (the public interest theory of licensing, Leland 1979).

determinants of the stringency of entry regulation.

3 Brief overview of the bar exam and the data

The structure of the bar exam is the same in almost all states and has remained stable over the past two decades. The exam is administered twice a year, in February and July.[3] It consists of the Multistate Bar Examination (henceforth MBE), a standardized test, and essay and case questions. The MBE contains 200 multiple choice questions developed by the National Conference of Bar Examiners, who are also responsible for correcting this portion of the exam. Using the results of a small sample of questions, which are repeated in different examinations over time and across states, scores are scaled so that any single MBE score represents a standard level of performance, regardless of when and where the exam is taken. Hence, the mean MBE score for candidates taking the exam in a given state and year is a cardinal measure of their average quality, and exam results can therefore be compared across states and years.[4]

Essay and case questions are set by state boards and graded at the state level, according to criteria set by each board.[5] In this case, a particular score does not necessarily correspond to a standard level of performance across states and years. However, most states have introduced essay score scaling. The most common scaling procedure is mean and variance scaling. Mean and variance scaling requires that each essay score be transformed so that the mean and variance of the distribution of *scaled* essay scores is equal to the mean and variance of the standardized test scores (for each exam). The scaled essay scores are therefore not affected by exam-specific unobserved differences in exam difficulty or in the severity of grading procedures (Crocker and Algina 1986, Linn 1993).[6]

[3] Exceptions are Delaware, Nevada and North Dakota, where the bar exam is held only once a year.

[4] A more detailed description of the MBE can be found at http://www.ncbex.org. A similar standardized test is the Graduate Record Examination (GRE), often used in the admission process to graduate courses.

[5] Some states have recently started to use essay and case questions developed by the National Conference of Bar Examiners (known as the Multistate Essay Examination and Multistate Professional Test). When this is the case, the Conference provides state boards with possible exam questions and some analysis of the issues involved in each question in order to facilitate grading. Even when using this service, state boards grade the answers independently, using standards set locally.

[6] An alternative scaling procedure is quantile by quantile equating. The results of the two techniques

The *overall* scores (the weighted average of the standardized test and *scaled* essay test score) thus share the same metric across states and years and can be compared.[7] Since the pass-fail decision is based on overall scores, the observed minimum quality standards for each state also share a common metric and provide a simple measure of exam difficulty. (In the rest of the paper, I will refer to the overall minimum quality standard as exam difficulty, or the minimum standard).[8] Data on minimum standards is available from either 1984 or from the introduction of comparable standards (reported in Table 1, column 1), whichever is later, to 2009.[9] Table 1, column 2 reports any changes in minimum quality standards, while Column 3 reports the corresponding date of each change. Column 4 reports the minimum quality standard in the last year of the sample. Table 1 thus provides sufficient information for reconstructing the time series of the minimum standard in each state.

Minimum quality standard data is matched with the number of total and successful candidates for each examination, which is available from the National Conference of Bar Examiners for each state and year. The data set also includes data on MBE scores, consisting of MBE mean scores at the state level for each examination. Exam-specific information was furnished by the state Bar Association or the Supreme Court office responsible for administering the exam. I aggregate the information at the yearly level by summing the number of total and successful candidates for the two exams each year and calculating the mean MBE score (weighted by the number of candidates).

Variability in potential supply is significant. MBE mean scores vary between 129 and

are not necessarily the same but differences are empirically small (see Lenel 1992).

[7] They range between 0 and 200, like the MBE scores.

[8] The weights given to the two exam components may vary across states. Empirically, the weight given to the standardized test varies between 50 percent and 65 percent. For realistic distribution of scores and standards, however, these differences do not affect the comparability of minimum standards.

[9] The main source of standard and grading procedure data is The Comprehensive Guide to Bar Admission Requirements, published annually by the American Bar Association and the National Conference of Bar Examiners. This source is complemented by information from various issues of The Bar Examiner, published by the National Conference of Bar Examiners (NCBEX). When standards are comparable, but not expressed on a 0-200 point basis, the standards have been converted to a 0-200 basis to increase the consistency of Table 1. In the Comprehensive Guide there is some uncertainty as to when some standards changed. Wherever possible, additional sources have been used to pinpoint the exact date of change. In the few cases where no such data was available, the earliest date compatible with the information in the Comprehensive Guide was used.

151 (Figure 1) and the standard deviation is 3.6. The number of bar exam candidates also varies significantly (Figure 2 and Table 2). Figure 1 shows that states with better candidates tend to have more difficult examinations. States with more candidates also appear to have slightly more difficult examinations (Figure 2).[10] California, for example, has relatively difficult examinations and a large number of relatively good candidates. Alabama, on the other hand, has a small number of relatively weak candidates.

3.1 Data limitations

Data availability has been a long-standing issue in the literature on licensing.[11] In this context, my data set provides an exceptionally rich source of information on licensing board behavior. Still, there are three important limitations in the data set. First, information on exam difficulty is not available for all the states (Table 1 reports information on 37 states). The reason for this is that the introduction of comparable standards based on standardized scores is a relatively new development in entry examinations. Some states still use grading procedures that do not allow quantitative comparison. Moreover, although they follow the grading procedures described above, some states do not publish their minimum standards.

The second limit to the data set concerns the availability of mean MBE score data (measuring bar exam candidates' quality), since only 12 licensing boards chose to provide this information.[12] This problem is mitigated by using data on pass rates and exam difficulty to infer the mean MBE score for additional states and years. Appendix 1 describes in detail the construction of the data set. The third limitation of the data set is that exam difficulty is not frequently changed within a given state (see Table 1), as changes in admission rules typically involve a time-consuming bureaucratic process. This limits the inferences one can make about state specific responses to changes in potential

[10] While the correlation coefficient between the two variables in Figure 1 is positive and statistically significant, for Figure 2 it is positive but not statistically significant.

[11] Kleiner (2006, p.199) notes that "...perhaps the largest barrier standing in the way of analysis of occupational licensing is that there is no well-organized national data set waiting to be exploited. (...) Moreover, state licensing boards often are reluctant to provide (...) information to the researchers".

[12] Alabama, Arizona, California, Colorado, Connecticut, Georgia, Maryland, Massachusetts, Missouri, Texas, Utah, and Virginia.

labor supply.

4 Empirical results

I estimate regressions of the general form

$$D_{i,t} = b_0 + q_{i,t-1}b_1 + N_{i,t-1}b_2 + \lambda_t + \delta_i + u_{i,t} \tag{1}$$

where $D_{i,t}$ is the exam difficulty in state i and year t; $q_{i,t}$ is the average quality of candidates, as measured by the average MBE score; $N_{i,t}$ is the log of the number of candidates; λ_t and δ_i are state and year fixed effects, and $u_{i,t}$ is the idiosyncratic error term. Since changes in minimum standards are determined and published in advance, my empirical specification (1) allows for a lagged impact of potential supply on exam difficulty.[13] Summary statistics are provided in Table 2.

Cross Sectional Evidence

Table 3, column 1-2 report OLS estimates of the pooled and cross sectional correlation between potential supply and difficulty of the bar exam. The impact of the quality and the number of candidates is positive and significantly different from zero (adding year fixed effects does not significantly affect the estimated coefficients). The magnitude of the coefficients is broadly consistent with the correlations described in Figures 1 and 2. An increase of one in candidates average quality implies an increase of about 0.7 in exam difficulty (measured on the MBE scale). A ten percent increase in the number of candidates implies an increase of about 0.085 in exam difficulty.[14] States with more candidates tend to have more difficult entry examinations.

There are three reasons why the results in columns 1-2 may be a biased estimate of the impact of potential supply on exam difficulty. First, bar exam candidates are likely to be aware of the systematic differences in exam difficulty across states, so relatively good candidates may be more likely to take the bar exam in states with higher standards.

[13] Section 4.1 explores alternative specifications of (1).

[14] Similar results are obtained dividing the number of candidates by the population of the state (see Table A1, column 1).

Weaker potential candidates may be more likely to move to a different state or a different type of job. Such a selection mechanism may lead to an upward bias in the estimated impact of quality, and a downward bias in the impact of the number of candidates. Second, candidates preparing for a difficult exam may study more than those taking an easier examination. Reverse causality may thus further bias upwards the impact of candidate quality. Third, there may be some omitted state characteristics that independently lead to high entry standards and high potential supply.[15]

Within State Evidence

With these considerations in mind, I next focus on states that changed their entry standards in the sample period, so that state-specific unobserved characteristics can be accounted for by using state fixed effects. This implies a substantial reduction in sample size (from 37 to 11 states), but also a reduction in unobserved heterogeneity. To ensure that the reduction in sample size does significantly affect the results, Table 3, columns 3-4 reproduce the results in columns 1-2 using the reduced sample. The impact of the number and quality of bar exam candidates is still positive and significantly different from zero, and the magnitude of the effects is even larger than before.

Table 3, column 5 reports the results controlling for state-specific fixed effects.[16] The impact of the number and quality of bar exam candidates is still positive. The magnitude of the coefficients is quite different from that obtained using cross sectional variability. The impact of quality is about half of that obtained in columns 3-4, while the impact of the number of candidates is 60 percent higher. These changes are consistent with a significant self-selection of candidates across states, and/or exam difficulty affecting candidates' effort in exam preparation, and/or unobserved state characteristics affecting both potential supply and exam difficulty.

The state fixed effects account for significant sources of potential bias in the estimates, but endogeneity may still be a problem when using within state variability: increases over

[15] For example, a state may have a particularly good educational system, thus leading to a large supply of bar exam candidates and a high average quality. In principle, such culture of excellence may also affect bar examiners, who may then set relatively high standards for admission to the profession.

[16] As in columns 1-2, adding year fixed effects does not affect the estimated coefficients.

time in exam difficulty may in fact result in worse candidates taking the exam in a different state, moving to a different profession, or studying harder for the exam. All of these would imply an upward bias in the coefficient of quality, and a downward bias in the coefficient of the number of candidates. The issue can be addressed using instrumental variables; these must be correlated with potential supply but not with the error term in (1).

Instrumental Variables

Bar exam candidates typically need to have a law school degree, which usually requires at least three years of law school. Within any given state, then, the quality of students admitted to law school three years before a given bar exam is likely to be correlated with the quality of bar exam candidates (after controlling for state fixed effects), since many students take the bar exam in the state where they studied. A similar argument can be made for the number of first-year law school students, which is likely to be correlated with the number of bar exam candidates three years later (after controlling for state fixed effects). Information on LSAT scores of admitted students provides a good measure of the candidates' average quality (the LSAT is a standardized examination used by law schools to screen applicants). Detailed information on class size for each law school in each year is also available from the American Bar Association. The magnitude and statistical significance of these correlations can be estimated; hence the empirical relevance of the instruments can be tested.

The quality of admitted students and their class size is unlikely to be affected by exam difficulty three years later (after controlling for state fixed effects). This is an assumption that needs to be maintained, but can be reasonably justified. First, the first three cohorts of students taking the bar exam after a change in standards could not possibly have known about such a change when they enrolled in law school. Hence, reverse causality and selection at the time of entry into law school can be completely ruled out. Second, even for later cohorts, it is unlikely that changes in bar exam difficulty of the magnitude observed in the data could be a significant factor in determining law school choice. Compared to differences across schools in ranking, quality, and selectivity, observed differences in bar exam difficulty within a state seem unlikely to determine law school choice. Moreover, law school graduates can choose to take the bar exam in a state different from where they studied. Thus, it is not clear why an increase in bar exam difficulty would deter students from attending their school of choice (among those who have admitted them).[17]

These considerations suggest that the quality and number of first-year law school students (lagged three years) can be reasonably excluded from the equation (1). Table 3, column 6 reports the 2SLS estimates of the impact of potential supply on exam difficulty. Table 4, columns 1-2 report the first stage estimates. As expected, column 1 shows that the number of matriculated students is positively correlated with the number of bar exam candidates three years later. Similarly, column 2 shows that the quality of law school students (LSAT score) is positively correlated with the quality of bar exam candidates three years later (MBE score). These estimated effects are statistically different from zero at a one percent confidence level. The partial R^2 of the first stage regressions show that the instruments account for a significant portion of the variability of the two endogenous regressors, 13 and 38 percent respectively. The F-tests of the excluded instruments in the first stage are large, and the null of weak instruments can be rejected using the thresholds of Stock and Jogo (2002).[18]

The 2SLS estimates in Table 3, column 6 show that the impact of the number of bar exam candidates on exam difficulty is again positive and significantly different from zero at conventional levels. Its magnitude is larger than in column 5. Consider the impact of doubling the number of candidates (by drawing from a given score distribution) in a hypothetical state with mean exam difficulty and mean score distribution: with no change in exam difficulty, about 73 percent (which is the average pass rate) of the new candidates would pass the exam.[19] In practice, however, the exam difficulty will grow in response to the increased potential supply by 11 (about 8 percent), which implies that only 36

[17]The application and admission process is complex and noisy. Law schools are very selective: about half of law school applicants do not receive any admission. Even those who make it into law school do not have the chance of choosing among a large number of alternatives. On average, students entering law schools received just 2.8 admissions. Detailed information on the law school admission process is reported in Courty and Pagliero (2010).

[18]The weak instrument problem is generally more relevant in overidentified than in just identified models.

[19]These figures are obtained for an hypothetical state with mean exam difficulty (134) and Gaussian score distribution with mean equal to the mean MBE score (141) and standard deviation equal to 12 (see Appendix 2).

percent of the new candidates will pass the exam.[20] Hence, about half of the effect on the number of entrants in the profession is offset by the increase in exam difficulty. The increase in the magnitude of the impact of the number of candidates is consistent with some remaining endogeneity in the within state regression (column 5). In fact, selection effects may lead to a negative correlation between exam difficulty and the number of bar exam candidates thus biasing downward the impact of the number of candidates in OLS regressions.

The 2SLS estimate of the impact of candidates' quality is smaller than in column 5 and not significantly different from zero. This also supports the idea that within state results were affected by some remaining endogeneity. The IV estimate is also far less precise than the corresponding OLS estimate (the standard error is almost double than in column 5) and the 95 percent confidence interval of the 2SLS estimate is $[-0.56, 0.10]$. Hence, on the one hand, the null of no impact of candidates' quality cannot be rejected. On the other, the power of the test is rather small, and the 95 percent confidence interval still includes values which imply a significant impact of candidate quality on the number of entrants in the profession.[21]

4.1 Robustness Results

Although examinations are by far the most common admission procedure, admission to the bar is sometimes possible without taking the bar exam. Lawyers licensed in other states may be admitted on motion, typically on the basis of reciprocity agreements.[22] In principle, the number of these admissions may affect lawyer supply and may therefore

[20] The relation between pass rate and exam difficulty is non linear. Consider n candidates taking a professional examination. Each candidate receives an overall exam score s, which is a random draw from the distribution $F(s)$. The difficulty of the exam, D, is the minimum quality allowed in the market. All candidates who score at or above the threshold pass the exam and enter the profession. The number of successful candidates is then $L = [1 - F(D)]n$ and the pass rate $L/n = 1 - F(D)$ is non linear in D.

[21] For example, 0.1 still implies that about 12 percent of the effect of increases in candidate quality on the number of entrants in the profession is offset by increases in exam difficulty.

[22] In 2004, there were fewer than 6,000 admissions on motion, but over 49,000 by examination (NCBEX). Only in the District of Columbia is this the main mode of admission to the bar. However, the results are not affected when I exclude the corresponding observations from the sample. Direct admission of law school graduates (by diploma privilege) is significant only in Wisconsin, which has been excluded from the sample.

impact exam difficulty. When I include the number of admissions on motion in my specification, the results are not substantially affected (Table A1, columns 2-4). The number of lawyers admitted on motion has a positive impact on exam difficulty. Although the magnitude of such an effect is small, this finding reinforces the conclusion that bar exam difficulty is affected by the supply side of the market for lawyers.

In addition to the bar exam, admission to the legal profession also requires passing the Multistate Professional Responsibility Examination (MPRE). The MPRE is a standardized multiple-choice examination based on law governing the conduct of lawyers, including the disciplinary rules and principles of professional conduct. Data on the minimum scores required for passing this exam is available for each state.[23] If higher minimum MPRE score were used by licensing boards as a substitute for a more difficult bar exam, one would expect that states with higher MPRE thresholds would have an easier bar exam, all other variables being held constant. However, there are virtually no changes in MPRE minimum scores, so the results in Table 3, column 5 and 6 cannot be affected.[24]

Admission to the bar also depends on meeting educational standards and moral character and fitness requirements. Although educational standards impose significant costs to candidates, they do not vary significantly across states, and are fixed for a given state.[25] The procedures for moral character and fitness evaluation cannot easily be compared across states and years, but there is no evidence of significant within state variability.[26] Moreover, the existing evidence suggests that these procedures directly affect only a very small number of candidates.

Equation (1) assumes that licensing boards react to a single lag in potential supply.

[23]The MPRE is required for admission to the bar in all but three US jurisdictions. Data on the number of MPRE candidates and their performance is not available. As opposed to the bar exam, most candidates take the MPRE during their second or third year of law school, well before applying for the bar exam. Overall, the complexity of the subjects tested on the MPRE is much lower than on the bar exam. The breadth of the subject also suggests that much less effort is usually required to pass (this is consistent with the lower emphasis given by review courses to MPRE preparation).

[24]When we exclude the one state, Missouri, in which a change in MPRE standard occurred in the sample period, there is no change in the results.

[25]Overall, most bar exam candidates hold a law school degree. In 2004, for example, only two states had more than 10 percent of total candidates without a US law school degree.

[26]In 2005, 19 states have no published character and fitness standards in The Comprehensive Guide to Bar Admission Requirements.

However, licensing boards may consider changes in potential supply over multiple years when revising entry standards. Table A2 provides a second set of robustness results describing the impact of the average potential supply in previous years. The results show a positive impact of potential supply on licensing exam difficulty.[27]

5 Conclusions

Occupational licensing is one of the most important labor market institutions today, yet the actual behavior of licensing boards is rarely examined because of a lack of data and the complexity of licensing requirements. This paper is the first attempt to study the impact of potential supply on the difficulty of the entry examination. The main finding is that supply considerations are important for explaining licensing requirements. In particular, increases in the number of potential entrants lead to more stringent entry requirements, even after controlling for the average quality of candidates.

The existence of a relationship between potential supply and entry requirements has a number of potentially important implications. Professional markets may be sheltered from the impact of policies increasing potential supply. For example, a policy increasing the availability of legal education, while holding quality constant, may increase the number of candidates but only partially increase the supply of lawyers. A second implication is that licensing may affect how groups with different average ability are represented within a profession. Consider an increase in the number of bar exam candidates (as the outcome of a policy subsidizing legal education, for example) which equally affects all groups of candidates. As standards increase, groups with lower average performance become less represented among the successful candidates.[28] Even if a similar policy only increases the number of candidates from a group with relatively low average bar exam performance, a

[27] For 2SLS estimation (column 6), the definition of the instruments is changed accordingly. The results are not affected using weighted averages with decreasing weights for longer lags. Similar results are obtained directly including lags of the number and quality of exam candidates (although standard errors increase).

[28] Since bar exam outcomes vary dramatically across ethnic groups, this effect may significantly affect ethnic diversity within the profession (Wightman 1998, p.27, reports 30 percent difference in pass rates between black and white candidates).

decrease in the fraction of successful candidates from such group cannot be ruled out.

From this point of view, it is worth considering the possibility of certification, as an alternative to licensing (Kleiner 2006). Certification permits any person to practice the profession, but a public or private institution certifies those who have achieved a given level of competence. Certification may increase the effectiveness of policies affecting potential labor supply (without affecting the representation of minorities in the profession), while still revealing information on practitioners' quality.

At a more general level, this paper shows that entry requirements respond to market forces and, hence, are not uniquely based on some abstract notion of consumer protection, unrelated to market conditions.[29] The results of this paper are clearly consistent with licensing boards restricting entry into the profession in order to increase salaries (Friedman and Kuznets 1945, Stigler 1971). However, at least in principle, they could also be explained by public interest theory (Leland 1979), provided there were large asymmetric information and consumers' valuation for quality (as measured by the bar exam) were sufficiently high. In such circumstances, the social planner trades off the welfare gains from higher quality with those deriving from increased availability of professionals (and lower prices). Hence, a social planner could partly offset increases in potential supply by increasing exam difficulty.

In practice, it seems difficult to explain the results of this paper based on the public interest theory. First, there seems to be no agreement in the legal profession on the extent to which performance at the bar exam is an appropriate variable to be used for screening potential entrants in the legal market (Society of American Law Teachers 2002). There is also little evidence that consumers value increases in exam difficulty (Pagliero 2011), which is a necessary condition for the explanation based on public interest theory. Moreover, there is evidence that increases in exam difficulty lead to increases in entry salaries in the legal profession, but no evidence that they disproportionately increase the lower deciles of the salary distribution, which would naturally occur if the bar exam screened out

[29] The stated objective of the bar exam is "to protect the public, not to limit the number of lawyers admitted to practice" (ABA and NCBEX 2000, p. ix).

the worse potential entrants (Pagliero 2010). Finally, it is unlikely that differences in asymmetric information across states are large enough to justify the large differences in exam difficulty observed in the data. It is not clear why asymmetric information should be more relevant in states with difficult exams (e.g., California) then in states with easier exams (e.g., Alabama).

In conclusion, the existence of a link between potential supply and the stringency of licensing regulation opens the debate on the impact of supply shocks and the effectiveness of public policy in professional markets. It also contributes to the ongoing debate on how the interests of the profession may affect labor market regulation.

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Appendix 1. Data construction and sources

The lack of complete information on MBE mean scores is the main limitation of the data set. However, one can infer MBE scores using information on pass rates and exam difficulty. The procedure is based on the assumption that the shape of the score distribution is stable over time. More specifically, I assume that the state specific score distribution is Gaussian, with a constant standard deviation.[30]

Consider, for example, the exam outcomes in subsequent years for a given state, with a given *constant* exam difficulty. If the standard deviation of the distribution does not change over time, then changes in pass rate from one year to the next will reflect changes in the location of the score distribution. Since there is a one to one relation between pass rate and the mean of the score distribution, changes in pass rate can then be used to infer changes in mean MBE scores (details provided below).

There are advantages and disadvantages to taking this approach. The main advantage is that I can partly compensate for the difficulty in obtaining information from licensing boards. Second, I can efficiently use the information on the number of successful and unsuccessful candidates, which is very precise, complete and publicly available. Hence, I can increase the number of observations and significantly improve the quality of the inference.[31]

The main drawback of this approach is that some assumptions about the score distribution are necessary. However, I test the robustness of the results using alternative assumptions and the results are not affected. Moreover, the proposed method seems reasonably accurate in capturing mean MBE scores variability, independently of the specific functional form assumptions. Overall, the advantages from efficiently using the available information on pass rates seem to outweigh the disadvantages from maintaining some assumptions on the score distribution.

[30] Although there is no direct evidence at the state level, the available information at the US level suggest that the overall shape of the score distribution is stable over time. Moreover, the standard deviation of the score distribution does not show any significant trend, suggesting that the assumption of constant standard deviation is realistic.

[31] The results are consistent with what I would obtain using the original data, but they are much more precise.

The procedure for recovering MBE mean scores is the following:

1. Consider how exam-specific results (that is, two separate exams for each state and year) are generated. Each candidate passes the bar exam if his/her overall score is above a given threshold. In exam k, in state i, candidates' scores are independent draws from a normal distribution with mean $\mu_{i,k}$ (equal to the mean MBE score for exam k) and unknown variance σ_i^2. Hence, the number of candidates passing the bar exam is defined, for each examination, by

$$P_{i,k} \equiv \left[1 - F\left(\frac{D_{i,k} - \mu_{i,k}}{\sigma_i}\right)\right] N_{i,k}. \tag{2}$$

   where $F(.)$ is the cumulative distribution function of the standardized normal distribution. The likelihood of observing P_k successful candidates out of N_k exam candidates is then

$$L = \prod_k F\left(\frac{D_{i,k} - \mu_{i,k}}{\sigma_i}\right)^{(N_{i,k}-P_{i,k})} \left[1 - F\left(\frac{D_{i,k} - \mu_{i,k}}{\sigma_i}\right)\right]^{P_{i,k}} \tag{3}$$

   where $D_{i,k}$ is the observed exam difficulty. Using information for the 12 states for which I can observe $D_{i,k}$, $\mu_{i,k}$, $N_{i,k}$, and $P_{i,k}$, maximization of the log-likelihood $\ln L$ provides estimates of σ_i.[32]

2. Having estimates of the standard deviation of the score distribution, one can recover the mean score even when it is not made available by licensing boards. Given how the pass rate is determined, and the fact that we exactly observe $D_{i,k}$, $P_{i,k}$, and $N_{i,k}$, $q_{i,t}$ can be computed inverting the identity (2),

$$q_{i,k} \equiv D_{i,k} - \widehat{\sigma}_i F^{-1}\left(1 - \frac{P_{i,k}}{N_{i,k}}\right) \tag{4}$$

   where $\widehat{\sigma}_i$ is the estimated standard deviation of the score distribution in state i (or

[32] The results are not significantly different when I assume that scores have a beta distribution, which can accommodate some skewness in the score distribution.

the mean $\overline{\sigma} = \frac{1}{12}\sum_{i=1}^{12}\widehat{\sigma}_i$, if $\widehat{\sigma}_i$ cannot be estimated because $\mu_{i,k}$ is not available).

Appendix 2. Instrumental Variables

The two instrumental variables are the LSAT mean score and the number of matriculated students in law schools for each state and year. Information on LSAT scores of admitted students is available from the ABA Official Guide to Law Schools. As the LSAT is a standardized examination, results can be compared across states and years. Detailed information on class size is also available from the same source. Both LSAT score and class sizes are aggregated at the state-year level (average LSAT scores are appropriately weighted).

Data on the instruments is available from 2009 to 1993, then there is a 7 year gap between 1992 and 1986, and then again one usable set of observations for 1985. Given the large gap in the instruments, observations for the instrumental variables before 1993 were dropped. This implies that the usable observations in Table 3, column 6 is significantly smaller than for OLS regressions (given the lags in the IVs, we can only use observations between 1997 and 2009, rather than 1989-2009). However, when the values between 1986 and 1992 are interpolated, the number of observations can be increased up to the level of the OLS regressions in Table 3 (columns 3-5). The results are not significantly affected (see Table A1, column 5). This suggests that the shorter time series used for the 2SLS results in Table 3 are not driving the results.

Figure 1. Bar exam difficulty and candidates' quality.

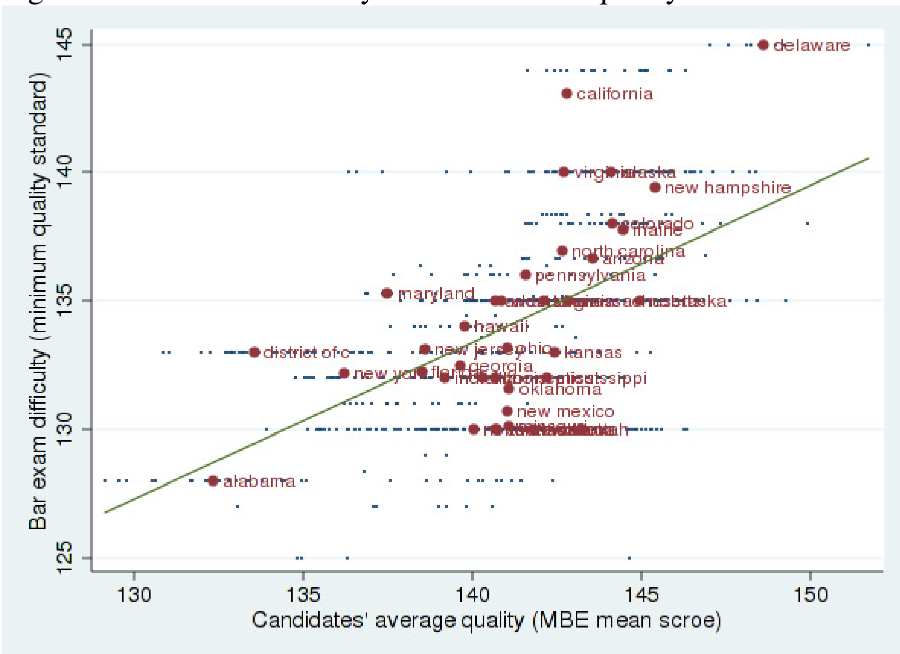

Figure 2. Bar exam difficulty and the number of candidates.

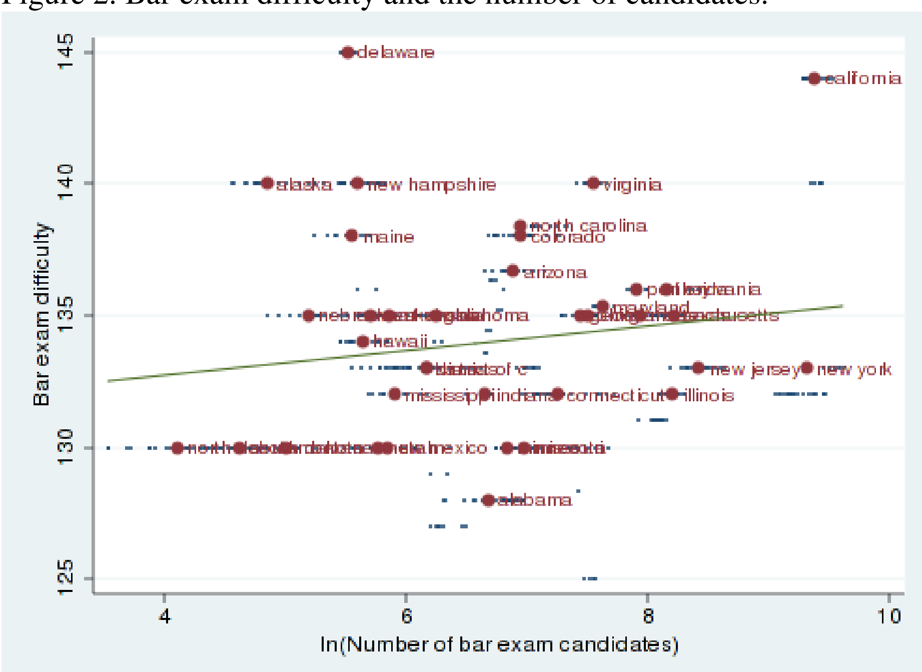

Table 1. Bar Exam Difficulty.

State	Starting Date of Comparable Standards (1)	Observed Changes in Bar Exam Difficulty (2)	Date of Change (3)	Bar Exam Difficulty in 2009 (0-200) (4)
Alabama	1990	-	-	128
Minnesota	1984	-	-	130
Missouri	1984	5, -3	1996, 2005	130
Montana	1999	-	-	130
New Mexico	1984	3, -3	1990, 96	130
North Dakota	1986	-	-	130
South Dakota	1989	-	-	130
Connecticut	1984	-	-	132
Illinois	2000	-	-	132
Indiana	2001	-	-	132
Mississippi	1995	-	-	132
D.C.	1984	-	-	133
Kansas	2000	-	-	133
New Jersey	1992	-2	1993	133
New York	1984	1	2005	133
Hawaii	1993	-	-	134
Arkansas	2002	-	-	135
Georgia	1984	5	1997	135
Massachusetts	1984	-	-	135
Nebraska	1996	-	-	135
New Hampshire	1984	-5	2007	135
Ohio	1984	-10, 3.33, 6.67	1992, 96, 97	135
Oklahoma	1984	2, 1, 4, 1	1991, 92, 95, 97	135
Texas	1994	-	-	135
Utah	1991	5	2006	135
West Virginia	1994	-	-	135
Maryland	2000	-	-	135.33
Florida	1984	2, 3	2003, 04	136
Pennsylvania	2001	-	-	136
Arizona	1991	-	-	136.67
Colorado	1987	-	-	138
Maine	1984	1, 2, 2, -2	1990, 92, 95, 2003	138
North Carolina	1984	-2.8, 0.8, 0.8, 0.8, 0.8, 1.6	1988, 90, 92, 94, 95, 96	138.4
Alaska	1992	-	-	140
Virginia	1998	-	-	140
California	1984	4	1990	144
Delaware	2000	-	-	145

NOTE: Bar exam difficulty is the minimum overall score required to pass the bar exam (measured on a 0-200 scale) in each state. Data on difficulty is available from either 1984 or the introduction of comparable standards (reported in Column 1), whichever is later, to 2009. Column 2 reports changes in difficulty, while Column 3 reports the corresponding date of each change. Column 4 reports difficulty in 2009. The information in Table 1 allows reconstruction of the time series of exam difficulty in each state.

Table 2. Summary Statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
Bar exam difficulty	681	134.01	4.02	125	145
Candidates' mean quality	681	141.02	3.63	129.17	151.71
Number of candidates (log)	681	6.72	1.31	3.53	9.60
Pass rate	681	0.73	0.10	0.37	0.93

Note: Bar exam difficulty and candidates mean quality (mean overall score) are measured on a 0-200 scale.

Table 3. The Impact of Potential Labor Supply on Bar Exam Difficulty.

	(1) OLS Exam difficulty	(2) OLS Exam difficulty	(3) OLS Exam difficulty	(4) OLS Exam difficulty	(5) OLS Exam difficulty	(6) 2SLS Exam difficulty
Candidates' mean quality, *t-1*	0.671***	0.697***	1.06***	1.18***	0.502***	-0.230
	(0.139)	(0.156)	(0.121)	(0.176)	(0.096)	(0.170)
Number of candidates (log), *t-1*	0.845*	0.874*	1.59**	1.74**	2.79*	11.22*
	(0.452)	(0.459)	(0.661)	(0.651)	(1.59)	(5.88)
Year f.e.?		Yes		Yes		
State f.e.?					Yes	Yes
Observations	681	681	275	275	275	143

Note: The table reports OLS and 2SLS estimates of the impact of the number and quality of bar exam candidates on exam difficulty. Robust standard errors clustered by state are reported in parentheses. In columns 3-6, states with no change in bar exam difficulty are excluded from the regression (see Table 1). In column 6, the 2SLS estimates are obtained using as IVs the number of matriculated students and the mean LSAT score for students accepted into law schools in the same state in *t-4*. The number of observations is smaller than in columns 3-5 because of limited availability of data on the instrumental variables (see Appendix 1and 3 for details on data availability). The first stage regression results are reported in Table 4. *** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 4. First Stage Regression Results.

	(1) Number of candidates	(2) Candidates' mean quality
First year law school class size (/1000)	0.244***	1.32
	(0.053)	(1.08)
LSAT average score	0.00384	0.698***
	(0.00757)	(0.0827)
State f.e.?	Yes	Yes
Observations	143	143
Partial R^2	0.14	0.40
F-test	12.71	37.79
(P-value)	(0.00)	(0.00)

Note: Robust standard errors clustered by state in parentheses. *** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A1. Robustness results.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) 2SLS
VARIABLES	Exam difficulty	Exam difficulty	Exam difficulty	Exam difficulty	Exam difficulty
Candidates' mean quality, *t-1*	0.790***	0.761***	0.804***	0.498***	-1.298
	(0.112)	(0.0976)	(0.112)	(0.0932)	(1.059)
Number of candidates (log), *t-1*		0.896**	0.933**	2.784	14.28*
		(0.432)	(0.432)	(1.593)	(7.890)
Number of candidates / state population, *t-1*	8,000***				
	(2,238)				
Admissions on motion, *t-1*		0.00158***	0.00176***	0.00147	
		(0.000218)	(0.000250)	(0.00157)	
Year f.e.?	yes		yes		
State f.e.?				yes	yes
Observations	681	681	681	275	231

Note: Column one reports the cross sectional correlation between potential supply and exam difficulty, as in Table 3, column 2, but the number of candidates is divided by the population in the state. Column 5 reports 2SLS estimates, as in Table 3, column 6. The number of observations is now larger (231) than in Table 3, column 6 because observations from 1989 to 2009 are used (see Appendix 2 for details). Robust standard errors clustered by state in parentheses. *** Significant at the 1% level, ** significant at the 5 percent level, * significant at the 10% level.

Table A2. Robustness results.

	(1) OLS Exam difficulty	(2) OLS Exam difficulty	(3) 2SLS Exam difficulty	(4) OLS Exam difficulty	(5) OLS Exam difficulty	(6) 2SLS Exam difficulty
Candidates' mean quality, [t-2, t-1]	0.743***	0.610***	-0.316			
	(0.169)	(0.110)	(0.268)			
Average Number of candidates (log), [t-2, t-1]	0.912*	3.776*	9.842*			
	(0.457)	(1.733)	(5.869)			
Candidates' mean quality, [t-3, t-1]				0.721***	0.601***	-0.305
				(0.158)	(0.107)	(0.227)
Average Number of candidates (log), [t-3, t-1]				0.888*	3.333*	10.67*
				(0.452)	(1.589)	(6.069)
State f.e.?	no	yes	yes	no	yes	yes
Observations	606	254	143	644	265	143

Note: The table reports OLS and 2SLS estimates of the impact of the average number and average quality of bar exam candidates on exam difficulty. The average number of exam candidates and their quality is computed for [t-2, t-1] or [t-3, t-1]. The 2SLS estimates are obtained using as IVs the average number of matriculated students and the mean LSAT score for students accepted into law schools in [t-5, t-4] and [t-6, t-4] in column 3 and 6 respectively. Robust standard errors clustered by state in parentheses. *** Significant at the 1% level, ** significant at the 5 percent level, * significant at the 10% level.

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