Doctors Without Borders? Re-licensing Requirements and Negative Selection in the Market for Physicians

Adriana D. Kugler* and Robert M. Sauer†

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Abstract

Re-licensing requirements for professionals that move across borders are widespread. In this paper, we measure the effects of occupational licensing by exploiting an immigrant physician re-training assignment rule. Instrumental variables and quantile treatment effects estimates indicate large returns to acquiring an occupational license and negative selection into licensing status. We also develop a general model of optimal license acquisition which, together with the empirical results, suggests that stricter re-licensing requirements may not only lead to practitioner rents but also to lower average quality of service in the market for physicians.

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*University of Houston, Universitat Pompeu Fabra and CEPR (adkugler@uh.edu).

†The Hebrew University of Jerusalem (mssauer@mscc.huji.ac.il).

1 Introduction

Restricted entry into an occupation through occupational licensing requirements is a widespread phenomenon. At least 18 percent of the work force in the United States is affected by occupational licensing, exceeding both minimum wage coverage and membership in unions. Occupational licensing is also widespread in many other countries. In the European Union, for example, occupational entry restrictions are thought to substantially affect incentives for internal migration and labor mobility between member states. Licensing requirements not only restrict entry into professional occupations, such as medicine, dentistry, and law, but also restrict entry into less skilled occupations such as haircutting and cosmetology (see Kleiner (2000)).

In the traditional theory of economic regulation, occupational licensing is generally thought of as an institution that allows practitioners to capture monopoly rents (Friedman and Kuznets (1945), Stigler (1971)). Licensing is regarded as a tool used by practitioners to restrict labor supply and drive up the price of labor. More recent theoretical analyses of occupational licensing, however, focus on the conditions under which occupational licensing can be socially beneficial. Licensing may improve the average quality of service offered by practitioners when the entry of less-competent practitioners is prevented, or when less-competent practitioners are forced to increase their investments in human capital (see, e.g., Shapiro (1986)). The social loss due to excess wages may be outweighed by the social gains from higher quality of service.

The theoretical ambiguity over the net social benefits of occupational licensing is accompanied by an inconclusive empirical literature. Empirical studies usually find higher mean earnings for individuals in regulated occupations, holding observed human capital levels constant (see, e.g., Muzondo and Pazderka (1980), Kleiner and Kudrle (2000) and Kleiner (2000)). But the data used in these studies generally do not permit identification of the causal effect of entry restrictions on earnings and thus inference on the presence of rents. Entry restrictions and self-selection into the regulated occupation are often confounded. Reliable evidence that licensing improves the average quality of service offered by practitioners is even more rare. The main difficulty in measuring quality effects is in obtaining accurate measures of practitioner quality.[1]

In this paper, the effects of occupational licensing are measured using data on the labor market outcomes of immigrant physicians in Israel. The data allow us to identify the returns to an occupational license free of biases due to non-random selection into licensing status. Identification of the returns is possible for several reasons. First, the immigrant physicians in the data are a relatively homogeneous group of individuals in terms of education and experience. Second, many immigrant physicians did not get re-licensed and/or obtain employment in their original profession. This is important since identification of the returns to an occupational license may be difficult for the simple reason that there may be very little variation in licensing status among individuals with similar education and training levels (Pashigian (1980)). Third, and perhaps most important, the Israel Ministry of Health assigned immigrant physicians to one of two different re-licensing tracks depending on previous experience. Track assignment is not directly based on unobservables and the two re-licensing tracks are inherently different in terms of the likelihood of acquiring a license.

The Israel Ministry of Health's assignment rule places immigrant physicians either on a re-training track that requires the passing of a general medical knowledge licensing exam (the exam track), or on a re-training track that grants an exemption to the exam and issues a temporary general practitioner license for six months (the observation track). The temporary license allows the practice of medicine under the observation of native physicians. At the end of the six month period, immigrant physicians on the observation track receive a permanent license with near certainty.

[1] Kleiner and Kudrle (2000) indirectly measure quality effects by comparing the dental health of individuals across states that vary in entry requirements for dentists. Angrist and Guryan (2003) examine the effect of teacher certification requirements on teacher quality as measured by educational background. Both studies find small quality effects.

Re-training track assignment for almost all of the immigrants in the sample follows a "20-year rule". Immigrants with more than 20 years of previous physician experience are assigned to the observation track, those with less than 20 years have to pass the re-licensing exam.

It is important to note that the physician re-licensing regime in Israel is not unique. In the US, for example, physicians that migrate across states must also be re-licensed and in many states exemption from a re-licensing exam is a function of previous physician experience. The "10-year rule" of state licensing boards requires migrant physicians that have not passed a national board exam within 10 years to take a Special Purpose Examination (SPEX) which tests their general medical knowledge. Physicians that have passed a national board exam within 10 years are exempt from the SPEX and are granted a license.[2] Since other countries use re-licensing regimes that are similar to that used in Israel, especially for immigrants or internal migrants, the results in this study may be quite relevant in other contexts.

According to OLS estimates of the returns to acquiring a medical license, immigrants that get re-licensed have mean monthly earnings that are between 90 and 114 percent higher than their unlicensed counterparts. OLS estimates, however, are biased to the extent that licensing status is related to potential outcomes without a license. Instrumental variables estimates that exploit the re-training assignment rule and isolate the returns to a license among individuals that would not have obtained a license had they not been assigned to the observation track, yield an increase in mean monthly earnings that is much higher than that estimated by OLS. IV estimates of the returns to a license range between 180 and 340 percent. The large IV estimates, compared to OLS, are suggestive of both the presence of rents and negative selection

[2] The states that require the SPEX for migrant physicians who have not passed a national board test within ten years or who are not board-certified are Alabama, California, Illinois, Louisiana, Maryland, Minnesota, Mississippi, Montana, North Carolina, Nevada, New York, Oregon, South Carolina and Texas. See http://www.ama-assn.org for details.

into licensing status.

In order to give an economic interpretation to the OLS and IV estimates, and address the effects of re-licensing on the average quality of service, we also develop a general model of optimal license acquisition. The theory is explicitly linked to the empirical work by providing theoretical expressions for the OLS and IV estimators according to the model (Card (1999), Rosenzweig and Wolpin (2000)). The expressions show that when IV estimates exceed OLS estimates, stricter re-licensing requirements may lead to lower average quality of service in the licensed occupation. The policy implication of the findings is that lowering the costs to immigrant physicians of acquiring a medical license may raise physician quality.

As a robustness check on the empirical results, the returns to an occupational license are also estimated using a quantile treatment effects (QTE) model (Abadie, Angrist and Imbens (2002)). The QTE model exploits the natural experiment that determines which physicians get licensed, as opposed to conventional quantile regression, and is less sensitive than standard IV techniques to the inclusion of high earnings outliers and zero earnings for the unemployed. QTE estimates show that the returns to an occupational license are largest at the upper quantiles of the earnings distribution. Conventional quantile regression estimates produce the largest returns at the lower quantiles. QTE estimates of the counterfactual *distribution* of earnings without a license also indicate negative selection into licensing status at all examined quantiles.

The rest of the paper is organized as follows. The next section briefly describes the institutional setting of immigrant physician re-licensing in Israel. Section 3 formulates the model of optimal license acquisition. Section 4 describes the data, reports OLS estimates and presents a graphical analysis of the correlation in the discontinuities in licensing and earnings outcomes which forms the basis of identification. Section 5 outlines the estimation strategy. Section 6 reports reduced form, IV and QTE estimates of the returns to a license. Section 7 summarizes and concludes.

2 Background

The recent mass immigration wave to Israel, from the former Soviet Union, contained an unusually large number of physicians. Between October 1989 and August 1993, approximately 12,500 Soviet physicians arrived in Israel, nearly doubling potential supply in the market for physicians. Even before the arrival of immigrant physicians, Israel had one of the highest physician to population ratios in the world. The number of doctors per 100,000 Israelis in 1989 was 285. For purposes of comparison, note that in the same year in the US, there were 216 doctors per 100,000 Americans. However, the demand for medical services in Israel also substantially increased during the immigration period as the Israeli population grew by 10%.

According to Israeli immigration law, physicians that are licensed to practice medicine in a foreign country, and that have their foreign medical credentials recognized by the Israel Ministry of Health, must pass a re-licensing exam in order to legally practice medicine. However, immigrant physicians that practiced clinical medicine and that have substantial previous physician experience are exempt from the re-licensing exam. Until November 1992, the cutoff number of years required for exemption from the licensing exam was 20. The cutoff was subsequently lowered to 14. The lowering of the cutoff was abrupt and not publicized beforehand. Approximately 96% of the Soviet immigrant physicians in our data were subject to the "20-year rule" rather than the "14-year rule".

Immigrant physicians that are granted an exemption from the licensing exam must work under observation for six months in designated public hospitals or community clinics. During the six month work under observation period, immigrants receive a salary and minimal income support from the Ministry of Absorption. At the end of the six month period these immigrants receive a permanent license in general medicine with near certainty.

Immigrant physicians that are assigned to the exam track are eligible, but not required, to participate in a government sponsored examination preparation course.

Over 90% of immigrants that are referred to the licensing exam choose to participate in a preparation course. Preparation courses last six months, are offered twice a year and are held in public hospitals throughout the country. In order to be accepted into a preparation course it is necessary to successfully complete a prior medical terminology language course that also lasts six months. Immigrant physicians that participate in the preparation course receive minimal income support from the Ministry of Absorption. A permanent license in general medicine is acquired after passing the exam.

Upon successful completion of the re-licensing requirements, all immigrant physicians, independent of previous experience, must request to be recognized as specialists in order to practice medicine in their former specialty. The Ministry of Health denies an overwhelming majority of these requests. Immigrant physicians whose requests are denied must fulfill a post-licensing residency requirement that includes successful completion of two specialty exams. The residency requirement can last a number of years depending upon medical specialty. The status of specialist is not required for performing rounds in hospitals or treating patients in residential communities as a general practitioner. Only a small percentage of immigrants were in specialist residency at the time of the immigrant physician survey.

3 The Model

The decision to acquire an occupational license can be described within a general model of optimal license acquisition. The model that we develop is similar to the training participation and earnings model described in Heckman, LaLonde and Smith (1999) but adds supply and average practitioner quality effects on mean wages in both unlicensed and licensed occupations.

The model assumes a continuum of workers of skill type η, where η is drawn from a distribution $F(\cdot)$ with support $[\underline{\eta}, \overline{\eta}]$. Individuals live for two periods and have a subjective discount rate r. In the first period, individuals choose whether to invest in acquiring a license or not. In the second period, all individuals work. Acquisition of a license in the first period involves both direct and indirect costs. The direct costs include the monetary equivalent of psychological costs of having to obtain a license, such as effort expended in studying for exams and/or meeting other licensing requirements. The direct costs also include tuition, fees and commuting expenses. The indirect costs are the foregone wages the individual could have earned in the unlicensed occupation in the first period. While direct costs are likely to be relatively lower for more skilled (higher η) individuals, opportunity costs (foregone wages) of acquiring a license are likely to be relatively higher. The assumption that direct and indirect costs vary among individuals of different types generates selection into the licensed occupation.

The direct costs of acquiring a license are specified as $\frac{C}{\eta}$, reflecting the assumption that it is relatively easier for more highly skilled individuals to study for the licensing exam. This functional form also captures the possibility that there is a positive correlation between skill level and pre-training assets. Highly skilled immigrants may be less liquidity constrained. Production functions in the licensed and unlicensed sectors, $Y_L(\eta, N_L)$ and $Y_U(\eta, N_U)$, are assumed to be increasing in η, thus generating higher opportunity costs to acquiring a license for more highly skilled individuals. It is also assumed that there is diminishing returns with respect to employment, N_L and N_U, in both occupations.

Individuals seek to maximize lifetime income by choosing whether or not to acquire a license. Individuals choose to acquire a license and work in the licensed occupation in the second period, rather than work in the unlicensed occupation in both periods, when

$$\frac{w_L - w_U}{(1+r)} \geq \frac{C}{\eta} + w_U. \tag{1}$$

w_L and w_U are the wages in the licensed and unlicensed occupations and are defined as the marginal products of labor in the two occupations, respectively. w_L and w_U are also functions of η and N_i, $i = L, U$, but these arguments are suppressed for convenience. Equation (1) states that a license will be acquired when the discounted increase in earnings in the second period is greater than or equal to the sum of direct and indirect costs in the first period.[3]

The decision rule can also be expressed in terms of the maximum direct cost that an individual of type η is willing to incur to acquire a license. The maximum direct cost is denoted as $C_{\max}^{\eta}$. $C_{\max}^{\eta}$ equates lifetime income in the two occupations,

$$C_{\max}^{\eta} = \frac{\eta[w_L - (2+r)\, w_U]}{(1+r)}. \tag{2}$$

An individual of type η chooses to work in the licensed occupation if $C_{\max}^{\eta} \geq C$ and chooses to work in the unlicensed occupation if $C_{\max}^{\eta} < C$.

$C_{\max}^{\eta}$ varies with η in the following way:

$$\begin{aligned} \frac{\partial C_{\max}^{\eta}}{\partial \eta} &= \frac{[w_L - (2+r)\, w_U]}{(1+r)} \\ &\quad - \frac{\eta[\frac{\partial w_L}{\partial \eta} - (2+r)\, \frac{\partial w_U}{\partial \eta}]}{(1+r)}. \end{aligned} \tag{3}$$

If higher skill reduces the direct costs of acquiring a license (the first term in (3)) by more than it increases foregone wages in the unlicensed occupation (the second term in (3)) then $\frac{\partial C_{\max}^{\eta}}{\partial \eta} > 0$. $\frac{\partial C_{\max}^{\eta}}{\partial \eta} > 0$ implies positive selection into licensing status. Lower skilled individuals with $\eta \in [\underline{\eta}, \widetilde{\eta}]$ work in the unlicensed occupation and higher skilled individuals with $\eta \in [\widetilde{\eta}, \overline{\eta}]$ work in the licensed occupation. $\widetilde{\eta}$ is the point in the skill distribution where $C_{\max}^{\eta} = C$. If $\frac{\partial C_{\max}^{\eta}}{\partial \eta} < 0$, there is negative selection into licensing status. Individuals with $\eta \in [\underline{\eta}, \widetilde{\eta}]$ work in the licensed occupation and individuals with $\eta \in [\widetilde{\eta}, \overline{\eta}]$ work in the unlicensed occupation.

[3]Uncertainty in successfully meeting licensing requirements or in obtaining a job in the licensed occupation after completing the requirements can be thought of as factors that reduce the discounted wage premium. Adding uncertainty does not change anything of substance.

Mean wages in the licensed and unlicensed occupations, according to the model, are

$$E(w_i) = \int_{\eta_{1i}}^{\eta_{2i}} \left[\frac{\partial Y_i(\eta, N_i)}{\partial N_i} \right] f(\eta) d\eta, \;\; i = L, U. \tag{4}$$

Under positive selection, $(\eta_{1L}, \eta_{2L}, N_L) = (\widetilde{\eta}, \overline{\eta}, 1 - F(\widetilde{\eta}))$ and $(\eta_{1U}, \eta_{2U}, N_U) = \left(\underline{\eta}, \widetilde{\eta}, F(\widetilde{\eta})\right)$. Under negative selection the L and U subscripts are reversed.

Of particular interest is the effect of stricter licensing requirements, or a higher C, on mean wages in (4). Under positive selection, the mean wage in the licensed occupation increases because $\widetilde{\eta}$ increases. A higher $\widetilde{\eta}$ reduces the supply of licensed workers ($N_L = 1 - F(\widetilde{\eta})$), raising wages for all skill types. A higher $\widetilde{\eta}$ also increases the lower bound of the integral, raising the average skill level of workers in the licensed occupation and thus the mean wage. Although $\frac{\partial E(w_L)}{\partial C} > 0$, $\frac{\partial E(w_U)}{\partial C}$ is, in general, ambiguous in sign. Since more individuals enter the unlicensed occupation, the mean wage is depressed, but these individuals also raise the average quality of workers in the unlicensed occupation. Note that negligible supply effects imply that both $\frac{\partial E(w_L)}{\partial C} > 0$ and $\frac{\partial E(w_U)}{\partial C} > 0$. Under negative selection, the same logic implies that $\frac{\partial E(w_L)}{\partial C}$ is ambiguous in sign and $\frac{\partial E(w_U)}{\partial C} < 0$. However, negligible supply effects yield $\frac{\partial E(w_L)}{\partial C} < 0$ and $\frac{\partial E(w_U)}{\partial C} < 0$.[4]

The theory outlined above can be linked to the empirical work by deriving theoretical expressions for the OLS and IV estimators (see Card (1999) and Rosenzweig and Wolpin (2000)). According to the model, the OLS estimator of the returns to a license is

$$\begin{aligned} E(w_L) - E(w_U) &= E(w|C^{\eta}_{\max} \geq C) - E(w|C^{\eta}_{\max} < C) \\ &= \frac{\partial \left[E(w|C^{\eta}_{\max} \geq C) \Pr(C^{\eta}_{\max} \geq C) \right]}{\partial \Pr\left(C^{\eta}_{\max} \geq C\right)} \end{aligned} \tag{5}$$

[4] The ambiguities in sign in the general case can be resolved through functional form specifications for the production functions and a distributional assumption on skill levels in the population.

$$
\begin{aligned}
& -\frac{\partial\left[E(w|C_{\max}^{\eta}<C)(\Pr(C_{\max}^{\eta}<C))\right]}{\partial(\Pr\left(C_{\max}^{\eta}<C\right))} \\
= \; & \frac{\partial E(w)}{\partial \Pr\left(C_{\max}^{\eta}\geq C\right)}.
\end{aligned}
$$

The OLS estimator is the difference in mean wages arising from differences in the probability of acquiring a license. Differences in the probability of acquiring a license are due to differences in skill levels. The OLS estimator does not yield the causal effect of acquiring a license.

The IV estimator of the returns to a license relies on the exogenous difference in C generated by different re-licensing regimes. According to the model, the two different re-licensing regimes, the exam track and the observation track, are a high C and a low C, respectively. Although it is the standard Wald expression that is used in estimation, it is convenient to express the IV estimator as a notional limiting case of the standard Wald expression when high C approaches low C (see Angrist, Graddy and Imbens (2000)). The limiting case facilitates comparison to OLS. The derivative-based expression for the IV estimator is:

$$
\begin{aligned}
\frac{\frac{\partial E(w)}{\partial C}}{\frac{\partial \Pr\left(C_{\max}^{\eta}\geq C\right)}{\partial C}} = \; & \frac{\partial E(w)}{\partial \Pr\left(C_{\max}^{\eta}\geq C\right)} \\
& +\Pr\left(C_{\max}^{\eta}\geq C\right)\frac{\frac{\partial E(w_L)}{\partial C}}{\frac{\partial \Pr\left(C_{\max}^{\eta}\geq C\right)}{\partial C}} \\
& +\left(1-\Pr\left(C_{\max}^{\eta}\geq C\right)\right)\frac{\frac{\partial E(w_U)}{\partial C}}{\frac{\partial \Pr\left(C_{\max}^{\eta}\geq C\right)}{\partial C}}
\end{aligned}
\tag{6}
$$

where $\frac{\partial \Pr\left(C_{\max}^{\eta}\geq C\right)}{\partial C}<0$. As shown in (6), the IV estimator is equal to the OLS estimator plus correction terms that are related to the difference in skill distribution between the two occupations. As opposed to OLS, the IV estimator is a causal expression. It yields the causal effect of acquiring a license for a subset of the licensed population, i.e., for individuals who acquire a license due to a change in C (Angrist, Imbens and Rubin (1996)).

Note that in the case of no supply effects ($Y_i(\eta, N_i) = Y_i(\eta)$, $i = L, U$) and positive selection into licensing status, the IV estimator is less than the OLS estimator because $\frac{\partial E(w_L)}{\partial C} > 0$ and $\frac{\partial E(w_U)}{\partial C} > 0$. In the case of no supply effects and negative selection, the IV estimator is greater than the OLS estimator because $\frac{\partial E(w_L)}{\partial C} < 0$ and $\frac{\partial E(w_U)}{\partial C} < 0$. The special case of no supply effects is the relevant empirical case since we are estimating the effect of licensing on the licensed in a world where people get licenses in the proportions in which we observe them. Neither the individual variation or the instrument used in this paper shift the supply curve.

4 The Data

The population of immigrant physicians in this study consists of immigrants that arrived in Israel from the former USSR between October 1989 and June 1992, that submitted a request to the Israel Ministry of Health to start the process towards re-licensing, that had their medical credentials in the former USSR recognized. Of the immigrants that declared at the airport, on the day of arrival, that they were physicians in the former USSR, 27% did not submit their credentials to the Ministry of Health. Of the immigrants that submitted their credentials, 3% did not have their credentials recognized. Of the immigrants that had their medical credentials recognized, 3% were not referred to one of the two re-training tracks. These latter immigrants were either required to complete a one year internship before being eligible for the exam track or were immediately granted recognition as specialists. The total number of immigrant physicians in this restricted population is $6,754$.[5]

Between the months of May and November of 1994, 731 of these $6,754$ immigrant physicians were surveyed, in face-to-face interviews, by Russian-speaking enumerators using a questionnaire written in Russian. The survey was conducted under the aus-

[5]Nonsubmitters to the Ministry of Health are much more likely than submitters to be over 55 years of age on arrival. Immigrants that did not have their credentials recognized are younger than those that had their credentials recognized.

pices of the JDC-Brookdale Institute of Jerusalem, The Israel Ministry of Health and the Israel Ministry of Immigrant Absorption. The random sample of 731 immigrant physicians was stratified by assigned re-training track and geographical region. The goal was to interview 10% of the restricted population. A reserve list of immigrants was prepared, according to the same stratification rules, to substitute for those on the original list that could not be interviewed. In total, $1,002$ immigrant physicians were approached for interviewing. In descending order of importance, those on the original list that were not interviewed were either not located, refused to be interviewed, return migrated, or had passed away.

4.1 Descriptive Statistics

Table 1 displays selected descriptive statistics for the sample by assigned re-training track. Of the 731 immigrant physicians in the sample, only 2 immigrants did not have a re-training track coded. Of the 414 immigrant physicians assigned to the exam track, according to either the "14-year rule" or the "20-year rule", 73% passed the re-licensing exam. Immigrants that were assigned to the exam track and that did not acquire a license either never took the exam or took the exam and failed. Of the 315 immigrant physicians assigned to the observation track, according to either the "14-year rule" or the "20-year rule", 89% worked under observation and acquired a permanent license. The 11% among this latter group that are coded as not having acquired a permanent license reported that they never looked for a place to begin work under observation.

The figures in Table 1 show that mean monthly earnings (including zeros for the unemployed), the employment rate and the rate of employment as a physician, at the time of the survey, are higher among immigrants assigned to the exam track. Individuals assigned to the exam track are, on average, 18 years younger and have 18 years less physician experience in the former USSR. These immigrants also have more children under the age of 18 living at home at the time of arrival. Note that a considerable proportion of immigrant physicians on the observation track are not employed as physicians. Immigrants that are employed but not working as physicians are mostly working as post-secondary education teachers, social workers, qualified nurses, optometrists, medical technicians and paramedics. There is a small proportion of immigrant physicians working in less skilled occupations as unqualified nursemaids, cleaners in institutions, security guards, and skilled and unskilled workers in industry.[6]

In terms of gender composition, size of last city of residence in the former USSR (more than $1,000,000$ inhabitants), continuation of studies in the former USSR towards an advanced medical degree and the number of months since arrival, the immigrants are quite similar by re-training track. There are only slight differences in marital status upon arrival, republic of origin and type of medical practice in the former USSR. There is a large difference in former specialist status. Note that over 95% of the immigrants in the sample arrived during the years 1990 and 1991. Overall, the similarities in immigrant characteristics by assigned re-training track, except for characteristics related to age, constitute strong evidence that re-training track assignment was indeed mainly a function of previous experience.

4.2 OLS Estimates

OLS estimates of the increase in mean monthly earnings (which include zeros for the unemployed) deriving from acquisition of a license are reported in Table 2. We concentrate on monthly earnings because there is little overall variation in hours worked among these immigrants and hours of work are poorly measured. Column (1) does not include any other covariates and yields a precisely estimated coefficient on licensed of 1279 New Israeli Shekel (NIS). In 1994, the year in which earnings are reported, 1 NIS is approximately equal to .33 US dollars. The estimated increase in

[6] Among immigrant physicians employed as physicians, 41% work for the government (local and national). The remainder work for HMO's and other private employers. Only 6% found physician work as a direct continuation of re-training.

earnings of 1279 NIS corresponds to a percentage impact of 109%.[7]

Column (2) adds covariates to the regression, but excludes previous physician experience. The other covariates include dummies for age upon arrival, year of arrival, months in Israel, gender, marital status, profession of spouse, number of children under 18 living at home upon arrival, size of last city of residence, Republic of origin, advanced medical degrees, previous specialist status, previous type of medical practice and type of reported earnings (after-tax and/or after other deductions). The coefficient on licensed in this latter regression is a precisely estimated 1211, which corresponds to a percentage impact of 98%.

Column (3) adds years of physician experience in the USSR and its square. The coefficient on licensed further decreases in strength to 1162 but is still precisely estimated. The percentage impact is 90%. It is interesting to note that Kleiner (2000) finds licensing effects on hourly earnings that are similar in magnitude. Licensed dentists earn 91% more than unlicensed biological and life scientists. Licensed lawyers earn 94% more than unlicensed economists.

Column (4) reports the results of adding an indicator for being employed as a physician. The physician dummy is an interaction between having acquired a license and being employed as a physician. The coefficient on licensed turns negative, is quite small in magnitude and is not precisely estimated. The coefficient on the physician dummy, however, is substantial. The OLS results do not indicate a significant return to a license when not employed as a practicing physician. Note that a significant coefficient on licensed in this latter specification would have been suggestive of a signalling value to license acquisition.

Columns (5) and (6) repeat the specifications in Columns (3) and (4) for the

[7] All standard errors are heteroskedasticity robust. The percentage impact is calculated as the ratio of the coefficient on licensed to the fitted value from the regression with the licensed dummy set to zero and other covariates set to the means among individuals with a license, when other covariates are included.

subsample of immigrants that have previous physician experience between 14 and 26 years. This subsample of immigrants defines the "discontinuity" sample. Restricting the analysis to the discontinuity sample helps control for differences in unobservables between immigrants of different ages (e.g., quality of medical education in the USSR) and isolates the subsample with the maximum variation in assigned re-training track.[8]

The estimated coefficient on licensed in the discontinuity sample is larger than in the corresponding specification in the full sample. The estimated coefficient in the specification with a quadratic in previous physician experience and no indicator for physician employment is a precisely estimated 1254. The percentage impact is 114%. Column (6) reports the results for the specification which adds the physician employment indicator in the discontinuity sample. The estimated coefficient on licensed is positive but is negligible in magnitude and imprecisely estimated.[9]

4.3 Graphical Discontinuity Analysis

The OLS estimates presented in the previous subsection do not exploit the Ministry of Health's re-training assignment rule. The assignment rule can be used to construct instrumental variables estimates of the returns to an occupational license even though the assignment rule is a near deterministic function of years of previous physician experience and previous physician experience directly affects earnings in the host country. Identification relies on matching discontinuities (or nonlinearities) in the relationship between previous physician experience and licensing status and discontinuities in the relationship between previous physician experience and earnings. The correlation between these discontinuities identifies the causal effect of acquiring a

[8] The experience levels 14 and 26 are the 45th and 75th percentiles, respectively, in the previous physician experience distribution. The experience distribution is skewed to the right with a mean of 16, a standard deviation of 11 and a median of 18.

[9] The effect of license acquisition on employment probabilities is similar to the effect of observation track assignment on physician employment, which is considered below.

license on earnings as long as it is the assignment rule and not some other mechanism that is generating the discontinuities in licensing outcomes.[10]

The discontinuities that arise in licensing and labor market outcomes, as a result of the re-training assignment rule, are illustrated graphically in Figures 1 through 3. The figures are smoothed by estimating weighted local linear regressions that do not straddle the break points of 14 and 20 years of previous physician experience (see Hahn, Todd and van der Klauuw (1998)). Figure 1 plots the proportion of immigrant physicians assigned to the observation track along with the residuals from a linear probability model that has acquisition of a license as the dependent variable and that excludes previous physician experience as a covariate. Note that the proportion assigned to the observation track is zero until 14 years of experience. Between 14 and 19 years of experience the proportion fluctuates between 12 and 33 percent. This is due to the small number (32 out of 729 immigrants in the sample) that were assigned to the observation track according to the later instituted "14-year rule". At 20 years of experience the proportion sharply jumps up and fluctuates between 92 percent and 100 percent. Immigrant physicians that had 20 or more years of previous physician experience and that were not assigned to the observation track did not previously practice clinical medicine. After 26 years of experience, the proportion remains at 100 percent. The license probability residuals jump up together with jumps in the proportion assigned to the observation track.

Figure 2 plots license acquisition residuals and physician employment residuals from separate linear probability models that exclude previous physician experience. The figure shows that employment as a physician follows licensing status quite closely. There are no apparent systematic differences. Figure 3 examines the relationship between monthly earnings residuals and license acquisition residuals. The matching of the discontinuity at 20 years of experience and the change in trend after 20 years

[10] For a discussion of the regression discontinuity identification strategy in general, see Angrist and Krueger (1999).

of experience is quite evident.

5 Estimation Strategy

The basic estimation framework that we consider is a linear, constant-effects model that connects the earnings of immigrant i at time t, Y_{it}, with the occupational licensing status of individual i at time t, L_{it}, plus a vector X_i of immigrant characteristics at the time of arrival, and a random error component specific to individuals at time t, ϵ_{it}:

$$Y_{it} = X_i'\beta + t\delta + L_{it}\alpha + \epsilon_{it}. \tag{7}$$

Time in Israel, t, is, like the elements of X_i, widely believed to be exogenous to potential labor market outcomes in Israel among those immigrants that arrived in the first three years of the immigration wave. t generically captures changes in language ability, social networks and knowledge of local institutions, and is also correlated with the size of the last city of residence in the former USSR (included in X_i). Immigrants that arrived earlier generally came from big cities in which there was greater access to information, government offices and consulates. Measures of English and Hebrew ability at the time of the survey and host country work experience are endogenous (and not included in X_i), but are also strongly correlated with t. In empirical implementation, t is represented by a series of six-month dummy variables.

The interpretation of equation (7) is that it describes the earnings of immigrants under alternative assignments of licensing status, controlling for any effects of X_i and t. However, since L_{it} is not randomly assigned and is likely to be correlated with potential earnings, ϵ_{it}, OLS estimates of (7) do not have a causal interpretation. Instrumental variables estimates of (7) do have a causal interpretation as long as it is reasonable to assume that, after controlling for X_i and t, the association between assignment to the observation track and monthly earnings is solely due to the association between observation track assignment and licensing status.

In IV estimation, the first stage relationship between licensing status, assignment to the observation track and X_i and t is:

$$L_{it} = X_i'\pi_0 + t\pi_1 + TR_i\pi_2 + \xi_{it}, \tag{8}$$

where $TR_i = 1$ indicates assignment to the observation track and $TR_i = 0$ indicates assignment to the exam track. The error term ξ_{it} is defined as the residual from the population regression of L_{it} on X_i and t and the instrument, TR_i. This residual captures other factors that are correlated with licensing status and ϵ_{it}.

The key identifying assumption that underlies estimation using TR_i as an instrument is that any effects of previous physician experience on monthly earnings in Israel are adequately controlled by the smooth functions of previous physician experience included in $X_i'\beta$ and "partialled out" of TR_i by the inclusion of smooth functions of previous physician experience in $X_i'\pi_0$. If this assumption is reasonable, then the discontinuities in earnings with previous physician experience, as depicted in the graphical analysis, is due to the acquisition of an occupational license.[11] The same discussion above carries through for measuring the effect of working as a physician in place of the effect of acquiring a license.

6 Estimation Results

6.1 Reduced Form Estimates

Reduced form estimates of the effect of being assigned to the observation track are reported in Table 3. Columns (1), (2) and (3) of Table 3 report the effect of being assigned to the observation track on mean monthly earnings. Without controls for other regressors or previous physician experience, there is a negative association between assignment to the observation track and monthly earnings. The track variable

[11] Card (1999) surveys evidence supporting the smoothness assumption in the relationship between experience and earnings.

is picking up a downward trend in mean earnings with previous physician experience. The association between being assigned to the observation track and monthly earnings becomes significantly positive with the addition of other regressors and previous physician experience and its square. The coefficient on track in this latter specification is 571 with a standard error of 255. The percentage impact is 14%. Column (4) reports the same specification as in Column (3) in the discontinuity sample only. The coefficient on track is stronger, 628, but somewhat less precisely estimated. The percentage impact increases to 23%.

Columns (5), (6) and (7) of Table 3 report the effect of being assigned to the observation track on licensing status. In all three linear probability models, assignment to the observation track increases the probability of acquiring a license. The estimated coefficient on track, without any other regressors, is .159. Including other regressors increases the estimated coefficient to .231. Adding previous physician experience and its square further increases the estimated coefficient on track to .338. Column (8) reports the same specification as in Column (7) in the discontinuity sample. The coefficient on track in this latter specification is .258. In all four specifications the coefficient on track is precisely estimated.

Columns (9), (10) and (11) of Table 3 report the effect of being assigned to the observation track on employment status as a physician in linear probability models. Adding previous physician experience yields a statistically significant coefficient of .234. The specification with previous physician experience in the discontinuity sample only, reported in Column (12), produces a slightly larger coefficient which is also quite close to the coefficient on track in the discontinuity sample in Column (8). It should be noted that the physician employment regressions in Columns (10) through (12) include interaction terms between previous experience and year of arrival that have no explanatory power in the license acquisition regressions.

As the reduced form estimates illustrate, the IV estimates of the returns to a medical license and the returns to physician practice differ only by a scale factor.[12] The IV returns to physician practice are, in general, larger than the IV returns to a license, as was found in the OLS results. In what follows, we focus on the returns to a license rather than on the returns to physician practice. The channel from track assignment to license acquisition is more straight-forward and provides lower bound estimates of the returns to a license.

6.2 Instrumental Variables Estimates

Instrumental variables estimates of the effect of acquiring a license are reported in Table 4.[13] Acquisition of a license is instrumented by assigned re-training track. Columns (1), (2) and (3) of Table 4 report the estimated coefficients on licensed without any other regressors, with other regressors but excluding previous physician experience, and with other regressors and linear and quadratic terms for previous physician experience, respectively. The estimated coefficient on licensed with other regressors and linear and quadratic terms for previous physician experience is 1638 with a standard error of 706. The percentage impact is 182%. Correcting for non-random selection in licensing status yields a percentage impact that is approximately double the corresponding percentage impact produced by OLS (90%).

Considering that instrumental variables estimates in a regression discontinuity design may be quite sensitive to the way in which the variable generating the discontinuity is controlled, Column (4) of Table 4 reports the results of including a third

[12]IV estimates of the return to a license can be calculated from the ratio of the coefficient in the reduced form earnings regression to the coefficient in the reduced form license acquisition. IV estimates of the return to physician practice can be calculated from the ratio of the coefficient in the reduced form earnings regression to the coefficient in the reduced form physician employment regression.

[13]The instrumental variables estimates reported in this subsection deviate somewhat from the ratio of the relevant reduced-form estimates in Table 3 due to different sample sizes.

order polynomial in previous physician experience. The estimated effect of a license in this latter specification is 1865 with a standard error of 864. The percentage impact grows to 262%.

Column (5) of Table 4 reports the results of including linear and quadratic terms for previous physician experience in the discontinuity sample only. The estimated coefficient on licensed further grows to 1886, but is somewhat less precisely estimated. The percentage impact is 342%. The corresponding percentage impact according to OLS in Table 2 is 114%. Narrowing the range of the discontinuity sample produces even larger percentage impacts, but they are less precisely estimated as the sample size increasingly shrinks.

Additional IV results of interest that are not shown in Table 4 for the sake of brevity are as follows. First, there are no significant interactions between licensing status and other covariates. In particular, there are no significant interactions between licensing status and time in Israel. Licensing status does not affect the slope of immigrant earnings profiles, only earnings levels. There are also no significant interactions between licensing status and previous physician experience. Second, including separate controls for the small number of immigrants physicians that were assigned to the observation track according to the "14-year rule" does not change the results.

We should mention that there are potential threats to identification of the returns to an occupational license in this study, but we do not believe that they are particularly problematic. For example, since 27% of all immigrants that reported themselves to be physicians upon arrival did not submit their credentials to the Ministry of Health, the sample could be biased. However, mostly all of these immigrants were over 55 years of age upon arrival.

Potentially more troublesome is the possibility that assignment to the exam track and/or failure to pass the exam may have lead to out-migration. Information on the outcomes of these immigrants would be missing from the sample. However, as mentioned in Section 2, return migration was one of the least important reasons for non-response to the survey. Only 3.7% of those approached to be interviewed were not interviewed because they had out-migrated or were absent from the country for an extended period of time.

Physicians in the former Soviet Union may have also decided not to immigrate to Israel (or delay immigration) based on knowledge of the assignment rule. However, immigrant physicians were asked on the survey if they were aware of the re-licensing process upon arrival to Israel, and only 4% responded that they had knowledge of re-licensing procedures. This is consistent with the widely held belief that early arrivals from the former USSR were panic migrants, not economic migrants.

Our interpretation of the large IV estimates, compared to OLS estimates, is that, consistent with standard economic theory, occupational licensing in the medical profession may lead to practitioner rents. Also, in light of the theoretical model of optimal license acquisition, the finding that IV estimates exceed OLS estimates suggests that the requirement of having to pass a re-licensing exam, rather than being observed on the job by native physicians, leads to lower average quality of service in the market for physicians. This latter conclusion is consistent with the simplest human capital models in the schooling literature which predict that ability bias is negative. Individuals with the lowest earnings potential go to school because their opportunity costs of schooling are the lowest (see Griliches (1977)).

6.3 Quantile Regression and Treatment Effect Estimates

The constant-effects IV model used to measure the returns to an occupational license has a drawback in that it does not allow for differential effects of acquiring a license at different points in the earnings distribution. This is problematic since the earnings distribution has a mass point at zero. In general, the effect of acquiring a license on participation may be substantially different from the effect of acquiring a license on conditional-on-positive mean earnings. An alternative estimation strategy that is less sensitive to the inclusion of zero earnings for the unemployed, that is less demanding than formal sample-selection models, and that is less sensitive to high earnings outliers, is the QTE model (Angrist (2001), Abadie, Angrist and Imbens (2002)). The QTE model modifies conventional quantile regression for inclusion of an endogenous binary regressor and provides a good robustness check on the conclusions reached from the standard IV model. The QTE model is briefly outlined in Appendix *A*.

The top panel of Table 5 reports quantile regression and QTE estimates of the effect of licensing status on monthly earnings. Licensing effects are measured at the .15, .25, .50, .75 and .85 quantiles of the monthly earnings distribution. Quantile regression treats licensing status as exogenous and produces the largest percentage impacts of acquiring a license, 93% and 117%, at the .15 and .25 quantiles, respectively. The percentage impact steadily declines at higher quantiles, falling to 59% percent at the .85 quantile. At each quantile the coefficient on licensed is precisely estimated.

QTE estimates that correct for the endogeneity of licensing status yield substantially different results. The percentage impact of acquiring a license at the .15 and .25 quantiles are both 50%, considerably lower than the quantile regression estimates. The percentage impact at the .50, .75 and .85 quantiles are, on the other hand, considerably higher than the quantile regression estimates. The QTE model produces the largest percentage impact, 169%, at the .85 quantile. At each quantile the coefficient on licensed is precisely estimated.

Note that the highest percentage impact of 169% at the .85 quantile is less than the percentage impact estimated in the corresponding specification in the constant-effects model in Table 4 (182%). This suggests that the licensing effect on mean earnings in the constant-effects model is relatively more sensitive to high earnings outliers than the inclusion of zeros for the unemployed.

The bottom panel of Table 5 reports licensing effects on median earnings in the discontinuity sample only. Effects at other quantiles are difficult to identify given the reduced variation in earnings and smaller sample size. The results indicate a large effect on median earnings, 239%. The corresponding percentage impact when treating licensed as exogenous is 108%. Both effects are precisely estimated. These percentage impacts stand in sharp contrast to the percentage impact on mean earnings in the discontinuity sample (342%). This again suggests greater sensitivity of standard IV to high earnings outliers than the inclusion of zeros.

The quantile regression and QTE estimates reported in Table 5 can be used to estimate the marginal distributions of monthly earnings without a license both for immigrants that acquired a license and immigrants that did not acquire a license. Potential earnings without a license for immigrants that acquired a license are obtained by using the QTE coefficients together with the covariate means among those that acquired a license and setting the licensing status dummy to zero. The counterfactual earnings of all immigrants with a license can be approximated by the counterfactual earnings of compliers (individuals whose treatment status is affected by the instrument), under the assumption that compliers are a random sample of all immigrants with a license. The monthly earnings without a license for immigrants that did not acquire a license are also computed conditional on the mean of the covariates among immigrants that acquired a license, and with the licensing status dummy set to zero, but using the quantile regression coefficients.

The figures in the top panel of Table 6 show that licensed immigrants have lower potential earnings without a license than unlicensed immigrants at all examined quantiles. The negative selection bias is greatest in the tails and at the median of the distribution, varying between 36% and 38%. The bottom panel of Table 6 shows that negative selection bias is also present at the median of potential earnings in the discontinuity sample.

7 Conclusion

This study measures the effects of occupational licensing requirements by exploiting an immigrant physician re-training assignment rule. OLS estimates of the returns to a license among immigrant physicians in Israel range between 90 and 114 percent. Instrumental variables estimates of the returns range between 180 and 340 percent. The large IV estimates, compared to OLS estimates, are suggestive of the presence of rents accruing to practitioners and negative selection into licensing status.

In order to give an economic interpretation to the OLS and IV estimates, we develop a general model of optimal license acquisition. The theoretical equivalents of the OLS and IV estimates according to the model show that when IV estimates exceed OLS estimates, stricter re-licensing requirements may lead to lower average quality of service in the licensed occupation. The policy implication of the results is that lowering the direct costs of acquiring a license may raise physician quality.

As a robustness check, the returns to an occupational license are also estimated using a quantile treatment effects (QTE) model. QTE estimates indicate that the returns to an occupational license are largest at the upper quantiles of the earnings distribution. Conventional quantile regression estimates indicate that the returns to a license are largest at the lower quantiles. QTE estimates also illustrate that standard IV estimates are more sensitive to high earnings outliers than the inclusion of zero earnings for the unemployed. QTE estimates of the counterfactual *distribution* of earnings without a license among those immigrants that obtained a license provide a rich picture of negative selection into licensing status.

The particular social experiment that we exploit in this paper to identify the causal effects of re-licensing requirements in the market for physicians may be relevant in other contexts. Other countries use similar licensing regimes for immigrants as well as internal migrants. Future research could examine the earnings and quality effects of re-licensing regimes in other countries and in other professions using a similar methodology to the one employed in this study.

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Appendix A

The Quantile Treatment Effects Model

The quantile treatment effects model specifies a linear relationship between earnings and licensing status at each quantile. That is,

$$Q_\theta \left[Y_i | X_i, L_i, L_{1i} > L_{0i}\right] = X_i' \beta_\theta + L_i \alpha_\theta \tag{9}$$

where L_{1i} denotes licensing status when assigned to the observation track ($TR_i = 1$) and L_{0i} denotes licensing status when assigned to the exam track ($TR_i = 0$). The time in Israel subscript is suppressed for convenience. The coefficient α_θ has a causal interpretation because L_i is independent of potential earnings outcomes conditional on X_i and being a complier ($L_{1i} > L_{0i}$). The proof is found in Abadie, Angrist and Imbens (2002).

The parameters of the quantile treatment effects model are estimated by minimizing the sample analog of

$$E\left[\kappa_i \rho_\theta \left(Y_i - X_i' b_\theta - L_i a_\theta\right)\right] \tag{10}$$

where ρ_θ is the "check function" and κ_i are weights that transform the conventional quantile regression minimand into a problem for compliers only. For computational reasons κ_i is replaced by an estimate of $E\left[\kappa_i | X_i, L_i, Y_i\right]$ where

$$E\left[\kappa_i | X_i, L_i, Y_i\right] = 1 - \frac{L_i \left(1 - E\left[TR_i | Y_i, L_i, X_i\right]\right)}{\left(1 - E\left[TR_i | X_i\right]\right)} - \frac{(1 - L_i) E\left[TR_i | Y_i, L_i, X_i\right]}{E\left[TR_i | X_i\right]}. \tag{11}$$

The first step estimate of $E\left[\kappa_i | X_i, L_i, Y_i\right]$ is obtained by separately estimating $E\left[TR_i | Y_i, L_i, X_i\right]$ and $E\left[TR_i | X_i\right]$ with a probit. Predicted values of $E\left[\kappa_i | X_i, L_i, Y_i\right]$ that are negative are set to zero leading to a reduced sample size. Standard errors are computed by bootstrapping the first and second step estimations 100 times.

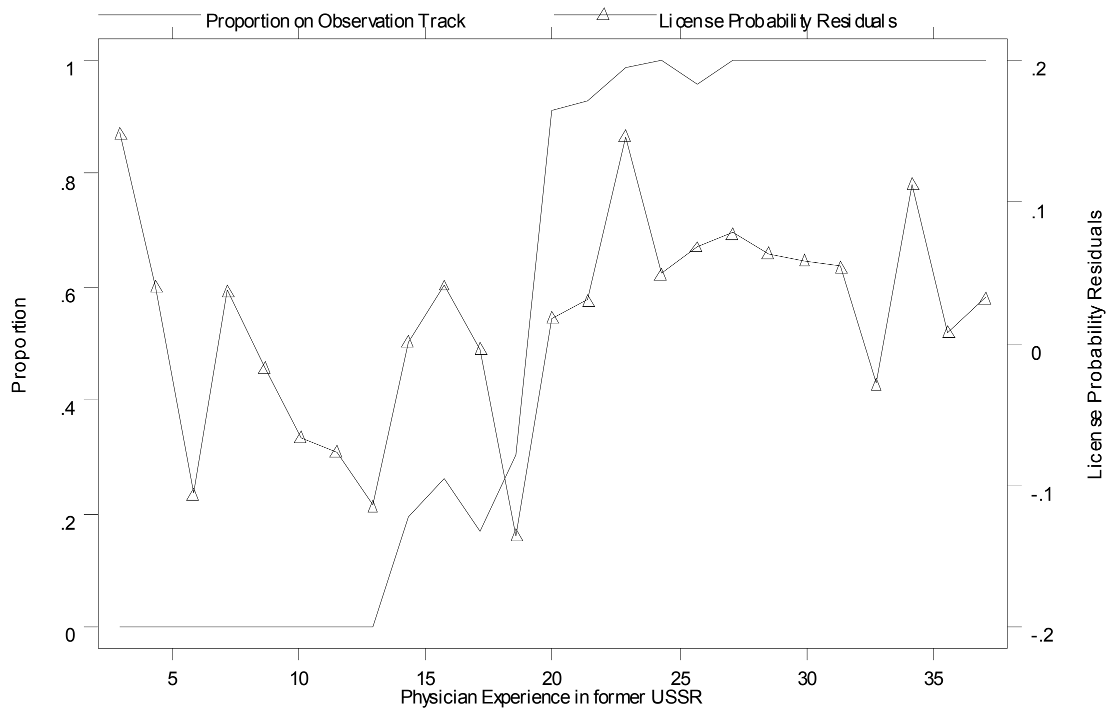

Figure 1: Track Assignment and License Acquisition

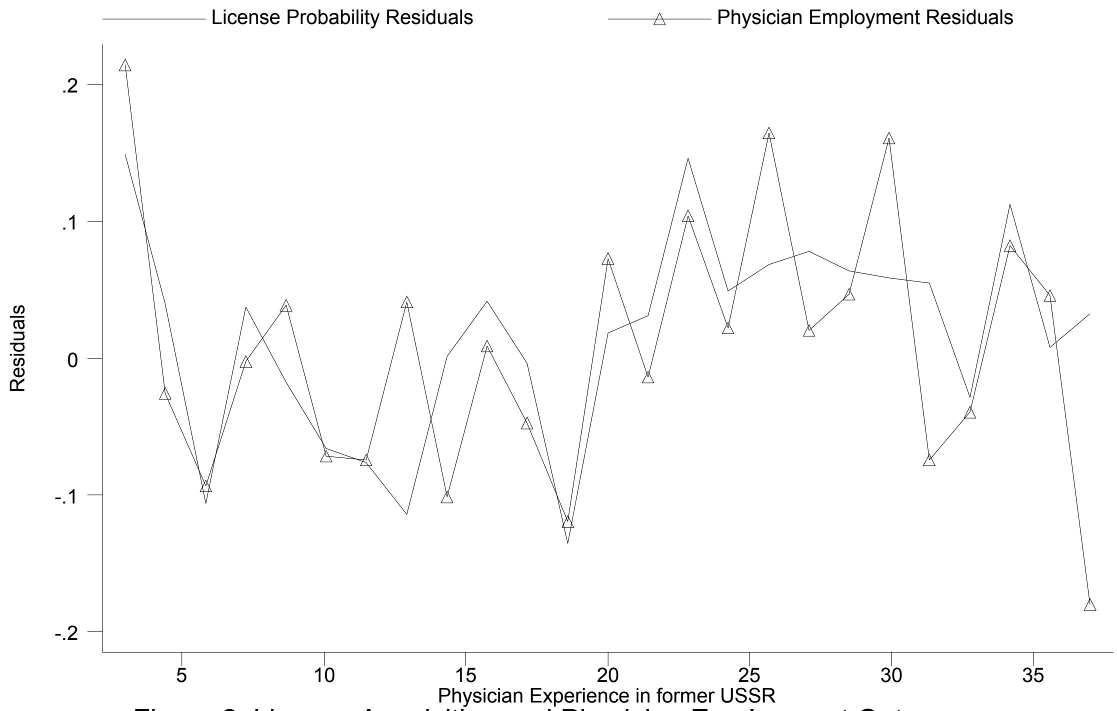

Figure 2: License Acquisition and Physician Employment Outcomes

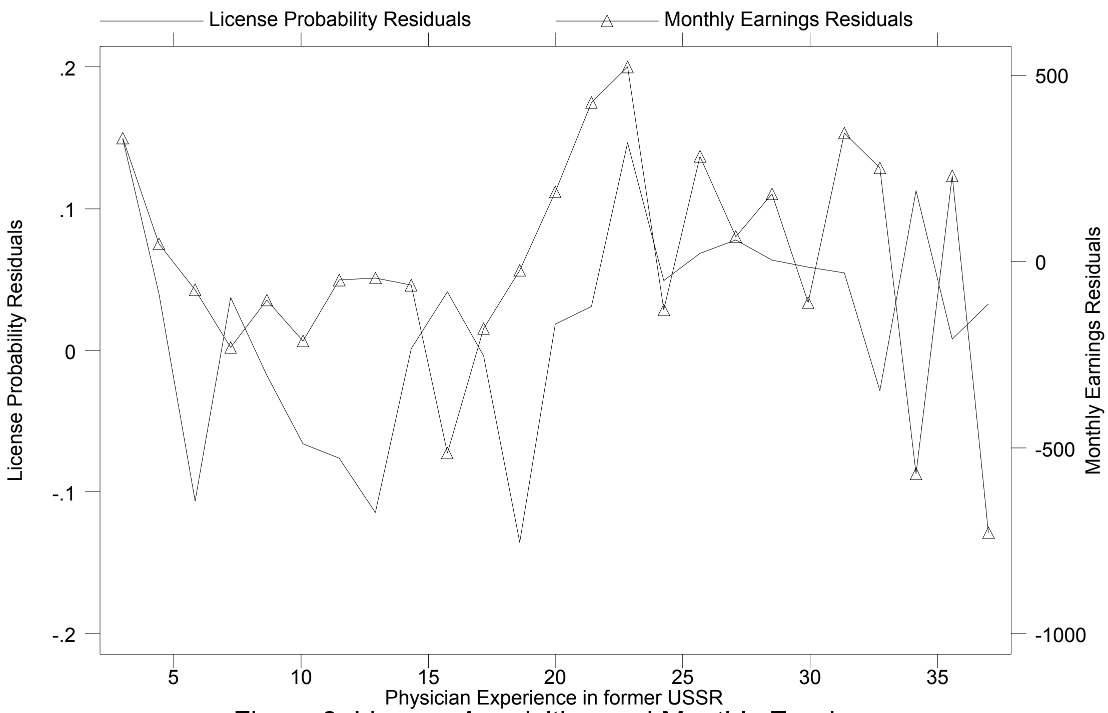

Figure 3: License Acquisition and Monthly Earnings

Table 1: Descriptive Statistics

Variable	Exam Track	Observation Track
% Licensed	72.71	88.57
% Employed	86.23	65.40
% Physician	58.70	37.14
Monthly Earnings (NIS)	2,552	1,703
	(1,811)	(2,011)
Months in Israel	44.31	42.68
	(6.24)	(7.45)
Age Upon Arrival	34.54	53.06
	(5.00)	(7.36)
Previous Physician Experience	10.32	28.18
	(4.82)	(7.57)
% Male	44.44	44.13
% Married Upon Arrival	84.30	79.36
No. of Children under 18 Upon	1.23	0.59
Arrival	(.75)	(.76)
% from Russia	46.14	41.59
% from Ukraine	16.67	23.81
% from City > 1,000,000	52.17	53.33
% Advanced Medical Degree	26.81	25.4
% Former Specialist	40.34	85.08
% Former General Practitioner	22.95	18.73
% Former Pediatrician	16.18	12.70
% Former OBGY	7.49	5.71
% Arrived in 1991/1992	77.3	67.62
N	414	315

Notes: The Table reports means and percentages by assigned re-training track. Standard deviations are in parentheses. Monthly earnings are in 1994 New Israeli Shekels (NIS) where 1 NIS equals 0.33 US dollars. There are 382 exam track earnings observations and 294 observation track earnings observations (including zeros for the unemployed).

Table 2: OLS Estimates of the Returns to a Medical License

	Full Sample				Discontinuity Sample	
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
Licensed	1,279	1,211	1,162	-175	1,254	169
	(140)	(140)	(141)	(138)	(373)	(358)
% Impact	1.095	.979	.904	-.067	1.137	.077
Physician	–	–	–	2,324	–	1,885
				(158)		(301)
Experience	–	–	4.90	56.21	1,111	928
			(25.1)	(23.24)	(547)	(462)
$Experience^2$	–	–	-1.35	-2.05	-27.15	-22.80
			(.61)	(.58)	(13.93)	(11.65)
Other Regressors	NO	YES	YES	YES	YES	YES
Root MSE	1,876	1,672	1,648	1,390	1,631	1,447
R^2	.0711	.2847	.3073	.5086	.3227	.4702
N	676	676	676	676	181	181

Notes: Robust standard errors are in parentheses. Other regressors include dummies for age upon arrival, year of arrival months in Israel, gender, marital status, profession of spouse, number of children, size of last city of residence, Republic of origin, advanced medical degrees, previous specialist status, previous type of medical practice and type of reported earnings (after-tax and/or after other deductions). The discontinuity sample in columns (5) and (6) uses the subsample of observations between 14 and 26 years of previous physician experience.

Table 3: Reduced Form Estimates of the Effect of Track on Monthly Earnings, License Acquisition and Physician Employment

	Monthly Earnings				Licensed				Physician Employment			
	Full Sample			Disc. Sample	Full Sample			Disc. Sample	Full Sample			Disc. Sample
Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Track	-849	42	571	628	.1587	.2305	.3383	.2853	-.2155	.0206	.2336	.2576
	(149)	(207)	(255)	(371)	(.0283)	(.0308)	(.0490)	(.0679)	(.0365)	(.0584)	(.0754)	(.1230)
% Impact	-.3325	.0094	.1409	.2262	–	–	–	–	–	–	–	–
Exp	–	–	-14.12	765	–	–	-.0053	-.2198	–	–	-.0222	-.1889
			(28.01)	(530)			(.0075)	(.1009)			(.0077)	(.1525)
Exp^2	–	–	-1.38	-19.49	–	–	-.0002	.0052	–	–	.0001	.0038
			(.62)	(13.52)			(.0002)	(.0025)			(.0001)	(.0038)
Other Reg.	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
RMSE	1,900	1,740	1,705	1,675	.3961	.3908	.3854	.3269	.4891	.4621	.4551	.4579
R^2	.0469	.2257	.2589	.2857	.0380	.0879	.1153	.2260	.0456	.1716	.1987	.2605
N	676	676	676	181	729	729	729	203	729	729	729	203

Notes: Robust standard errors are in parentheses. Other regressors include dummies for age of arrival, year of arrival, months in Israel, gender, marital status, profession of spouse, number of children, size of last city of residence, Republic of origin, advanced medical degrees, previous specialist status, previous type of medical practice and type of reported earnings (after-tax and/or after other deductions). The discontinuity sample in Columns (4), (8), and (12) uses the subsample of observations between 14 and 26 years of previous physician experience. The licensed and physician employment regressions are linear probability models. The physician employment regressions include interaction terms between experience and year of arrival.

Table 4: 2SLS Estimates of the Returns to a Medical License

Regressors	Full Sample (1)	(2)	(3)	(4)	Disc. Sample (5)
Licensed	-5,244	178	1,638	1,865	1,886
	(1,516)	(863)	(706)	(864)	(1,043)
% Impact	-.827	.086	1.818	2.617	3.422
Experience	–	–	-1.24	44.90	1,210
			(25.16)	(76.64)	(619)
Experience²	–	–	-1.17	-3.90	-29.84
			(.62)	(4.34)	(15.82)
Experience³	–	–	–	.0407	–
				(.0639)	
Other Regressors	NO	YES	YES	YES	YES
Root MSE	3,245	1,722	1,659	1,672	1,646
R^2	–	.2417	.2982	.2883	.3099
N	676	676	676	676	181

Notes: Robust standard errors are in parentheses. Licensed is instrumented with Track. Other regressors include dummies for age upon arrival, year of arrival, months in Israel, gender, marital status, profession of spouse, number of children, size of last city of residence, Republic of origin, advanced medical degrees, previous specialist status, previous type of medical practice and type of reported earnings (after-tax and/or after other deductions). The discontinuity sample in Column (5) uses the subsample of observations between 14 and 26 years of previous physician experience.

Table 5: Quantile Regression and Treatment Effects Estimates

	Quantile Regression Estimates					Treatment Effects Estimates				
	0.15	0.25	0.5	0.75	0.85	0.15	0.25	0.5	0.75	0.85
					A. Full Sample					
Licensed	359	644	997	1,455	1,507	119	257	1,115	1,589	2,774
	(130)	(163)	(143)	(178)	(320)	(4)	(63)	(65)	(267)	(212)
% Impact	.932	1.175	.832	.782	.588	.496	.499	1.466	1.076	1.688
Pseudo R^2	.1626	.2467	.2397	.2116	.2055	.1190	.1744	.2315	.1579	.1748
N	676	676	676	676	676	548	548	548	548	548
					B. Discontinuity Sample					
Licensed	–	–	1,093	–	–	–	–	1,793	–	–
			(520)					(310)		
% Impact	–	–	1.076	–	–	–	–	2.386	–	–
Pseudo R^2	–	–	.1897	–	–	–	–	.2413	–	–
N	–	–	181	–	–	–	–	164	–	–

Notes: Other regressors include a quadratic in previous physician experience, dummies for age upon arrival, year of arrival, months in Israel, Republic of origin, advanced medical degrees, previous specialist status, previous type of medical practice and type of reported earnings (after-tax and/or after other deductions). The discontinuity sample is the subsample of observations between 14 and 26 years of previous physician experience. Bootstrapped standard errors are in parentheses. The bootstrapped standard errors when licensed are treated as endogenous and adjusted for the first step estimation.

Table 6: Earnings Quantiles without a License

	Quantiles				
	0.15	0.25	0.5	0.75	0.85
			A. Full Sample		
Licensed Immigrants	239	515	760	1,476	1,643
Unlicensed Immigrants	385	548	1,199	1,859	2,563
% Selection Bias	-.379	-.060	-0.366	-.206	-.359
			B. Discontinuity Sample		
Licensed Immigrants	–	–	751	–	–
Unlicensed Immigrants	–	–	1,016	–	–
% Selection Bias	–	–	-.261	–	–

Notes: The table reports monthly earnings quantiles without a license for immigrants that acquired a license and for immigrants that did not acquire a license. Earnings without a license for immigrants that acquired a license are calculated using quantile treatment effect estimates. Earnings without a license for immigrants that did not acquire a license are calculated using quantile regression estimates. The discontinuity sample is the subsample of observations between 14 and 26 years of previous physician experience.