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

Mario Pagliero*

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Abstract

This paper provides the first empirical evidence of a positive impact of the quality and number of potential entrants on entry requirements in professional markets. The estimated effects are so large that increases in the quality of candidates are completely offset by increases in exam difficulty and therefore do not lead to any long run increase in the number of successful candidates. Variations in the number of candidates are also significantly (but not completely) offset by changes in exam difficulty. About one third of the additional candidates that otherwise would have passed the examination fail because of the increase in standards. These results are not in line with public interest theory of licensing. The classic rent seeking view of licensing can explain some (but not all) of the results.

JEL: L4, L5, J4, K2.

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*University of Turin, Department of Economics and Finance, 10134 Turin, Italy, and Collegio Carlo Alberto; email: pagliero@econ.unito.it. I would like to thank Pascal Courty, Francesca Cornelli, Christos Genakos, David Genesove, Robert Sauer and Frank Verboven for discussions and suggestions.

1 Introduction

Entry into a large number of professions requires permission of state licensing boards and demonstration of some degree of competency. In addition to lawyers, the focus of this paper, examples include accountants, auditors, teachers, nurses, engineers, psychologists, barbers and hairdressers. According to Kleiner (2000), more than 800 occupations are licensed in at least one U.S. state. Professional licensing directly affects 18 percent of U.S. workers, more than the percentage affected by either minimum wage or unionization. To enter a regulated profession, candidates have to meet the standards set by licensing boards. This usually includes passing a licensing examination and meeting educational, residency and moral character and fitness requirements.

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 institution that allows practitioners to capture monopoly rents by restricting entry (Friedman and Kuznets 1945, Friedman 1962, 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).

Regardless of their approach, economists agree that licensing boards adjust entry requirements in response to changes in the number and quality of individuals attempting to enter the profession. (I will refer to these individuals as the potential labor supply.) When entry requirements are held constant, an increase in the potential supply results in increased entry into the profession. Both approaches predict that entry requirements will adjust in response to the increased supply of professionals. Different means of adjusting the stringency of entry requirements are available to licensing boards, according to the institutional setting. If there is an entry examination, for example, "the regulatory board can raise the test scores required to pass the exam thus reducing the number of new entrants" (Kleiner 2006, p.8); Alternatively, licensing boards can adjust educational or residency requirements in response to oversupply conditions.[1]

While the existence of a causal link between potential labor supply and licensing stringency is accepted in the literature, there is no direct evidence as to whether the potential labor supply affects entry requirements. There are two basic problems in attempting to estimate such a causal link. The first is data availability. Measuring the stringency of entry requirements is difficult, especially since admission to a regulated profession usually requires taking a professional examination. While licensing boards can manipulate exam difficulty, their behavior is not generally observable to the researcher. Moreover, measures of candidate quality are not typically available either. The second problem is that one rarely observes exogenous changes in potential supply. Candidates choose where and when to apply for admission and how much to invest in preparation for the entry examination. Therefore, studying the impact of potential supply on licensing stringency requires taking into account the potential endogeneity of both the number of applicants and their quality.

In this paper, I study the impact of the potential labor supply on the difficulty of the licensing exam in the US market for lawyers, also known as the bar exam. This market is an appropriate setting for studying this relationship for three reasons. First, accurate data is available on exam difficulty, average candidate ability, number of candidates and pass rates. The availability of this data is an upshot of the detailed grading procedures for the bar exam. Second, the structure of the bar examination is the same for the states and years in my sample, but the exam difficulty, number and quality of candidates vary significantly. Therefore I can use a panel data approach for identifying the link between labor supply and exam difficulty. The third advantage is that there are instruments that

[1] Kleiner (2006) reports that "...states like Florida, Arizona, Hawaii, and California have traditionally had longer continuous residency requirements for many regulated professions, presumably to keep persons from states with more inclement weather during winter months from moving to the state" (p.11); Following a decline in demand for dental services in the 1980s, the American Dental Association dealt with the oversupply situation by restricting entry to professional education (p.69).

can be used to isolate the impact of changes in the quality and number of candidates. I use historical data on the quality and size of the cohorts of students finishing high school and applying for college, in each state, 8 years before the actual date of the bar examination. The average SAT score and number of SAT candidates are arguably exogenous to the bar exam difficulty 8 years later. However, these variables are empirically correlated with the number and quality of bar exam candidates.

Two sets of anecdotal empirical facts suggest the possibility of a link between potential supply and bar exam difficulty. First, states with better or more numerous candidates tend to have more difficult examinations (Figures 1 and 2). Second, the timing of standard changes is strongly consistent with increases in the number and quality of candidates (Figures 3-5). In addition, simple OLS regressions show a strong correlation between the quality of candidates and exam difficulty. In line with this evidence, panel data regressions accounting for endogeneity provide strong evidence for the existence of a positive impact of the number and quality of candidates on the difficulty of the bar exam. This is true after controlling for state and year-specific fixed effects and a variety of other factors. The magnitude of the effect of both number and quality of candidates is so large that, according to my estimates in Table 4, increases in candidate quality are completely offset by increases in exam difficulty and do not lead to any long run increase in the number of successful candidates. Changes in the number of candidates are also significantly (but not completely) offset by changes in exam difficulty. About one third of the additional candidates that would otherwise have passed the examination fail because of the increase in standards.

A number of factors indicate that the estimated link between potential supply and difficulty may be causal. These include the overall consistency of the anecdotal evidence, the simple OLS regressions and, finally, the IV panel data regressions. Given that occupational licensing has replaced unions as the main labor market institution (Kreuger 2006), an understanding of the determinants of licensing restrictions has become extremely important. This paper provides the first estimates of the impact of the main variables that are believed to affect entry requirements into professional markets. One of the main issues for regulators and the public alike is whether the public interest theory of regulation has greater weight relative to capture theory (Kleiner 2006, p.39). The results of this paper can be used to inform the ongoing debate about this issue and about 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).

The classic view of licensing predicts that changes in exam difficulty will completely offset shocks to both the quality and number of candidates, so that the number of successful candidates entering the profession remains unaffected. This prediction does not hold under the modern view of licensing. Yet the sign and magnitude of the estimated impact of changes in quality is perfectly consistent with this prediction. The sign of the impact of changes in the number of candidates is also consistent with classic theory, although to a lesser extent than predicted. Other variables considered relevant to licensing stringency by public interest theory (Leffler 1978) have no significant impact on exam difficulty. Overall, my results are difficult to reconcile with the public interest theory.

The structure of the paper is as follows. Section 2 discusses the link between potential supply and licensing board behavior in light of the existing theories of licensing. Section 3 provides a brief description of the bar examination and its grading procedures. Section 4 presents empirical evidence supporting the proposed positive relationship between potential supply and exam difficulty. Section 5 investigates the consistency of the results with the two alternative views of licensing and Section 6 draws some implications for the broader policy debate. Section 7 provides robustness results and Section 8 concludes. A data appendix with a description of sources is also provided.

1.1 Related literature

Although the stringency of entry requirements is the key variable controlled by licensing boards, there is surprisingly little research on the subject. 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 suggestive, there are clear limitations in using pass rates as a measure of licensing strictness, since pass rates 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 fraction 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 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), labor mobility (Pashigian 1979), the origins of licensing (Law and Kim 2004) and the effects of entry restrictions (Schaumans and Verboven 2006).[2] To my knowledge, the literature does not provide any evidence of a systematic link between potential supply and licensing stringency.

2 The link between labor supply and licensing stringency

According to the classic view, licensing boards set entry restrictions to limit the number of successful candidates, the optimal number being a function of the demand for professional services and the number of professionals already in the profession. Holding entry requirements constant, exogenous increases in the number and quality of candidates (potential supply) would result in more entrants than desired. Therefore, licensing boards raise entry requirements to offset such increase. This clearly establishes a causal link between potential supply and exam difficulty.

The second view (the modern theory of licensing) is based on the basic assumption that consumers do not observe the quality of professionals, but licensing boards do. According to this view, consumers infer the quality of professionals based on the minimum

[2] The legal literature has also discussed the causes and consequences of professional licensing (Curcio 2002, Merrit, Hargens and Reskin 2001, the Society of American Law Teachers 2002, Perlman 2004).

quality standard set by the regulator. Consumers value higher minimum standards, all other variables being equal, because they guarantee a higher quality of professionals in the market. Licensing boards set standards by weighting the marginal benefit and loss from higher minimum standards and the decreased number of professionals admitted.[3] Licensing boards face a trade-off between admitting more candidates and admitting better candidates. The number of candidates and their quality distribution (potential supply) determine this trade-off and set the fundamental constraint faced by licensing boards. Exogenous changes in potential supply modify this trade-off and therefore affect the boards' decisions. This implies the existence of a link between potential supply and exam difficulty. Thus, both the classic and the modern view of licensing predict a causal relationship between potential supply and the stringency of entry requirements.

3 Brief overview of the bar exam

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.[4] It consists of the Multistate Bar Examination (henceforth MBE), a standardized test, and essay and case questions. Since 1981, all but two states (Louisiana and Washington) have used the MBE as part of the bar examination. 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, irrespective of when and where the exam is taken. MBE mean scores are a cardinal measure of the quality of bar exam candidates, and results can therefore be compared

[3] And they do so according to their objectives or, more appropriately, those of their members. Assuming that the objective pursued by boards is social welfare, Leland (1979) showed that professional licensing might remedy the market failure derived from asymmetric information and could increase welfare with respect to the free entry equilibrium.

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

across states and years.[5]

Essay and case questions are set by state boards and graded at the state level, according to criteria set by each board.[6] In this case, a single 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. 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).[7]

The overall scores (the weighted average of the standardized test and essay test score) thus share the same metric across states and years and can be compared. Since the pass-fail decision is based on overall scores, the observed minimum quality standards for each state share a common metric and provide a simple measure for exam difficulty. (In the rest of the paper, I will refer to bar exam overall minimum score as exam difficulty, or minimum standard).[8] Data on minimum quality standards is available from either 1984 or the introduction of comparable standards (reported in Table 1, column 1), whichever is later, to 2005. Table 1, column 2 reports any changes in the 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. With this information, this table is sufficient to reconstruct the time series of the minimum standard in each state. Standards differ significantly across both states and years. For example, a change in exam

[5] 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 economics graduate courses.

[6] 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.

[7] An alternative scaling procedure is quantile by quantile equating. The results of the two techniques are not necessarily the same but differences are empirically small (see Lenel 1992).

[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.

difficulty from the level of Alabama to the level of California would imply a drop in pass rate from 79% to 39%, equivalent to more than 22,000 additional candidates per year failing the examination at the national level.[9]

Minimum quality standard data is matched with the number of takers and passers in each examination. My data set also includes data on MBE scores, which consists of MBE mean scores at the state level for each examination. I collected this information directly from the Bar Association or the Supreme Court office responsible for administering the exam (data collection took over one year starting in the summer of 2002). States vary in the amount of data disclosed (see Appendix 2 for details).

4 Empirical evidence of the number and quality of candidates affecting exam difficulty

4.1 Anecdotal evidence

Figure 1 reports the average MBE score and exam difficulty in the 16 states for which data is available on both variables. States with better candidates tend to have more difficult examinations. Overall, the correlation between exam difficulty and candidate quality (MBE score) is 0.6 and is significantly different from zero at a 1 percent confidence level. States with more candidates (relative to the number of lawyers) tend to have more difficult examinations (Figure 2). California and Virginia, for example, have relatively difficult examinations and a large number of relatively good candidates. Alabama and Montana, at the other extreme, have relatively easy examinations. The former has the lowest candidate quality, the latter one of the lowest number of exam applicants per lawyer.

The period 1990-1997 saw a general increase in bar exam difficulty. The increase in standards averaged 1.3 on the MBE scale for each year during this period, as opposed to -0.4 in other years. Over 80 percent of all observed changes occurred in the period

[9] I use for comparison a normal distribution, with a mean equal to the mean MBE score and the variance equal to the mean variance in the US for the period 1981-2003. Figures on successful candidates are based on 60,000 candidates per year. The magnitude of changes in standards is discussed in detail by Pagliero (2005).

1990-1997. Figure 3 reports the frequency of states that changed their standards in each year. The yearly frequency is computed as the number of states changing standards over the total number of states for which standards were comparable. On average, 10 percent of the states changed their standard in each year during the period 1990-1997. Only 2 percent changed their standards each year during the remaining years from 1984.[10]

Figure 4 shows the mean MBE score of candidates taking the bar exam in the US for the period 1984-2003. Following a period of stability through the late 80s, the average MBE score increased and peaked in 1994. It then declined in the late 90s. This increase in quality of candidates corresponds to (or slightly precedes) an increase in pass rate, which shifted from 65 percent in 1984 to 74 percent in 1994 (this is also reported in Figure 4). In spite of the higher quality of candidates, pass rates in 2000 fell to the level of 1984. This corresponds to the increase in exam difficulty in the 90s, coinciding exactly with the peak in quality.[11] The number of candidates also increased dramatically during the mid 90s. Figure 5 reports the total number of candidates taking the bar examination in the US during the period 1984-2003. The number of candidates per year increased dramatically between 1990 and 1997. The exam difficulty increased during the same years in which the number and quality of candidates increased.

4.2 Empirical specification

I estimate regressions of the general form

$$D_{i,t} = b_0 + q_{i,t-1}b_1 + N_{i,t-1}b_2 + X_{i,t-1}b_3 + \lambda_t + \delta_i + u_{i,t} \qquad (1)$$

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 number of candidates divided by the number of lawyers in the state; $X_{i,t}$ is a matrix of exogenous variables

[10]The data used for computing the frequency of change includes some instances in which a clear change in the grading can be identified, but its sign and magnitude cannot be measured. Appendix 2 describes these cases.

[11]While the mean MBE scores changed, the variance of their distribution did not show systematic variations over the sample period. Changes in pass rates cannot be attributed to changes in distribution variance.

affecting demand for legal services; λ_t and δ_i are state and year fixed effects, and $u_{i,t}$ is the idiosyncratic error term.

In my sample, changes in exam difficulty occur at the beginning of the year (that is, starting with the February exam). I aggregate the information at the yearly level by summing the number of takers and passers for the two exams within each year and calculating the mean MBE score (appropriately weighted) for each state and year in the sample. The limited availability of MBE score data restricts my sample to 122 state-year observations, which cover two significant changes in standards (Georgia in 1997 and Maine in 1995).

Variability in the two main regressors is significant in my sample. Figures 1 and 2 illustrate the cross sectional variability of mean MBE scores and the total number of candidates. The variability over time is also significant (Figure 3 and 4). Since changes in minimum standards are usually determined in advance, my empirical specification (1) allows for a lagged impact of potential supply on exam difficulty. As discussed in the section on robustness, the results are not significantly affected by using different lags. The matrix X includes gross state product per capita as a proxy for demand for legal services. Pashigian (1977) provides strong evidence linking gross product per capita with demand for legal services. The matrix X also includes an index for state population to control for changes in market size. Using alternative measures of market size, such as the level of gross state product, does not significantly affect the results. In the next section, I shall include a richer set of regressors which may in principle be linked with exam difficulty, as suggested by the literature (Leffler 1978). The results are not affected.

Data limitations

Data availability has been a long-standing issue in the literature on licensing. Kleiner (2000, 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". In this context, my data set provides a unique source of information on licensing board behavior.

With these considerations in mind, there is one important limitation in this data set: The sample includes little time series variability in standards. This is partly due to the low frequency with which standards are changed, but also, more importantly, to the large number of state-year observations that had to be excluded from the analysis. This is for three reasons. First, the introduction of comparable standards based on standardized scores is a relatively new development in entry examinations in the market for lawyers. Some states still use grading procedures that do not allow quantitative comparison. Second, although they follow the standard grading procedures described above, some states do not publish their minimum standards. Finally, some state boards simply declined my requests to disclose information on key variables such as MBE mean scores. I address this limitation by estimating exam difficulty for a number of states and years for which no information on the minimum score is provided (see Section 7). This introduces more time-series variability in the dependent variable and increases sample size by over 16 percent. Overall, the results are not affected, but still caution needs to be used in extrapolating the results out of the sample.

4.3 Regression results

Table 2 reports aggregate summary statistics for each variable. Table 3, column 1 reports OLS pooled regression results. The impact of changes in quality is positive and its magnitude significant. A unit increase in MBE mean score implies a 0.8 increase in the minimum standard (which is measured on the same scale as the MBE). The impact of changes in the number of candidates, relative to the number of active lawyers, is not significantly different from zero in this specification. Table 3, column 2 reports the results controlling for the two main demand side regressors: The size of the state (measured by its population) and gross state product per capita. The inclusion of these two additional regressors does not affect the results. Table 3, column 3 reports the fixed effects panel data regression results. The impact of quality on difficulty remains positive and significant, although its magnitude is smaller than in column 2.

The results in Table 3 imply a positive impact of the quality of candidates on exam difficulty but no impact of their number. Before attempting to draw any conclusions from these results, one must consider how endogeneity may affect the results. The positive correlation between difficulty and quality may be generated or reinforced by two mechanisms. First, higher exam difficulty may provide incentives to students to study more, inducing a positive correlation between difficulty and quality. Second, higher difficulty in a particular state may induce low quality students not to apply for admission or to apply in a different state. This may also generate a positive correlation between the observed difficulty and candidate quality. The non-significant correlation between the number of candidates and exam difficulty shown in Table 3 may also result from the combination of the hypothesized effect and candidates' endogenous response. Higher exam difficulty makes the legal profession less attractive than other occupations (or the legal profession in a different state), so the number of candidates may decrease. This may result in a negative (or zero) correlation between exam difficulty and the number of candidates.

4.4 Instrumental Variables regression results

Given the potential impact of endogeneity, what I require is instruments that are correlated with the quality and number of candidates but not with the unobserved error term affecting exam difficulty in (1). In other words, I need to find sources of exogenous shocks to the quality and size of the cohorts of candidates taking the bar exam. There are a number of factors influencing the quality and size of cohorts of bar exam candidates. However, these cohorts also differ for historical reasons, and one can exploit this exogenous variability to isolate the relation of interest.

I have chosen to use historical SAT verbal and math scores as indicators of the quality of the cohort of students leaving high school, and the number of SAT candidates as an indicator of the size of the cohort. The SAT is a standardized entry test often required by colleges awarding degrees in the arts, social sciences and natural sciences. It has the advantage of measuring the performance of a large pool of candidates, and not only those going to law school. Some of these students will eventually choose to go to law school 4 years later, upon graduation from college. A smaller subset will eventually take the bar examination, after graduation from law school (3 years after entering law school).

The size and average quality of the cohorts taking the SAT score in each state are used as instruments for the number and quality of bar exam candidates 8 years later. Although a student can complete college and law school within 7 years, there are a number of reasons to suspect that the average time between college admission and the bar exam is longer. First, one in four matriculated law students attends only part-time (ABA 2006). Second, one third of candidates fail the bar exam and a large number of them repeat the test in later years (in 2004, 29 percent of bar exam candidates were repeaters). Finally, not all candidates take the exam immediately upon graduation. All these factors delay taking the bar exam. In Section 7, I explore the impact of using different lags (from 7 to 9 years) and find that the results are robust.

Consider the cohort of students leaving high school 8 years before the bar exam under consideration. The quality and size of this cohort of students is unlikely to be significantly correlated with any unobservable variable specific to the market for lawyers that could potentially affect exam difficulty. In fact, very few of these students graduate from college, choose to attend law school and eventually apply for admission to the bar after graduation. The presence of state and year fixed effects in (1) makes it highly unlikely that aggregate labor market shocks could generate a correlation between quality and number of high school graduates and the error term.

First stage regression

Historical average SAT scores show a surprising correlation with average MBE scores. To illustrate, Figure 6 reports national MBE and SAT mean scores (the average of the math and verbal section of the test) in t-8. The correlation in Figure 6 is 0.77 and is statistically significant. Figure 7 reports the number of bar exam candidates (divided by the number of lawyers) and the lagged (t-7) number of SAT candidates in the US (deviations from the trend). These two variables are also significantly correlated (the correlation is 0.77). This pattern of correlations carries on at the state level. For example, Figures 8 and 9 report the analogous figures for Georgia. The simple correlations between the two series in Figures 8-9 are positive and significant (0.76 and 0.85 respectively).

Overall, these figures suggest the existence of a correlation between the instruments and MBE mean scores and the number of bar exam candidates.[12]

Because SAT score data is available for both the math examination and the verbal examination, it provides a rich set of instruments, as the two variables measure different characteristics of students' ability which may have a different impact on bar exam performance. Table 5 reports the first stage regression results. Overall, the lagged SAT scores and the number of SAT takers are significantly correlated with the number and the quality of bar exam candidates. As expected, the first stage results show that the lagged number of SAT takers is positively correlated with the number of bar exam candidates. In addition, cohorts that score relatively high on the verbal and low on the math component of the SAT lead to a higher number of bar exam candidates (see Table 5, columns 1, 3 and 5). This result suggests that students more inclined to verbal analysis are more likely to choose the legal profession. Controlling for ability, MBE mean scores are negatively correlated with cohort size (see Table 5, columns 2 and 4). This could be due to a number of reasons. For example, large student cohorts may increase class size and thus reduce the quality of education. Alternatively, truly motivated students (or those with some other unobservable skill that is important for succeeding at law school) may be less represented in larger cohorts. (The actual explanation is irrelevant for my purposes in this paper). Table 5 also provides some evidence that cohorts with higher math SAT scores and lower verbal SAT scores achieve higher MBE scores.

IV regression results

Table 4, column 1 reports the regression results obtained using the same specification as in Table 3, column 2. The coefficient for the number of candidates is now positive and significantly different from zero. The magnitude is significant: a 1 percent increase in the number of candidates per lawyer implies an increase in difficulty of 0.9 on the MBE scale. The impact of quality remains positive and its magnitude is substantially unchanged. An

[12]Figure 6 and 8 use a 8-year lag while Figure 7 and 9 use a 7-year lag. Empirically, there is a slightly higher correlation between the quality measures using an 8-year lag, and between the two measures of the number of candidates using a 7-year lag. The estimated results are not dependent upon this difference in lag structure and are robust to different lag specifications.

increase in the quality of candidates implies an increase in exam difficulty of the same amount. The same conclusions are reached when including state fixed effects in column 2. The IV regression results suggest that endogeneity played a role in the previous results. After controlling for endogeneity, the impact of the number of candidates is positive and statistically significant.

Table 4, column 3 includes educational attainment and the fraction of immigrant population in each state as additional regressors.[13] According to public interest theory, as noted by Leffler (1978), higher educational attainment and a lower fraction of immigrant population should lead to a lower minimum standard. The first variable is related to consumers' capacity to collect and evaluate information concerning the quality of professionals, while the second is related to the amount of local knowledge available to consumers. Consumers with relatively high levels of education and more local knowledge should be less affected by asymmetric information and thus benefit less from high entry standards. This should be reflected in lower standards in the state. In practice, the coefficients of these two variables are both non-significant.

5 Testing the alternative views of licensing

The traditional theory of licensing makes strong predictions about the sign and magnitude of the impact of changes in potential supply on exam difficulty. Since the number of entrants is the only consideration for the captured profession, potential supply does not constrain the choice of the desired minimum standard.[14] Therefore, the theory predicts perfect offsetting of changes in potential supply. Following an increase in number and/or quality of candidates, licensing boards should raise entry requirements just enough to keep the number of successful candidates unchanged in the long run. According to the

[13] Educational attainment is the fraction of the population aged 25 or over holding a bachelor's degree or higher qualification (Census Bureau, *Current Population Survey*). The fraction of immigrant population is the number of tax exemptions for people who moved to the state within the year relative to the total number of tax exemptions. Both immigration from other states in the US and from other countries is included (Internal Revenue Service).

[14] Unless the number of applicants is lower than the desired number of entrants. In this case licensing standards are not binding.

classic theory,

- Prediction 1: An increase in number and/or quality of candidates leads to an increase in exam difficulty.
- Prediction 2: The magnitude of the impact of changes in potential supply on exam difficulty is such that the number of successful candidates is unaffected.

The first prediction may also hold under the modern view of licensing (including public interest theory). The second prediction, however, does not. In this case, changes in exam difficulty cannot exactly offset both changes in quality and number of candidates. Appendix 1 formally derives this prediction.

5.1 Empirical test

Each of the N bar exam candidates is assigned a score s, with mean m, which is a cardinal measure of the candidate's ability (or quality) and candidates with score above a given minimum standard pass the examination and enter the profession. Denote this minimum threshold, the exam difficulty, by D. Theory motivates the existence of a causal relationship between the number of exam candidates, their average mean score (potential supply), and exam difficulty, $D(N, m)$. Prediction 1 can be restated as

$$\frac{dD}{dm} > 0 \quad \text{and} \quad \frac{dD}{dN} > 0. \qquad \text{(Prediction 1)}$$

We can now turn to Prediction 2 introduced above. Denote by $F(s-m)$ the score distribution, continuous and scale invariant, and by $f(s-m)$ its density. Continuity is analytically convenient but not necessary. Scale invariance simply requires that the pass rate will not be affected if both exam difficulty and mean quality increase by the same amount, that is $dF/ds = -dF/dm$. In Section 7, I test and cannot reject this assumption in the data. The number of candidates passing the exam can then be written as

$$P = [1 - F(D-m)]N. \qquad (2)$$

Prediction 2 states that changes in the number of candidates and mean score should not affect the number of passers, that is, $dP/dm = 0$ and $dP/dN = 0$. Given scale invariance, $dP/dm = 0$ holds if and only if $dD/dm = 1$. The second equality ($dP/dN = 0$) requires

$$\frac{dP}{dN} = [1 - F(D - m)] - Nf(D - m)\frac{dD}{dN} \tag{3}$$

be equal to zero. A marginal increase in the number of candidates impacts the number of successful candidates in two ways. First, holding the exam difficulty constant, it increases the number of successful candidates in proportion to the exam pass rate. This is the first term in (3). Second, it increases the exam difficulty, thereby increasing the number of candidates failing the exam. The additional number of unsuccessful candidates depends on the product of the total number of candidates N, the density at the current minimum standard $f(D-m)$, and the marginal effect on exam difficulty, dD/dN. This is the second term in (3). An increase in the number of candidates has no impact on the number of successful candidates if and only if the two effects exactly offset each other. Therefore, Prediction 2 can be written as

$$\frac{dD}{dm} = 1 \quad \text{and} \quad \frac{dD}{dN} = \frac{1 - F(D - m)}{Nf(D - m)}. \tag{Prediction 2}$$

Prediction 2 requires testing whether dD/dN is equal to the ratio of the pass rate and the number of marginal candidates. Both predictions can be tested using estimates of the impact of quality and number of candidates on exam difficulty.

5.2 Empirical evidence

Prediction 1

Overall, Prediction 1 cannot be rejected by the data. The evidence indicates a positive impact of candidate quality on exam difficulty. In all my specifications the marginal effect of an increase in MBE score is positive and statistically significant, as predicted. The second part of Prediction 1 is also broadly confirmed by the results. After controlling for endogeneity, the impact of an increase in the number of candidates is consistently positive and significantly different from zero.

Prediction 2

Testing the first part of Prediction 2 is straight-forward. The restriction $b_1 = 1$ is almost never rejected by the data at conventional confidence levels. The magnitude of the impact of quality is precisely that predicted. An increase in student quality is matched one to one by increases in difficulty. Testing the second part of Prediction 2 requires an estimate of the density computed at the threshold D, $f(D-m)$. The estimated density for the average difficulty and the average quality observed in the sample is 0.03. That is, an increase of 1 in exam difficulty (on the MBE scale) implies a decrease of approximately 3 percent in the exam pass rate. This figure is robust to the estimation strategy and is in line with existing evidence on the distribution of bar exam scores. In Section 7, I describe the estimation procedure.

Using the average pass rate in my sample (0.7) and the average number of candidates per lawyer (0.07), an increase of one percent in the number of candidates per lawyer should cause an increase in exam difficulty of 3 on the MBE scale.[15] In fact, the estimated coefficient b_2 is just below 1. For example, in Table 4, it is 0.9, with a 95 percent confidence interval (0.2, 1.5). Although the magnitude of the effect is significant, the effect does not completely offset the impact of an increase in the number of candidates on the number of successful candidates. Approximately 35 percent of the increase in the number of successful candidates due to an increase in the number of candidates is canceled by the increase in exam difficulty.

Public interest view of licensing

The classic view of licensing does quite well in explaining the impact of potential supply on exam difficulty, but its predictions are still not fully borne out in the data. One may ask, then, whether the results are consistent with public interest theory (that is a special case of the modern view of licensing, where the objective of the regulator is social welfare). Following the literature, assume that consumers are heterogeneous

[15] My predictions are not affected whether weighted or unweighted average pass rates are used.

in their taste for quality. As standards increase, the number of consumers who dislike further increases in minimum standards increase (Leffler 1978). Therefore, under public interest theory, as standards increase, the marginal social benefit from a larger number of successful candidates will increase, relative to that of higher minimum quality. Hence, one would expect partial offsetting of changes in candidate quality (so that, as a result of an increase in the quality of candidates, both the minimum standard and the number of candidates increase). This prediction is in contrast with the magnitude of the estimated impact of candidate quality on exam difficulty.

Although the academic and public debate has mainly focused on the comparison of the classic view and public interest theory of licensing, the actual objective function of licensing boards needs not exactly correspond to either theory, as licensing boards may aggregate the interests of different groups rather than serving a single economic interest (Peltzman 1976). Licensing regulations are the result of interaction between politicians and members of professional associations. Kleiner (2006) provides a description of the process by which licensing is obtained by professional associations (p.31), but the link between interaction on political markets and licensing regulations remains for the largest part to be explored.

6 The impact of licensing on diversity and investment in exam specific skills

Licensing affects how groups with different average ability are represented within the legal profession. Consider an increase in the number of candidates (for example, this may be the outcome of a policy subsidizing legal education) which affects equally all groups of candidates. As standards increase, groups with lower average performance become less represented among the successful candidates. 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).

There is little evidence on differences in average MBE performance across ethnic groups. However, the existing evidence suggests that the impact of licensing on diversity is substantial. In July 2004 the average MBE score in Texas was 143.4 for white and 134 for black, bar exam pass rates were 81 and 45 percent and black candidates were 13 percent of white candidates. A 5 percent increase in the number of candidates per lawyer implies an increase in exam difficulty of 4.5 on the MBE scale. The resulting pass rates are 66 and 26 percent respectively for the two groups.[16] The pass rate for black applicants is slightly more than half of that of white applicants before the change, it is only 40 percent after the change. The ratio of the number of black successful candidates and white successful candidates decreases by almost 30 percent (from 0.074 to 0.052).

Consider now a shift in the score distribution of candidates, due, for example, to an increase in the quality of legal education. Although candidates are better, diversity in the profession will not increase, as the minimum standard increases to offset the change in candidate quality. Finally, consider a policy that increases the number of candidates from a group with lower average bar exam performance. Standards will tend to decline as quality of candidates decreases, but they will tend to raise as the number of candidates increases. The combined effect depends on how the candidates' score distribution is distorted and, in general, I cannot rule out a decrease in the fraction of successful candidates from the group with lower performance.

Each candidate applying for admission generates a negative externality on other candidates, since standards increase with the number of applicants. Similarly, each candidate taking a review course to increase her bar exam score generates a negative externality on other candidates, as standards increase with average exam performance. This implies that candidates have incentives to overinvest in exam specific skills. In practice, an industry has developed around bar exam preparation courses and almost all law graduates take a specialized bar review course.[17] While it is individually rational for students (and law

[16] These figures are computed assuming normal score distributions with the standard deviation implied by the observed exam difficulty, mean MBE score and pass rate. Results are robust to deviations from normality.

[17] Students take this into account in selecting law school courses (see, for example, http://www.law.wisc.edu/ current/selectingcourses.htm).

schools) to invest in bar exam preparation courses that increase exam performance, this will not, on average, increase the pass rate nor the supply of lawyers. It may increase professional quality, but only to the extent that higher performance at professional exams leads to higher quality of professional services. The existence of such a link is a topic of debate (see, for example, the Society of American Law Teachers 2002).

7 Robustness and additional results

Admission on motion

Although admission by examination is by far the most common admission procedure, admission to the bar is sometimes possible without taking the bar examination. Lawyers licensed in other states may be admitted on motion. In 2004, there were fewer than 6,000 admissions on motion, but over 49,000 by examination (NCBEX). Only in the District of Columbia (which is not considered in my sample) is this the main mode of admission to the bar. Direct admission of law school graduates (by diploma privilege) is significant only in Wisconsin, which has also been excluded from my sample. In principle, the number of admissions through these other two channels should affect lawyer supply and may therefore impact exam difficulty. I include the number of admissions on motion and by diploma privilege (divided by the number of lawyers) in my specification, but results are not affected (Table 6 and 7, Panel 1). Similarly, results are unchanged if we add an indicator variable for whether admission on motion is possible.

Additional requirements for admission to the bar

In addition to the bar exam, admission to the legal profession also requires meeting educational standards and moral character and fitness requirements and passing the Multistate Professional Responsibility Examination (MPRE). Although educational standards impose significant costs to candidates, they do not vary significantly across states and years. 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. The procedures for moral character and fitness evaluation cannot easily be compared across states and years (in 2005, 19 states have no published character and fitness standards). Although detailed data on the number of candidates rejected on the grounds of unfit moral character and fitness is not available, it is likely that these procedures directly affect only a very small number of candidates.

The MPRE is a standardized, sixty question, two-hour, multiple-choice examination based on law governing the conduct of lawyers, including the disciplinary rules and principles of professional conduct. The MPRE is required for admission to the bar in all but three US jurisdictions. Data on the minimum scores required for passing this exam is available for each state, but there is no consistent relation between the minimum MPRE score and the number and quality of bar exam takers.[18] If higher minimum MPRE score were used by licensing boards as a substitute for more difficult bar exam, one would expect that states with higher minimum MPRE would have an easier bar exam, all other variables being held constant. However, when I include in my main specification the minimum MPRE score for each state, the results are not affected and the impact of MPRE on bar exam difficulty is not significantly different from zero (Table 6 and 7, Panel 2).

State specialization and lag choice

Some states are specialized in the legal service industry and specialization may not be fully captured by my control variables. This issue was explored by including the share of gross state product of the legal market to measure the differences in the weight of the legal industry in each state. The results are not affected (Tables 6 and 7, Panel 3). The period between the decision and the implementation of a change in standards may vary, and information on this issue is not generally available. Therefore, the assumption of a one year lag in (1) may not be appropriate. The results of estimating the basic model with a 2-year lag in the two main regressors are robust (they are reported in Tables 6 and 7, Panel 4).

As argued above, the impact of a shock to the number and quality of high school

[18] 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).

graduates may in practice affect the bar exam between 7 and 9 years later. Figures 6-9 show that both a 7-year and an 8-year lag are consistent with the data. Table 7, Panel 7 reports the results using as instrument the average SAT scores and number of takers for t-7, t-8 and t-9. Results are unchanged.

Number of candidates per capita

Measuring potential supply requires accounting for differences in market size. Until now, potential supply has been determined by dividing the number of candidates by the number of lawyers in each state. This is not the only possible measure of potential supply. In Tables 6 and 7, Panel 5 I use the number of exam candidates divided by the population in the state. The results are not affected.

Extended sample

The main limitation of the data is the limited time series variability in standards and coverage of the sample. I increase the sample size in two ways. First, assuming a specific score distribution (for example normal or beta), I use the available information on pass rates and MBE mean scores to estimate minimum standards. This approach is potentially useful as some states follow the grading procedures described above but do not reveal their minimum standards. This procedure is described in Pagliero (2005). I can precisely estimate standards for Texas and Pennsylvania and, to a lesser extent, for Virginia.[19] In total I add up to 20 observations on estimated standards (16 percent of sample size). Second, the data for some of the regressors is incomplete before 1990. Since data on minimum standards and MBE scores is available before 1990 for only two states (Massachusetts and Colorado, in total 9 observations), I have excluded these observations from the sample in my main results to maintain a constant sample size for all specifications and thus make comparisons easier. When these observations are included, the sample size increases up to 24 percent. Results are not affected (results are reported in Tables 6 and 7, panel 6).

[19]For some states and years, I can compare estimated standards with observed standards. Therefore I can observe the actual performance of the difficulty estimator. For the first 2 states, estimated standards are never significanlty different from observed standards. Viriginia is the next state with the smallest estimated bias.

The determinants of pass rate variability

This section examines the impact of exam difficulty and the mean quality of candidates on pass rates ($P/N = (1 - F(D))$. There are two reasons for this. First, I can test the assumption made in Section 5.1 that the score distribution is scale invariant, that is $d(P/N)/dD = -d(P/N)/dm$. Second, I can obtain an estimate of the density $f(D, m)$, that is necessary to predict the impact of the number of candidates on exam difficulty according to the classic theory of licensing (Section 5.2). In fact, the impact of changes in standards on pass rates is equal to the score distribution evaluated at the minimum standard ($-d(P/N)/dD = f(D, m)$). Estimates of $d(P/N)/dD$ and $d(P/N)/dm$ can be obtained by assuming a specific functional form for $F()$. Table 8 reports the results when assuming uniform score distribution and estimating

$$(P/N)_{i,t} = \beta_0 + \beta_1 D_{i,t} + \beta_2 m_{i,t} + e_{i,t} \tag{4}$$

by ordinary least squares. Table 8 shows that the impact of a marginal increase in difficulty is not significantly different from the impact of a marginal decrease in candidate quality; I cannot reject that $d(P/N)/dD = -d(P/N)/dm$. Both β_1 and β_2 are not significantly different from 0.03, which is the figure used to compute the predictions on the magnitude of the impact of potential supply on exam difficulty according to the traditional theory. The variability of the estimates in Table 8 does not significantly affect my predictions. Clearly, the assumption of a uniform distribution is not intuitively appealing, since score distributions tend to be approximately Gaussian or at least bell-shaped. A second limitation of (4) is that it assumes no heterogeneity in score distributions across states and years. In Pagliero (2005), I relax both assumptions and estimate the marginal effects $d(P/N)/dD$ and $d(P/N)/dm$ assuming that the scores are normally (or beta) distributed and allowing for heterogeneity. Overall, the results are not significantly different from those obtained with a simple linear specification.[20]

[20] When I explicitely consider the existence of two, possibly different, score distributions for the February and July examinations, the predicitons for the impact of the number of candidates on exam difficulty do not significantly change.

Additional instruments

Changes in exam difficulty in a neighboring state generate some variability in number and quality of candidates that can be used to estimate (1). A more difficult exam in a neighboring state makes the profession relatively more attractive, particularly for low quality candidates. Therefore, the number of bar exam applicants will increase and their quality decrease. In Table 7, panel 8, I report the regression results using as an additional excluded instrument the lagged average difficulty in neighboring states (weighted using real gross state product per capita). Results are not affected. In the first stage regression, a more difficult exam in neighboring states has a small positive impact on the number of candidates and a significant negative impact on candidate quality. Similar results are obtained using the average difficulty of the bar exam in all other states (not necessarily adjacent).

8 Conclusions

Professional licensing is one of the most important labor market institutions today, yet the actual behavior of licensing boards is rarely examined because of lack of data and the complexity of licensing requirements. According to the existing literature, licensing boards should respond to changes in potential labor supply. This paper uses data from the US market for lawyers to provide the first systematic evidence on the link between potential labor supply and the strictness of the licensing requirements. In this market, the licensing regulations and exam grading procedures lend themselves quite naturally to analysis of licensing board behavior. The primary methodological contribution is the attainment of consistent estimates of the impact of potential supply on exam difficulty. I find that increases in quality and number of candidates significantly increase exam difficulty. The magnitude of the effects is so large to completely offset the impact of changes in candidate quality on the number of successful candidates. Changes in the number of candidates is only partially offset by changes in difficulty. These results are unchanged when explicitly considering admission on motion, additional requirements for admission and a number of alternative econometric specifications.

The results suggest that professional markets are largely sheltered from the impact of policies increasing potential supply. For example, increasing the quality of potential entrants through improved education will not significantly increase the average pass rate nor the supply of professionals. An increase in the availability of legal education, while holding quality constant, will increase the number of candidates but only partially increase the supply of lawyers. More than one third of the additional candidates who would otherwise have passed the exam fail because of increases in standards. The same result applies to shocks in labour force participation, which will only partially impact licensed professions because of the adjustment in entry requirements. The evidence provided in this paper on the impact of potential supply on licensing stringency is largely (but not fully) consistent with the classic theory of licensing. The complete off setting of changes in quality is also difficult to reconcile with public interest theory. In addition, other variables believed to be correlated with exam difficulty under public interest theory do not significantly affect minimum standards.

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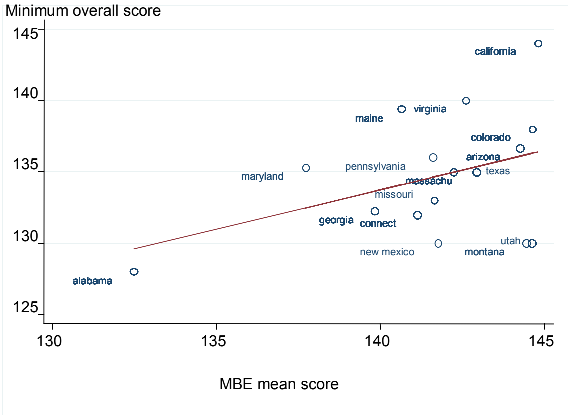
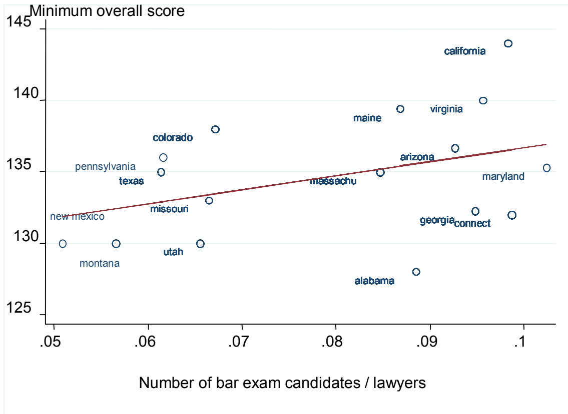
Figure 1. Bar exam difficulty and candidate quality



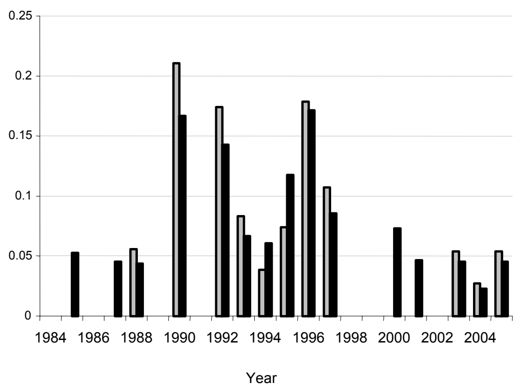
Note: The figure reports the average minimum overall score for passing the bar examination (on a 0-200 scale) and the average Mutistate Bar Examination (MBE) score by state (on a 0-200 scale). The MBE is a standardized test and scores can be compared across states. The line reports the OLS fitted values (Minimum score = 6 + 0.55MBEmean).

Figure 2. Bar exam difficulty and number of candidates



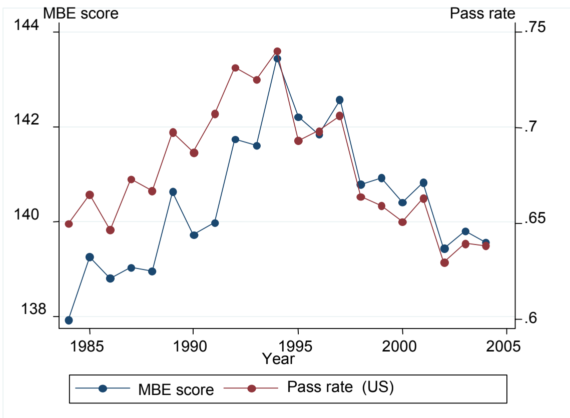
Note: The figure reports the average minimum overall score for passing the bar examination (on a 0-200 scale) and the average number of bar exam candidates divided by the number of lawyers by state (ABA). The line reports the OLS fitted values (Minimum score = 27 + 98*Candidates/lawyers).

Figure 3. Frequency of standard changes



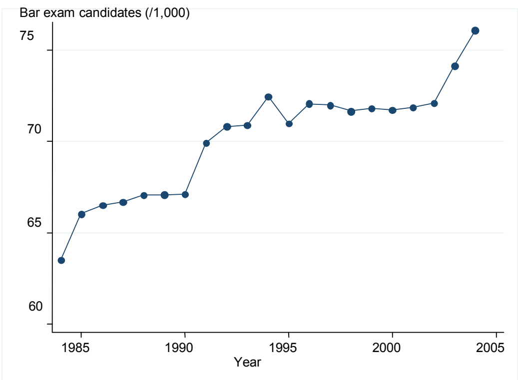
Note: The grey bars report the frequency of standard changes (see Table 1, column 2). The black bars report the frequency of standard changes including changes occurring in periods in which their sign and magnitude could not be measured (see Appendix 2 for details).

Figure 4. Average MBE score and average pass rate



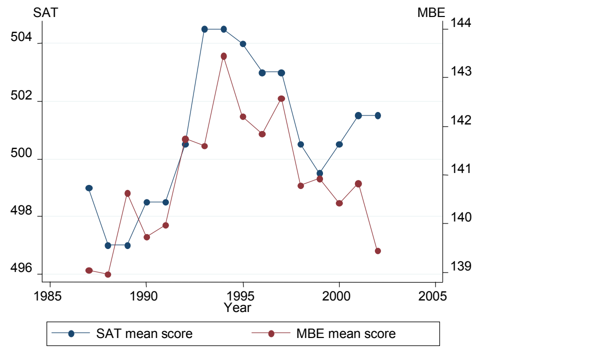
Note: The figure reports the average Multistate Bar Examination in the US and the average bar examination pass rate (total number of successful candidates / total number of candidates) in the US.

Figure 5. Number of bar exam candidates



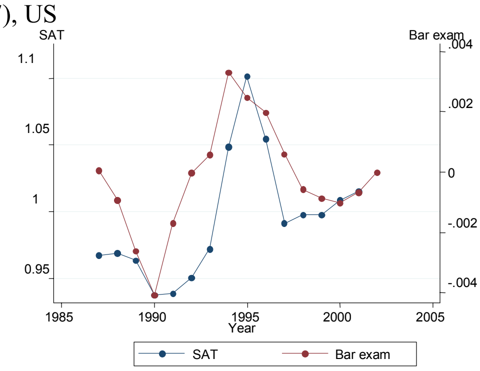
Note: The figure reports the total number of candidates (/1,000) taking the bar examination in the US by year.

Figure 6. MBE mean scores and SAT scores (t-8), US



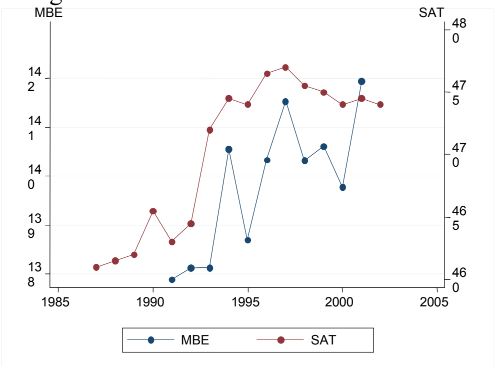
Note: The figure reports the MBE mean score by year in the US and the SAT mean score 8 years earlier.

Figure 7. Bar exam candidates and SAT candidates (t-7), US



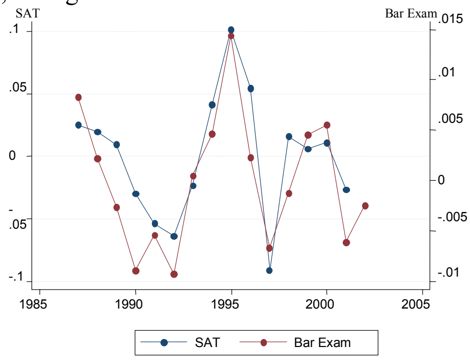
Note: The figure reports the number of bar exam candidates divided by the number of lawyers in the US (deviations from the trend) and the number of SAT candidates 7 years earlier (/1,000,000).

Figure 8. MBE mean score and SAT mean score (t-8), Georgia



Note: The figure reports the MBE mean score and the SAT mean score (average of the verbal and math sections) 8 years earlier.

Figure 9. Bar exam candidates and SAT candidates (t-7), Georgia



Note: The figure reports the number of bar exam candidates divided by the number of lawyers in Georgia (deviations from the trend) and the number of SAT candidates 7 years earlier (deviations from the trend).

Table 1. Minimum standards

State	Starting Date of Comparable Standards (1)	Observed Changes (2)	Date of Change (3)	Minimum Quality Standard in 2005 (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
Utah	1991	-	-	130
Connecticut	1984	-	-	132
Illinois	2000	-	-	132
Indiana	2001	-	-	132
Mississippi	1995	-	-	132
District of Columbia	1984	-	-	133
Kansas*	2000	-	-	133
New Jersey	1992	-2	1993	133
New York	1984	1	July 2005	133
Hawaii	1993	-	-	134
Arkansas	2002	-	-	135
Georgia	1984	5	1997	135
Massachusetts	1984	-	-	135
Nebraska*	1996	-	-	135
Ohio	1984	-10, 3.33, 6.67	1992, 96, 97	135
Oklahoma	1984	2, 1, 4, 1	1991, 92, 95, July 97	135
Texas*	1994	-	-	135
West Virginia	1994	-	-	135
Maryland*	Jul-00	-	-	135.33
Florida	1984	2, 3	July 2003, July 04	136
Pennsylvania*	Jul-01	-	-	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
New Hampshire	1984	-	-	140
Virginia	1998	-	-	140
California	1984	4	1990	144
Delaware	2000	-	-	145

NOTE: Minimum quality standard is the minimum overall score (mean of the MBE score and essay scaled score) required to pass the bar exam (minimum scores are measured on a 0-200 scale). Data on minimum quality standards is available from either 1984 or since the introduction of comparable standards (reported in Column 1), whichever is later, to 2005. Column 2 reports changes in the minimum quality standards, while Column 3 reports the corresponding date of each change. Column 4 reports the minimum quality standard in 2005. The information in Table 1 is sufficient to reconstruct the time series of the minimum standard in each state.

* For some years, the data allowed changes in grading procedures to be identified before the introduction of comparable standards (Column 1). See Appendix 2 for details.

Table 2. Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Minimum standard *(D)*	135.3	4.4	128.0	144.0
Bar exam candidates per lawyer, %, *(N)*	8	2	4	15
MBE mean score *(q)*	141.5	3.7	128.9	147.0
Bar exam candidates	2308	2902	136	12131
Bar exam successful candidates	1487	1525	94.0	6877
Bar exam pass rate	0.7	0.09	0.47	0.92
Population (state mean =1)	1.03	0.06	0.87	1.23
Real gross state product per capita (/1,000)	29.6	5.4	20.5	44.6
Educational attainment	24.6	5.8	10.1	38.7
Fraction of migrant population	3.6	1.4	1.5	6.8

Note: The table reports summary statistics for the 122 observations used to estimate model (4). Minimum standard is the minimum overall score (mean of the MBE score and essay scaled score) required to pass the bar exam (minimum scores are measured on a 0-200 scale). Bar Exam candidates is the number of bar exam candidates in the state, successful candidates is the number of candidates passing the bar exam. MBE mean score is the average Multistate Bar Examination score (measured on a 0-200 scale). The population index is computed as population divided by the state mean population (between 1985 and 2002, data from the Bureau of Economic Analysis). Real gross state product per capita is measured in thousands of 1996 dollars. Educational attainment is the fraction of population aged 25 or over with a bachelor's degree or higher qualification (Census Bureau, Current Population Survey). The fraction of immigrant population is the number of tax exemptions for people who moved to the state within the year relative to the total number of tax exemptions. Both immigration from other states in the US and from other countries is included (Internal Revenue Service).

Table 3. The impact of number and quality of candidates on exam difficulty (panel data regressions)

	(1)	(2)	(3)
MBE mean score *($q_{i,t-1}$)*	0.780	0.855	0.353
	(0.189)***	(0.201)***	(0.097)***
Bar exam candidates per lawyer *($N_{i,t-1}$)*	0.460	0.583	-0.070
	(0.485)	(0.413)	(0.069)
Population		-11.687	1.853
		(11.374)	(1.519)
Real gross state product per capita		-0.103	-0.071
		(0.173)	(0.049)
Year fixed effects?	Yes	Yes	Yes
State fixed effects?	No	No	Yes
Observations	122	122	122
R-squared	0.42	0.44	0.38

Note: The dependent variable is the minimum overall score (mean of the MBE score and essay scaled score) required to pass the bar exam (minimum scores are measured on a 0-200 scale). All regressors are lagged one year. MBE mean score is the average Multistate Bar Examination score (measured on a 0-200 scale). The number of bar exam candidates per lawyer is measured in percentage. The population index is computed as population divided by the state mean population (between 1985 and 2002, data from the Bureau of Economic Analysis). Real gross state product per capita is measured in thousands of 1996 dollars. Robust standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. The impact of number and quality of candidates on exam difficulty (instrumental variable panel data regressions)

	(1) IV	(2) IV	(3) IV
MBE mean score *($q_{i,t-1}$)*	1.470	1.198	1.011
	(0.760)*	(0.525)**	(0.352)***
Bar exam candidates per lawyer *($N_{i,t-1}$)*	0.874	0.877	0.903
	(0.393)**	(0.371)**	(0.345)***
Population	-13.198	-11.916	-11.499
	(7.893)*	(6.795)*	(6.274)*
Real gross state product per capita	0.227	0.256	0.052
	(0.148)	(0.170)	(0.160)
Educational attainment			0.131
			(0.081)
Fraction of migrant population			0.338
			(0.654)
Year fixed effects?	Yes	Yes	Yes
State fixed effects?	No	Yes	Yes
Observations	122	122	122

Note: The dependent variable is the minimum overall score (mean of the MBE score and essay scaled score) required to pass the bar exam (minimum scores are measured on a 0-200 scale). All regressors are lagged one year. MBE mean score is the average Multistate Bar Examination score (are measured on a 0-200 scale). The number of bar exam candidates per lawyer is measured in percentage. MBE mean score and bar exam candidates per lawyer are treated as endogenous. The instruments are the number of SAT candidates and the average verbal and math SAT scores 8 years earlier (divided by the respective state means; the first stage regression is reported in Table 5). The population index is computed as population divided by the state mean population (between 1985 and 2002, data from the Bureau of Economic Analysis). Real gross state product per capita is measured in thousands of 1996 dollars. Educational attainment is the fraction of population aged 25 or over with a bachelor's degree or higher qualification (Census Bureau, Current Population Survey). The fraction of immigrant population is the number of tax exemptions for people who moved to the state within the year relative to the total number of tax exemptions. Both immigration from other states in the US and from other countries is included (Internal Revenue Service). Robust standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. First stage regressions

Dependent variable:	(1) Bar exam candidates per lawyer *($N_{i,t-1}$)*	(2) MBE mean score *($q_{i,t-1}$)*	(3) Bar exam candidates per lawyer *($N_{i,t-1}$)*	(4) MBE mean score *($q_{i,t-1}$)*	(5) Bar exam candidates/ population (*1,000)
SAT verbal score (t-8)	1.291	-36.601	1.254	-49.229	4.529
	(0.312)***	(30.772)	(0.316)***	(28.355)*	(1.299)***
SAT math score (t-8)	-0.868	25.882	-0.827	39.771	-2.506
	(0.282)***	(27.776)	(0.286)***	(25.681)	(1.173)**
SAT candidates (t-8)	0.044	-5.631	0.041	-7.551	0.141
	(0.021)**	(2.115)***	(0.022)*	(1.985)***	(0.089)*
Population and real GSP per capita?	Yes	Yes	Yes	Yes	Yes
Educational attainment and fraction of migrant population?	No	No	Yes	Yes	No
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
State fixed effects?	Yes	Yes	Yes	Yes	Yes
R-squared	0.52	0.52	0.52	0.61	0.49
Test excluded instruments	F(3,91)=5.97	F(3,91)=3.07	F(3,89)=5.51	F(3,89)=6.62	F(3,91)=4.75
	P-value=0.00	P-value=0.03	P-value=0.00	P-value=0.00	P-value=0.00

Note: All regressors but SAT scores are lagged one year. The average SAT scores and the number of SAT takers are divided by state means and lagged 8 years. MBE mean score is the average Multistate Bar Examination score (are measured on a 0-200 scale). Real gross state product per capita and population are included in all regressors (coefficients are not reported). Educational attainment and the fraction of immigrant population are included in column 3 and 4 (coefficients are not reported). * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Robustness results

	(1)	(2)	(3)
Panel 1. Including admissions on motion.			
MBE mean score *($q_{i,t-1}$)*	0.775	0.850	0.351
	(0.205)***	(0.217)***	(0.097)***
Bar exam candidates per lawyer *($N_{i,t-1}$)*	0.469	0.604	-0.069
	(0.506)	(0.390)	(0.070)
Admissions on motion per lawyer	0.094	0.146	-0.054
	(0.734)	(0.576)	(0.105)
Panel 2. MPRE included			
MBE mean score *($q_{i,t-1}$)*	0.799	0.860	0.357
	(0.232)***	(0.270)***	(0.099)***
Bar exam candidates per lawyer *($N_{i,t-1}$)*	0.432	0.596	-0.068
	(0.607)	(0.508)	(0.072)
MPRE minimum score	-0.026	0.002	-0.040
	(0.241)	(0.218)	(0.038)
Panel 3. GSP share of the legal industry			
MBE mean score *($q_{i,t-1}$)*	0.735	0.811	0.328
	(0.165)***	(0.176)***	(0.084)***
Bar exam candidates per lawyer *($N_{i,t-1}$)*	0.361	0.502	-0.112
	(0.385)	(0.348)	(0.076)
GSP legal services	254.040	309.768	291.683
	(370.841)	(423.986)	(102.095)***
Panel 4. Two year lag			
MBE mean score *($q_{i,t-2}$)*	0.803	0.896	0.285
	(0.183)***	(0.195)***	(0.117)**
Bar exam candidates per lawyer *($N_{i,t-2}$)*	0.331	0.485	0.006
	(0.411)	(0.351)	(0.067)
Panel 5. Bar exam candidates per capita			
MBE mean score *($q_{i,t-1}$)*	0.717	0.771	0.376
	(0.170)***	(0.184)***	(0.098)***
Bar exam candidates per capita (*1,000)	2.396	7.041	0.239
	(7.262)	(7.138)	(1.298)
Panel 6. Extended sample			
MBE mean score *($q_{i,t-1}$)*	0.652	0.626	0.606
	(0.154)***	(0.157)***	(0.091)***
Bar exam candidates per active lawyer *($N_{i,t-1}$)*	0.096	0.103	0.009
	(0.118)	(0.111)	(0.102)

Note: The dependent variable is the minimum overall score (mean of the MBE score and essay scaled score) required to pass the bar exam (minimum scores are measured on a 0-200 scale). The specification used in the three columns corresponds to that of Table 3, column 1, 2 and 3 respectively. Year fixed effects are included in all specifications, state fixed effects in column 3. Population and Real GSP per capita are included in columns 2 and 3. All regressors are lagged one year (apart from panel 4). MBE mean score is the average Multistate Bar Examination score (measured on a 0-200 scale). The number of bar exam candidates per lawyer and admissions on motion per lawyer are measured in percentage. The population index is calculated as population divided by the state mean population (between 1985 and 2002, data from the Bureau of Economic Analysis). Real gross state product per capita is measured in thousands of 1996 dollars.

In panel 1, admissions on motion also include admissions by diploma privilege. In panel 2, MPRE minimum score is the Multistate Professional Responsibility Examination score required to be admitted to the state bar (Maryland does not use the MPRE, the corresponding 3 observations are excluded from the sample in panel 2). In panel 3, GSP legal services is the share of Gross State Product of the legal services industry. In panel 4, all the variables are lagged two years (the number of observations is 112). In panel 5, the number of bar exam candidates is divided by the population in the state. In panel 6, all observations and estimated standards for Texas, Pennsylvania and Virginia are included (the total number of observations is 151 in column 1 and 143 in columns 2 and 3). Robust standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. Robustness results (IV regression)

	(1)	(2)	(3)
Panel 1. Including admissions on motion			
MBE mean score $(q_{i,t-1})$	1.516	1.180	1.009
	(0.839)*	(0.530)**	(0.358)***
Bar exam candidates per lawyer $(N_{i,t-1})$	0.874	0.875	0.903
	(0.407)**	(0.369)**	(0.347)***
Admissions on motion	-0.042	-0.056	-0.008
	(0.293)	(0.260)	(0.250)
Panel 2. MPRE included			
MBE mean score $(q_{i,t-1})$	-0.722	1.190	1.016
	(1.351)	(0.510)**	(0.344)***
Bar exam candidates per lawyer $(N_{i,t-1})$	0.021	0.817	0.849
	(0.489)	(0.341)**	(0.320)***
MPRE minimum score	0.289	0.025	0.046
	(0.312)	(0.109)	(0.105)
Panel 3. GSP legal industry			
MBE mean score $(q_{i,t-1})$	1.340	1.228	1.009
	(0.749)*	(0.621)**	(0.413)**
Bar exam candidates per lawyer $(N_{i,t-1})$	0.883	0.890	0.899
	(0.486)*	(0.464)*	(0.429)**
GSP legal services	-50.843	-40.180	-9.567
	(261.371)	(246.861)	(248.789)
Panel 4. Two year lag			
MBE mean score $(q_{i,t-2})$	3.555	1.298	0.895
	(4.765)	(0.534)**	(0.247)***
Bar exam candidates per lawyer $(N_{i,t-2})$	0.990	0.838	0.558
	(1.256)	(0.389)**	(0.223)**
Panel 5. Bar exam candidates per capita			
MBE mean score $(q_{i,t-1})$	1.111	0.955	0.841
	(0.515)**	(0.444)**	(0.317)***
Bar exam candidates per capita	0.229	0.232	0.231
	(0.082)***	(0.085)***	(0.081)***
Panel 6. Extended sample			
MBE mean score $(q_{i,t-1})$	1.348	1.157	1.014
	(0.386)***	(0.273)***	(0.292)***
Bar exam candidates per lawyer $(N_{i,t-1})$	0.928	0.811	0.695
	(0.389)**	(0.373)**	(0.338)**
Panel 7. Average instruments for t-7, t-8 and t-9			
MBE mean score $(q_{i,t-1})$	1.083	0.982	0.923
	(0.491)**	(0.391)**	(0.302)***
Bar exam candidates per lawyer $(N_{i,t-1})$	0.713	0.744	0.806
	(0.265)***	(0.271)***	(0.274)***
Panel 8. Additional instrument			
MBE mean score $(q_{i,t-1})$	1.036	1.233	1.122
	(0.532)*	(0.380)***	(0.335)***
Bar exam candidates per lawyer $(N_{i,t-1})$	0.786	0.884	0.845
	(0.321)**	(0.369)**	(0.340)**

Note: The dependent variable is the minimum overall score (mean of the MBE score and essay scaled score) required to pass the bar exam (minimum scores are measured on a 0-200 scale). The specification used in the three columns corresponds to that of Table 4, column 1, 2 and 3 respectively. Year fixed effects, population and real GSP per capita are included in all specifications, state fixed effects in column 2 and 3. The fraction of immigrant population and educational attainment are included only in column 3. The number of bar exam candidates per lawyer and admissions on motion per lawyer are measured in percentage. MBE mean score and bar exam candidates per lawyer are treated as endogenous. The instruments are the number of SAT candidates and the average verbal and math SAT scores 8 years earlier. All regressors are lagged one year (apart from panel 4). MBE mean score is the average Multistate Bar Examination score (measured on a 0-200 scale). The population index is calculated as population divided by the state mean population (between 1985 and 2002, data from the Bureau of Economic Analysis). Real gross state product per capita is measured in thousands of 1996 dollars. In panel 1, admissions on motion also include admissions by diploma privilege. In panel 2, MPRE minimum score is the Multistate Professional Responsibility Examination score required to be admitted to the state bar (Maryland does not use the MPRE, the 3 corresponding observations are excluded from the sample in panel 2). In panel 3, GSP legal services is the share of gross state product of the legal services industry. In panel 4, all the variables are lagged two years (the number of observations is 112). In panel 5, the number of bar exam candidates is divided by the population in the state. In panel 6, all observations and estimated standards for Texas, Pennsylvania and Virginia are included (the total number of observations is 143 in column 1 and 2, 134 in clolumn 3). In panel 7, the instruments are the average of SAT scores (math and verbal) and number of SAT candidates for 7, 8 and 9 years before the bar exam. Robust standard errors are in parentheses. In panel 8, the average exam difficulty in neighboring states (weighted by GSP) is used as additional instrument. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. The impact of exam difficulty and candidate quality on pass rate

	(1)	(2)
Minimum score	-0.021	-0.021
	(0.005)***	(0.005)***
MBE mean score	0.023	0.023
	(0.003)***	(0.004)***
Year fixed effects?	No	Yes
R^2	0.79	0.80
Test $\beta_1 = -\beta_2$	F(1,15) = 0.51	F(1,15) = 0.54
	P-value = 0.49	P-value = 0.47

Note: The dependent variable is the bar exam pass rate. Minimum score is the minimum overall score (mean of the MBE score and essay scaled score) required to pass the bar exam (measured on a 0-200 scale). MBE mean score is the average Multistate Bar Examination score (measured on a 0-200 scale). The number of observations is 126. The last row reports the test of equality of the impact of minimum score and MBE mean score on pass rate.

Appendix 1. Distinguishing the two theories of licensing

Consider the setting described in Section 5.1. Under the classic theory of licensing, the board is not interested in lawyers' quality but only in the number of entrants. The licensing board observes the number of candidates, their quality distribution and chooses D on the support of the score distribution to maximize the objective function $U(P, X)$, which depends on the number of passers P and a set of exogenous variables X describing, for example, the local demand for legal services.[21] Assume there is an optimal number of successful candidates, $P^*(X)\epsilon(0, N)$ such that $U(P^*(X), X) > U(P, X)$ for any $P \neq P^*(w)$. If $N > P^*(X)$,the minimum standard chosen by the licensing board is the unique threshold D^* such that $P^*(X) = N[1 - F(D^*, m)]$, that is $D^*(X, N, m) = F^{-1}(1 - \frac{P^*(X)}{N}, m)$. If $N \leq P^*(X)$, $D^*(X)$ is such that $P^*(X) = N$. In the second case, when the number of exam candidates is smaller than the optimal number of candidates, the licensing exam is not binding. (Empirically, this case is clearly less interesting.) Changes in N and m are offset by changes in standards, so that the number of passers is unchanged, therefore $\frac{dP^*(X)}{dN} = 0$ and $\frac{dP^*(X)}{dm} = 0$.

This result does not hold for the modern theory of licensing. Quality now plays an essential role. The board now values both the number of passers and their minimum quality D according to the objective function $U(P, D, X)$. This objective function may correspond to social welfare under the public interest view of licensing, but does not need to be the case. The objective of the licensing board may aggregate the preferences of different groups within the profession, the public and consumers. [22]

Assume that $U()$ is continuous, increasing and concave in P and D. Given the existing pool of candidates, there is a trade-off between the quality-increasing and the competition-reducing effects of higher standards. The licensing board faces the constraint given by (2) in Section 5.1. The optimal number of passers $P^{**}(N, m, X)$ and minimum standard $D^{**}(N, m, X)$ are such that the marginal rate of substitution (MRS) is equal to the

[21] The assumption that professional organizations have well defined objective functions is a useful device for analysis. It has been used in a different context, for example, by MaCurdy and Pencavel (1986).

[22] In this simple formulation, licensing boards use the minimum standard D as a measure of quality. However, the board may consider other measures of quality (for example average quality) but the logic of the analysis remains the same.

trade-off between passers and minimum quality, $(dU(P,D,X)/dP)/(dU(P,D,X)/dD) = dP/dD$. Changes in N and m clearly affect the constraint, this trade-off and the choice of the optimal number of candidates to be admitted.

Proposition 1 *It cannot be that both* $\frac{dP^{**}(X)}{dN} = 0$ *and* $\frac{dP^{**}(X)}{dm} = 0$.

Proof. By contradiction. Consider an increase in m. For the number of passers $P^{**}(N,m,X)$ to remain unchanged, it must be that $dD = -dm$. Since $dP/dD = -Nf(D-m)$, the slope of the constraint at the optimum is unchanged, $\frac{d}{dm}(\frac{dP}{dD}) = 0$. This requires that MRS is constant, given P^{**}, that is $dMRS/dD_{|P^{**}(N,m,X)} = 0$. Consider now a change in N. For the number of passers $P^{**}(N,m,X)$ to remain unchanged, it must be that $\frac{dD}{dN} = \frac{1-F(D,m)}{Nf(D-m)}$ which implies that $\frac{d}{dN}(\frac{dP}{dD}) = -f(D-m) - \frac{df(D-m)}{dD}\frac{1-F(D-m)}{f(D-m)} < 0$. Therefore $dMRS/dD_{|P^{**}(N,m,X)} < 0$. ■

Figures A1 and A2 illustrate this result. An increase in mean quality shifts the constraint faced by the licensing board, without affecting the trade-off between admitting more candidates and increasing minimum quality. For the licensing board to exactly offset the changes in candidates' quality, it must be the case that the marginal benefit from admitting more candidates (relative to the marginal loss from decreasing minimum quality) remains constant as exam difficulty increases. On the contrary, for the licensing board to exactly offset changes in the number of candidates, it must be the case that the marginal gain from admitting more candidates increases.

Appendix 2. Data and Sources

Minimum standards

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 (ABA 2005). 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 were converted to a 0-200 basis to increase the consistency of Table 1. In the *Comprehensive Guide* there is some uncertainty over when some standards changed. Where possible I used additional sources to locate the exact date of change. In the cases in which none was available and uncertainty persisted, I used the earliest date compatible with the information in the *Comprehensive Guide*.

For some years, the data reported in *The Comprehensive Guide* allowed changes in grading procedures to be identified before the introduction of comparable standards (Table 1, column 1). It is not possible to precisely determine the sign or the magnitude of these changes. In Kansas, the data allows changes in grading procedures to be identified during the period between 1994 and 2000. In particular, the grading procedures changed in 2000. In Nebraska, between 1984 and 1996, the grading procedures changed in 1996. In Texas, between 1993 and 1994, the grading procedures changed in 1993. In Maryland, between 1984 and July 2000, the grading procedures changed in 2000. In Pennsylvania, between 1984 and July 2001, the grading procedures changed in 1995 and in 2001. In Colorado, between 1984 and 1987, the grading procedures changed in 1985 and in 1987. In Wisconsin, between 1987 and 2002, the grading procedures changed in 1995, in 2000 and in 2001.

MBE scores and exam candidates

Minimum quality standard data is matched with the number of takers and passers in each examination (NCBEX). In contrast to data on exam difficulty, data on exam results is available from 1981 to 2002. MBE data consists of mean scores at the state level for each examination. I requested this information directly to the Bar Association or the

Supreme Court office responsible for administering the exam in each state (by mail and telephone). A number of states decided not to reveal their MBE scores and those who did disclose information varied significantly in how much they chose to disclose. The yearly state MBE mean scores are weighted using the number of exam candidates. I also have national US average scores, for each examination, from 1981 to 2002 (NCBEX). The data on MBE is available for Alabama from 1990, Montana from 1999, New Mexico from 2001, Utah from 1997, Connecticut from 1990, Missouri from 1996, Arkansas from 1992, Georgia from 1991, Massachusetts from 1983, Texas from 1990, Maryland from 1987, Pennsylvania from 1995, Arizona from 1990, Colorado from 1977, Virginia from 1980, California from 1992, Idaho from 1991, Kentucky from 1999, Michigan from 1995, Tennessee from 1983 to 2002. MBE scores by ethnic groups are reported by Klein and Bolus (2004). The research paper is available from the Texas Board of Law Examiners, http://www.ble.state.tx.us/one/analysis_0704tbe.htm.

MPRE, additional requirements and number of lawyers

Data on MPRE minimum scores is available in the *Comprehensive Guide*, together with information on educational, moral character and fitness requirements. NCBEX reports the number of bar exam applicants by source of legal education. There are two sources of information on the number of lawyers by state, the American Bar Association (National Lawyer Population Survey) and the American Bar Foundation (the Lawyer Statistical Report). The first provides annual data, while the second is published only every 3-5 years (and requires estimating the missing observations). The Lawyer Statistical Report has the advantage of counting only once those lawyers admitted to more than one state bar. I used this second source of data to create the variables used in the estimation. I connected the series using the procedure in Pashigian (1977): $L_t = L_{t-n}(1 - d_{t-n,t})^n + \sum_{i=1}^{n} A_{t-i}(1 - d_{t-n,t})^i$ where L_t is the observed stock of lawyers in year t, A_t the number of admissions to the bar in year t (NCBEX) and $d_{t-n,t}$ the exit rate from $t-n$ to t. Results are not significantly affected by the source of data.

Figure A1. The impact of an increase in candidate mean quality on exam difficulty (holding the number of successful candidates P** constant).

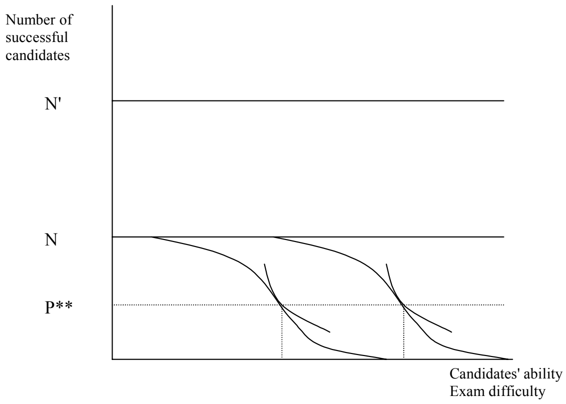


Figure A2. The impact of an increase in the number of candidates on exam difficulty (holding the number of successful candidates P** constant).