Physicians' Occupational Licensing and the Quantity-Quality Trade-off*

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Abstract: Occupational licensing is a quality regulation that increases quality but reduces quantity. We provide a framework to empirically quantify this trade-off and apply it to the context of physicians's licensing in Chile, where both access to care and quality of care are a primary concern. Using quasi-exogenous variation driven mostly by the recent immigration of physicians, we show that both the quantity and the quality of physicians matter for the production of health. We then evaluate the equilibrium effects of relaxing the current licensing threshold and find a positive impact on patient outcomes throughout the sample period despite the significant changes in the labor market fundamentals produced by the migration wave.

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1 Introduction

The shortage of physicians is a long-standing and increasingly urgent concern. Providing adequate healthcare access is estimated to require at least an additional 7 million physicians globally, and a deficit of 125 thousand physicians is projected by 2034 for the United States alone (Haakenstad et al., 2022; Association of American Medical Colleges, 2024).

Licensing requirements in the medical profession have been routinely signaled as a key contributor to physician shortages with unclear benefits from increased quality.[1] However, assessing the quality-quantity trade-off embedded in licensing requirements has proven difficult; it requires credible estimates of its effects on the quantity and quality of physicians, as well as their impacts on access and quality of care. At the same time, a growing migration of physicians worldwide has made licensing an increasingly binding policy in destination countries like the US, potentially changing the nature and magnitude of its associated trade-offs.[2]

In this paper, we provide a simple framework to highlight the key economic fundamentals that govern the quantity-quality trade-off when deciding the stringency of licensing requirements. This framework reveals a set of sufficient statistics needed to evaluate the optimality of the licensing requirements in place, by quantifying the net benefits of locally changing the licensing stringency. We then use rich administrative data from Chile to estimate those sufficient statistics and evaluate the optimality of the licensing policy currently used to appoint public sector physicians in the country.

Chile provides an ideal setting to study physician licensing and how its design may depend on changing labor market fundamentals like increased immigration. The number of physicians taking the licensing exam increased fivefold between 2009 and 2018, largely driven by an unprecedented increase in the number of foreign test-takers. In tandem with this surge, passing rates decreased from 92% to 58% during this period. Despite the large migration influx, the healthcare system is still strained and 25% of the country's annual mortality is explained by individuals who die while on a waiting list. Finally, the Chilean licensing exam has characteristics and purposes similar to those applied in different countries, including the US.[3]

[1] A highly influential criticism of licensing in the medical profession can be found in Friedman (1962). Svorny (2004) provides a more recent literature review.

[2] In the United States, the number of physicians born and educated abroad has increased by 30% since 2004 and currently represents 20% of the total count (Association of American Medical Colleges, 2023). Similarly, in OECD countries, an increasingly growing share of physicians are foreign-trained physicians and now constitute 30% of the physician workforce (Socha-Dietrich and Dumont, 2021). Still, it is estimated that only one-third of employed foreign physicians are on track to practice medicine and that licensing plays a critical role in explaining this fact (Federal Reserve Bank of Minneapolis, 2022).

[3] Similar tests are the USMLE in the US, the NCE in France, and the NMLE in Japan.

Our theoretical framework highlights the quantity-quality trade-off embedded in the design of licensing policies. There is a production function for hospital care, where the quantity and quality of physicians are key inputs. The planner faces an exogenous distribution of scores and has a licensing technology that provides a noisy signal of a physician's quality. The planner grants licenses to those with a signal above a threshold. Changing the licensing threshold affects outcomes depending on two sets of sufficient statistics; the output elasticities with respect to the quantity and quality of labor, and the elasticity of those inputs with respect to the licensing threshold. The input elasticities, in turn, depend on the distribution of quality in the population of test-takers and on the precision of the licensing technology (i.e., the signal-to-noise ratio). Generally, a higher output elasticity with respect to quantity, a lower output elasticity with respect to quality, and a lower precision decrease the optimal licensing threshold.

The empirical part of the paper is devoted to estimating the sufficient statistics needed to evaluate the effects of locally changing the licensing threshold on health outcomes. We begin by estimating the latent quality of physicians with a model of licensing scores and retaking behavior. The model enables us to leverage the observed test score histories to infer the precision of the licensing test and to predict test-taking behavior under counterfactual thresholds, which impacts the number of test-takers over time. We find that the test has a relatively high signal-to-noise ratio, especially for foreigners. As a consequence, scores are informative proxies for physicians' latent qualities, and licensing policies can indeed affect the quality distribution across hospitals. To estimate the resulting elasticities of the quantity and quality of labor with respect to the licensing threshold, we estimate a microfounded labor matching function between physicians and hospitals. Guided by the theory we approximate the matching function as a flexible hospital-specific function of physicians' latent quality and other observables, as well as of observable proxies for labor-market tightness. As such, the labor-market elasticities vary with counterfactual licensing thresholds as tightness depends on how many physicians pass the exam.

We proceed by providing novel estimates on the output elasticities with respect to the quantity and quality of physicians. We focus on access and quality of care as key outcomes, which jointly determine the value added provided by the healthcare sector. We measure access primarily as the number of patients seen as a fraction of potential patients (i.e., the "service rate"), and we measure quality of care by patient mortality. As a key contribution, we are able to address the identification challenges related to the endogeneity of inputs in the estimation of production functions with an instrumental variables (IV) approach. Specifically, we use a shift-share IV design leveraging the increase in the labor supply of physicians brought primarily by the immigration wave as well as by the expansion of medical schools in the country (Altonji and Card, 1989; Autor et al., 2013;

Borusyak et al., 2022). Our estimates reveal that access to care significantly increases with the number of physicians but not with their quality. We estimate an elasticity of the service rate with respect to the number of physicians of 1. We also find that both the quantity and quality of physicians matter for quality of care. We document that the elasticity of the in-hospital death rate with respect to the number of physicians is 0.8 and that one point (0.23 SD) increase in the average physicians' quality decreases death rates by 0.04%. We show that these results are not driven by changes in patient composition and are robust to alternative measures of hospital performance.

Equipped with estimates for the sufficient statistics, we quantify the net benefits of marginally lowering the licensing threshold in the Chilean healthcare context. We begin by assessing the short-term effects of lowering the threshold in 2018, the end of our sample period, and five years after the onset of the large migration wave. Our results imply that lowering the threshold would have increased access with minimal detrimental effects on quality. On net, population health would have improved as a consequence. We then investigate how the short-run effects differ across the different phases of the migration wave. Overall, we find a robust positive short-run effect of the policy throughout our sample period, despite the large changes in market fundamentals produced by the migration wave. Still, the policy effects are non-monotonic over time; the largest returns would have occurred in the middle of the migration wave when the number of marginal physicians was large and the stock of physicians already hired was still relatively low. We finish by estimating the long-run effects of the policy, considering that retaking can dampen the effects of licensing thresholds as scores may improve over attempts. In fact, in our context, more than 80% of test-takers who failed their first attempt in 2013 passed by 2018. As a consequence, we find that the effects of lowering the threshold decrease with time. However, there are still net benefits in 2018 of permanently lowering the threshold in 2013.

Our paper contributes to several strands of the literature. We add to a long-standing debate about the desirability of occupational licensing in healthcare (Friedman and Kuznets, 1945; Friedman, 1962; Svorny, 2004; Kleiner, 2014; Kleiner et al., 2016) and other settings, particularly in the public sector (Kleiner and Wang, 2023; Angrist and Guryan, 2008; Kleiner, 2011; Larsen et al., 2020). Relative to this literature, we provide a framework for understanding the quantity-quality trade-off embedded in licensing and empirically evaluate the stringency of licensing policies in relevant outcomes. Close to our work, Kleiner and Soltas (2023) provides a general equilibrium framework to estimate the welfare effect of licensing policies in the US under competitive product and labor markets. In contrast to their work, we use direct quality measures to derive the social value of licensing instead of relying on wages and equilibrium conditions.[4]

[4]Our setting and framework allow us to work in a labor-matching market where wages do not clear the market.

We also contribute by providing quasi-experimental evidence on the impact of physician quantity on health outcomes. Previous work has shown a correlation between location mortality and the number of physicians (Finkelstein et al., 2021) or infant health and the number of primary care physicians (Carrillo and Feres, 2019). Instead, we use quasi-exogenous variation to show direct evidence that physician quantity matters for health outcomes in tertiary care. Moreover, we complement previous research studying whether physician quality matters. Examples in the literature include the impacts of elite medical training (Doyle et al., 2010), medical school exit exams (Guarin et al., 2021), and physicians' value-added (Fletcher et al., 2014; Ginja et al., 2024). However, to our knowledge, there is no empirical evidence showing that licensing scores are associated with health outcomes. Finally, we contribute to a scant literature estimating production functions in healthcare (Gaynor et al., 2015; Grieco and McDevitt, 2017). Relative to this literature, we make progress by exploiting exogenous variation in inputs to estimate the elasticity of service rates and mortality with respect to the quantity and quality of physicians.

2 Background

2.1 Institutional Setting

The Chilean Public Healthcare System: The healthcare system in Chile is divided into public and private insurers and providers. Our focus is on public providers, which mainly serve patients with public insurance. Public insurance covers approximately 80% of the population and is financed through monthly contributions deducted from labor income, cost-sharing mechanisms, and resources from the general government.[5]

The public health insurance provides coverage within the network of public providers, with varying levels of copayment determined by income and family size. Individuals who cannot afford to pay are granted free access to the public system, ensuring nearly universal health coverage in public hospitals. Beneficiaries of the public insurer may also opt for private providers, although the copayment for such "out-of-network" services is significantly higher than those in the public network.

The network of public hospitals is composed of 181 hospitals that belong to one of 29 different referral regions called Health Services (*Servicios de Salud*).[6] The referral and counterreferral system

[5]Individuals also have the option to redirect their health contributions toward purchasing private insurance, which covers 15% of the population. The remainder 5% is covered through schemes exclusively for the police and armed forces. In practice, public insurance primarily serves the relatively more disadvantaged population, while wealthier, healthier, and younger individuals tend to opt for private insurance (Pardo, 2019).

[6]The number of 181 hospitals corresponds to hospitals that are present every year throughout our study period 2011-2019.

also operates at this level. Individuals must register with their local primary healthcare provider, and those requiring specialized care are referred to one of the public hospitals within their region. Referrals follow strict and predetermined guidelines based on diagnosis, location, and other patient demographics.[7] Hospitals are categorized into three levels of complexity, low, medium, and high, depending on their size and the range of medical services they offer.

Physician Licensing: To work in the healthcare sector, physicians are required to pass the EUNACOM exam (*Examen Único Nacional de Conocimientos de Medicina*).[8] The exam was established in 2009 and follows the characteristics and purposes of medical licensing exams in other countries.[9] It comprises a theoretical section and a practical section. The theoretical section corresponds to a multiple-choice test with 180 questions covering various areas of medical knowledge. The score reflects the candidate's absolute performance and is not standardized relative to other test-takers.[10] To pass, candidates must achieve a score of 51 or higher out of 100 points.

Upon passing the theoretical section, the candidates must complete a pass-or-fail practical section, which involves an examination in a real or simulated clinical environment. However, this requirement is waived for candidates with medical degrees from local universities and for physicians with a medical degree from a select group of countries with which the Ministry of Health has bilateral agreements.[11] The practical portion of the exam is largely not binding (Kunakov et al., 2018).

Importantly, approving the EUNACOM automatically validates the medical degrees of foreign-trained physicians, granting them the same job and training opportunities as locally trained physicians.[12]

Physician's Hiring and Wages in the Public Sector: Physicians can work in both the private and public sectors. In the private sector, employment operates under standard market dynamics, where wages, benefits, and working conditions are negotiated directly between employers and em-

[7] Patients can also be admitted directly to hospitals through the ER in cases of emergency.

[8] Although the exam is not technically mandatory for physicians in private healthcare organizations, it is effectively binding across all healthcare institutions because passing it is legally required to treat patients covered by public health insurance, regardless of the treatment location. This explains why, *de facto*, most private healthcare institutions only consider applications admissible if candidates include EUNACOM approval. The performance in the EUNACOM is also determinant for accessing training opportunities, as it plays a key role in admissions to residency programs in the country.

[9] Comparable exams include the Medical Licensing Examination (USMLE) in the U.S., the Medical Council of Canada Qualifying Examination (MCCQE) in Canada, the National Competency Exam (NCE) in France, the National Medical Licensing Examination (NMLE) in Japan, and the Korean Medical Licensing Examination (KMLE) in Korea. For an in-depth discussion of the exam and evidence of its validity and reliability, see Mena (2021).

[10] A key objective of the EUNACOM designers is to make the difficulty of the exam comparable across years. Empirically, we observe that although the scores are not standardized, the distribution of scores at local universities is very similar across years.

[11] Argentina, Brazil, Colombia, Ecuador, Spain, the United Kingdom, and Uruguay

[12] Countries that allow all prospective physicians hoping to work in a given jurisdiction to take a licensing exam include Canada, Hong Kong, Japan, Korea, the United Arab Emirates, and the United States (Archer et al., 2017).

ployees. In contrast, in public hospitals, wages are legally regulated and follow a public-sector wage schedule, with annual adjustments based on sector-wide wage revisions.[13] Hiring in public hospitals is decentralized and managed by the regional Health Services within the budgetary constraints established by the Ministry of Health. Health Services determine staffing needs for hospitals and hospital directors oversee the recruitment process. Although passing the EUNACOM exam is sufficient for eligibility, hospitals reportedly consider the candidate's EUNACOM score an important factor in hiring decisions.

2.2 Changes in Physician's Labor Market Fundamentals

In line with similar trends in other OECD countries, the number of physicians per capita in Chile has increased in the last two decades, driven by a growing number of domestic graduates and greater reliance on foreign-trained physicians (OECD, 2019). Figure 1-A shows that the number of new physicians enrolled in the National Registry of Healthcare Providers rose from around 1,000 in 2001 to over 4,000 in 2019. Figure 1-B shows the number of physicians working in public hospitals and their hourly wages from 2011 to 2019. During this period, the influx of newly registered physicians led to a 60% increase in full-time physicians in public hospitals. Despite this significant growth in the workforce, hourly wages remained flat after accounting for sector-wide remuneration adjustments. This wage rigidity aligns with established wage-setting policies.

One-third of the increase in newly registered physicians shown in Panel A is attributed to the growing number of locally trained physicians, driven by an expansion in the local supply of medical schools. The remaining two-thirds of the increase is explained by an unprecedented inflow of foreign-trained physicians into the system.[14][15] Panels C and D of Figure 1 show that the increase in physicians is strongly reflected in the number of EUNACOM test-takers and their migration status. In 2013, the number of foreign-trained physicians taking the exam was relatively small, with most failing to meet the minimum required score to validate their degrees. By 2018, the

[13] This is similar to the pay scales for physicians in the NHS, which are determined nationally through negotiations between government bodies and medical unions.

[14] While immigrants represented 2% of the population in 2011, this figure rose to 8% by 2022 (INE, 2024), largely driven by the mass migration of Venezuelans to Chile and other countries in the region, which began in late 2015 following the collapse of the Venezuelan economy. The Venezuelan migration to Chile and other countries in the region has been leveraged as a shock to explore the impacts of migration on various outcomes, including crime (Ajzenman et al., 2023), labor markets (Lebow, 2022; Olivieri et al., 2022; Bahar et al., 2024), and discrimination (Groeger et al., 2024), among others.

[15] Differences in remuneration and non-wage amenities are well-documented "push" and "pull" factors in physician migration (OECD, 2019). Various pieces of evidence highlight Chile as an attractive destination for medical professionals in Latin America, driven by significant wage differentials and better working conditions. Physicians in Chile can earn up to eight times more than their counterparts in Argentina, fueling temporary migration among Argentine physicians (Castro, 2024). Similarly, professional insecurity, low salaries, and limited social recognition have prompted physicians to emigrate from Venezuela (Hernández and Ortiz Gómez, 2011).

number of foreign-trained physicians taking the EUNACOM exam had increased nearly tenfold, and foreign physicians outnumbered local graduates taking the exam by 2.5 to 1. Not only did the mass of foreign-trained physicians increase, but the distribution also shifted to the right, indicating that many were able to validate their medical degrees.[16]

Figure 1: Physician's Labor Market

A. Registered Physicians

B. Physician's Wages in Public Hospitals

C. Scores in 2013

D. Scores in 2018

Notes: Panel A shows the number of newly registered physicians in the National Registry of Healthcare Providers between 2001 and 2019. This registry includes all healthcare workers legally allowed to practice in Chile. The bars are divided into locally-trained physicians (light red) and foreign-trained physicians (light blue). Panel B plots the growth of full-time equivalent physicians in public hospitals on the left y-axis and their average wages on the right y-axis, both indexed to 2011 (set equal to 1). Data come from SIRH (2019). Panels C and D display the distribution of test scores for locally-trained (red) and foreign-trained (green) physicians in 2013 and 2018, respectively. The dashed line in both graphs represents the minimum passing score.

In spite of the large migration influx, physicians remain scarce. As of 2019, Chile had 17.5 physicians per 10,000 inhabitants—nearly half the average of countries with a comparable burden of diseases, injuries, and risk factors (33.4 physicians per 10,000). This figure also falls below the

[16]The share of physicians in Chile who are foreign-trained increased from 15% to 24% between 2014 and 2019, and is currently similar to that of Canada and the US, and higher than the OECD average (OECD, 2015, 2019). Importantly, we do not find evidence of an increase in the share of foreign healthcare workers beyond physicians. We discuss this in greater detail in Appendix B.

minimum threshold of 20.7 physicians per 10,000 needed to achieve an effective Universal Healthcare coverage score of 80 out of 100 at the global level proposed by Haakenstad et al. (2022). The shortage of physicians is also reflected in the current long waiting lists, with approximately 3 million individuals—15% of the population—awaiting medical attention. An estimated 40,000 individuals die annually while on waiting lists, representing 25% of the country's annual mortality.

3 Data and Summary Statistics

3.1 Data Sources

Our main analysis combines four data sources: a matched employer-employee data for all public hospitals, the National registry of public health care provides, data on licensing scores, and individual-level discharge data. We combine these data with data on waitlists in some additional empirical exercises.

Employer-employee Data for Public Hospitals: We use matched employer-employee administrative records managed by the Ministry of Health. The records cover the universe of physicians employed in all public hospitals in Chile between 2011 and 2019 (SIRH, 2019). These data consolidate information from various public health organizations into a unified registry, providing comprehensive records for payroll processing and workforce management, including detailed wage data, and employment information. We complement these data with hospital-level characteristics, including size, location, and referral area, among others (DEIS, 2020).

National Registry of Public Healthcare Providers: We use a registry of all physicians (and other healthcare professionals) legally authorized to practice in Chile (RNPI, 2024). The registry is managed by Chile's Superintendency of Health (*Superintendencia de Salud*), and provides detailed information on registered healthcare professionals, including their nationality and details of their professional degree including title, date of issuance, and the name and country of the granting institution. For degrees obtained abroad, the registry includes the date of revalidation in Chile.

Licensing Exam Scores: We use confidential score records for all physicians who have taken the national licensing exam, EUNACOM. These data were provided directly by ASOFAMECH (*Asociación de Facultades de Medicina de Chile*), the organization responsible for administering and overseeing the exam (ASOFAMECH, 2019). The dataset includes the date and scores of the theoretical portion of the EUNACOM for every attempt made by the universe of physicians who have taken the exam.

Individual-level Discharge Data: We measure outcomes using administrative records of individual-level inpatient events in all public hospitals in Chile from 2011 to 2019 (DEIS, 2019). The data include diagnoses (ICD-10 codes), discharge or death dates, and patient characteristics such as birth date, gender, residence, and health insurance type. We link these data at the individual level with the universe of death records processed by the Vital Records Office, which includes deaths outside public hospitals.[17]

Waiting Lists: We access individual-level administrative records of waiting lists for surgical procedures and specialist consultations for non-prioritized conditions (SIGTE, 2019), obtained through a Freedom of Information Act (FOIA) request.[18] In Chile, primary care physicians refer patients to hospitals for specialist consultations or surgical procedures, placing them on a waitlist. We observe each patient's entry and exit dates, along with the assigned hospital.

3.2 Data Aggregation and Outcomes

We construct a hospital-by-year panel dataset using all the sources of information described above. We assess hospital performance in terms of access and quality. Our primary measure of access is the yearly hospital service rate, defined as the number of admissions in a given year divided by the eligible population in the hospital's referral region in the corresponding year. We also use surgery rates (inpatient surgeries as a proportion of admissions) and exits from the waitlist as additional access measures in some robustness exercises.

Our primary measure of quality is the hospital's yearly average death rate, defined as the ratio between deaths and admissions in a given year. We complement this in-hospital death rate with the death rate resulting from counting deaths within 28 days of a patient's admission—regardless of the place of death—following Gaynor et al. (2013). In robustness exercises, we also replace death rates with complication rates. We calculate complication rates as the number of patients discharged and later readmitted for inpatient care (within 3 months) due to an ICD-10 code related to infections, hemorrhage, or other complications, divided by the total number of admissions.

Since EUNACOM was introduced in 2009, we impute scores for physicians who did not take the exam.[19] Our imputation procedure assigns scores to a physician from region or origin r working at

[17] We only have access for these records until 2018.

[18] Waitlists are divided into prioritized and non-prioritized conditions. The "Explicit Healthcare Guarantees" program, established by law, prioritizes specific diseases with evidence-based procedures and timelines for diagnosis and treatment. See Menares and Muñoz (2025) for details.

[19] Before the introduction of EUNACOM, Chile had a voluntary National Medical Examination (EMN) administered in Chilean medical schools from 2003 to 2008. Prior to the EMN, licensing requirements varied: local medical graduates were required to pass the Medical Surgeon Degree Examination, while foreign-trained physicians had to

hospital h by combining the average score of all physicians at hospital h (the grand mean) and the differential score of physicians from region r working at hospital h (the group mean). To estimate this differential score, we model licensing scores as a function of region-of-origin fixed effects at the hospital level, imposing sum-to-zero constraints on the fixed effects. We then adjust these estimates using empirical Bayes, such that group differentials are shrunk towards zero as estimates' precision decreases (Efron and Morris, 1973; Walters, 2024). In Appendix A, we present additional details on our imputation procedure and conduct robustness checks of the main results using LASSO as an alternative imputation method (Murdoch et al., 2019).

3.3 Descriptive Statistics

Appendix Table A.1 provides descriptive statistics of the data used in the main analysis. Panel A summarizes key patient and hospital characteristics. Patients are predominantly female (57%), and 30% are under the age of 29. As expected, most (97%) of patients in public hospitals are covered by public insurance. The in-hospital death rate averages 3.28%, while the 28-day death rate is higher, at 5.07%. Hospitals serve an average of 5,656 patients annually, corresponding to an average service rate of 2%. The average length of stay is 4.03 days, and complication rates average 11.41%. Hospitals perform an average of 2,018 surgeries annually. They employ, on average, around 77 physicians.

Panel B describes the evolution of test scores across multiple years. The number of test takers increased steadily over the period, from 1,389 in 2009 to 7,121 in 2018. Average test scores declined sharply between 2009 and 2013, dropping from 71.8 to 56.1 and then stabilized, to reach 53.9 in 2018. The proportion of test takers who achieved a passing score (≥ 51) had an equivalent trend and fell from 92% in 2009 to 58% in 2018. Notably, the number of tests falling within the [40–51] range increased substantially over the years, from 87 in 2009 to 1,552 in 2018, reflecting a growing mass of physicians that would be licensed under a slightly lower passing score.

4 Simple Licensing Problem

We begin with a simple theoretical framework to study the economic fundamentals that determine the optimal licensing policy in our context. We focus on a particular margin, namely the stringency of the requirement as determined by the passing score of the licensing exam.

The licensing technology is based on a noisy signal s of quality θ. The output of interest (e.g.

complete a Foreign Medical Qualification Revalidation Examination.

hospital production) is an increasing function of labor $L(\underline{s})$ and a quality index $\mathring{\theta}(\underline{s})$,

$$Y(\underline{s}) = F\left(L(\underline{s}), \mathring{\theta}(\underline{s})\right),$$

where $\underline{s}$ is the licensing threshold (passing score), $F_L > 0$ and $F_{\mathring{\theta}} > 0$. This production function generates a quality-quantity trade-off in the licensing policy, as long as there is positive mass in the support of s and the quality input is positively related to the cutoff; $\mathring{\theta}(\underline{s})' > 0$. Specifically, the elasticity of the outcome with respect to the licensing threshold, $\eta^Y_{\underline{s}} \equiv \frac{\partial Y}{\partial \underline{s}} \frac{\underline{s}}{Y}$ equals

$$\eta^Y_{\underline{s}} = \underbrace{\eta^Y_L \eta^L_{\underline{s}}}_{\text{Licensing Quantity Effect}} + \underbrace{\eta^Y_{\mathring{\theta}} \eta^{\mathring{\theta}}_{\underline{s}}}_{\text{Licensing Quality Effect}}, \tag{1}$$

where η^Y_L and $\eta^Y_{\mathring{\theta}}$ are the output elasticities with respect to the quantity and quality inputs, respectively, and $\eta^L_{\underline{s}}$ and $\eta^{\mathring{\theta}}_{\underline{s}}$ denote the elasticities of each input with respect to the licensing threshold. The impact of the policy variable $\underline{s}$ on the outcome $Y(\underline{s})$ is fully characterized by these four *sufficient statistics*.[20] On the one hand, increasing the threshold decreases output by reducing the quantity of labor. This *Licensing Quantity Effect* depends on the output elasticity with respect to quantity, and the elasticity of labor with respect to the threshold. On the other hand, increasing the threshold increases output by improving quality. This *Licensing Quality Effect* depends on the output elasticity with respect to quality and the elasticity of quality with respect to the threshold.

Moreover the ratios of input and output elasticities are sufficient to determine the sign of the effect of changing the licensing threshold on the outcome as

$$\eta^Y_{\underline{s}} > 0 \iff \eta^Y_L / \eta^Y_{\mathring{\theta}} > -\eta^{\mathring{\theta}}_{\underline{s}} / \eta^L_{\underline{s}} \tag{2}$$

Parametrizing the model allows us to gain further insights into the microfoundations for the elasticities governing the quality-quantity trade-off in licensing. Let the signal s have a distribution with density $h(s)$ and total mass m. Physicians who pass the exam can either work at the hospital or go to an outside option. We let $p(s|\underline{s})$ the share of physicians with score s who match with the hospital. This probability may depend on the licensing score through equilibrium effects in the labor market.

[20] Chetty (2009) provides a general framework for welfare analysis from a set of sufficient statistics that are derived using envelope conditions under the assumption that agents make optimal decisions. However, Chetty (2009) also notes that the assumption of optimizing behavior is not necessary as long as the researchers can estimate the terms included in the derivative of welfare with respect to the policy variable of interest. That is indeed our case. For the interested reader, in Appendix C we recast the licensing problem as a maximization problem and derive Equation 1 in that framework using envelope conditions.

The total labor function is therefore $L(\underline{s}) = m \int_{\underline{s}}^{\infty} h(s)p(s|\underline{s})ds$. Let the quality index be equal to the exponential of average quality, $\mathring{\theta} = \exp(\bar{\theta}(\underline{s}))$, with $\bar{\theta}(\underline{s}) = 1/L(\underline{s}) \int_{\underline{s}}^{\infty} \theta(s)h(s)p(s|\underline{s})ds$. Finally, the production function has a Cobb-Douglas form with $F\left(L, \bar{\theta}\right) = L^{\alpha_L} \cdot \exp(\bar{\theta})^{\alpha_{\bar{\theta}}}$.

Under this parametrization, the elasticity of output with respect to the licensing threshold $\underline{s}$ can be written as

$$\eta_{\underline{s}}^{Y} = \alpha_L \cdot \eta_{\underline{s}}^{L} + \alpha_{\bar{\theta}} \cdot \tilde{\eta}_{\underline{s}}^{\bar{\theta}},$$

where $\eta_{\underline{s}}^{L}$ is the elasticity of labor with respect to the licensing threshold and $\tilde{\eta}_{\underline{s}}^{\bar{\theta}}$ is the semi-elasticity of quality with respect to the threshold.

In the absence of equilibrium effects in the labor market, i.e. when $\partial p(s|\underline{s})/\partial \underline{s} = 0$, the elasticities can be expressed as simple functions of the underlying model parameters. The elasticity of labor with respect to the threshold is

$$\eta_{\underline{s}}^{L} = \frac{-m \cdot h(\underline{s}) \cdot p(\underline{s}|\underline{s}) \cdot \underline{s}}{L}, \tag{3}$$

which depends on the mass of workers at the threshold and the fraction of them matching with the hospital. In turn, each marginal worker lowers average *scores* by an amount equal to $\mathbb{E}[s|s > \underline{s}]$. The degree to which average *quality* is affected depends on the precision of the licensing score as a signal of quality. Let $s = \theta + \epsilon$, with $\epsilon \sim N(0, \sigma_\epsilon^2)$ and $\theta \sim N(\mu_\theta, \sigma_\theta^2)$. Defining the signal-to-noise ratio as $\text{SNR} \equiv \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2}$, the semi-elasticity of quality with respect to the licensing threshold can be written as:

$$\tilde{\eta}_{\underline{s}}^{\bar{\theta}} = -\eta_{\underline{s}}^{L} \cdot \text{SNR} \cdot (\mathbb{E}[s|s > \underline{s}] - \underline{s}) \tag{4}$$

On net, the elasticity of outcome with respect to the threshold is therefore

$$\eta_{\underline{s}}^{Y} = \frac{-m \cdot h(\underline{s}) \cdot p(s|\underline{s}) \cdot \underline{s}}{L} \cdot (\alpha_L - \alpha_{\bar{\theta}} \cdot \text{SNR} \cdot (\mathbb{E}[s|s > \underline{s}] - \underline{s})) \tag{5}$$

The first term measures the number of marginal workers, whereas the second term is the net effect of a marginal worker on production. The quantity effect of an extra worker is α_L. However, the marginal worker decreases average quality by $\text{SNR} \cdot (\mathbb{E}[s|s > \underline{s}] - \underline{s}))$. This term, multiplied by the return on quality, gives the quality effect of the marginal worker.

Under this parametrization, condition 2 can be stated as

$$\frac{\alpha_L}{\alpha_{\bar{\theta}}} > \text{SNR} \cdot (\mathbb{E}[s|s > \underline{s}] - \underline{s})$$

Whether decreasing the licensing threshold increases output depends on whether the output elasticity with respect to quantity over the output elasticity with respect to quality is higher than the effect of average quality of a marginal worker. The later increases with the distance between the average score and marginal score, and the precision of the signal.

The optimal licensing threshold $\underline{s}^*$ can be implicitly characterized with a simple expression:

$$\underline{s}^* = \mathbb{E}[s|s > \underline{s}^*] - \frac{\alpha_L}{\alpha_{\bar{\theta}}} \cdot \frac{1}{\text{SNR}}.$$

The optimal threshold increases with the mean score. A higher mean allows the planner to have more quantity for any given level of quality. Also, the optimal threshold decreases with the output elasticity with respect to labor and increases with the output semielasticity with respect to quality. It is also lower when the licensing technology is imprecise (i.e., low signal-to-noise ratio), as in such cases a higher threshold can only weakly differentiate between high- and low-quality physicians.

Objective Function Let patient's health in the absence of treatment (e.g., probability of survival if not treated) be equal to $m(X)$ such that all heterogeneity across patients is captured by their characteristics X; and let $\Delta m(X, \bar{\theta}(\underline{s}), L(\underline{s}))$ be the value added of health care treatment, e.g., the reduction mortality risk if treated under a healthcare system characterized by inputs $\bar{\theta}(\underline{s}$ and $L(\underline{s})$. Denoting the unconditional distribution of X by dG_X, the set of patients who receive treatment under the licensing cutoff $\underline{s}$ by $\mathcal{I}(\underline{s})$, and the conditional distribution of their characteristics by $dG'_{X|\underline{s}}$, we can write population health as follows:

$$\begin{aligned} H(\underline{s}) &= \underbrace{\int_X m(X) dG_X}_{H^0} + \underbrace{|\mathcal{I}(\underline{s})|}_{\text{service rate}} \times \underbrace{\int_X \Delta m(X, \bar{\theta}(\underline{s}), L(\underline{s})) dG'_{X|\underline{s}}}_{\text{per-patient treatment value added}} \\ &= H^0 + Y(\underline{s}), \end{aligned}$$

where H^0 represents baseline health and $Y(\underline{s})$ captures the impact of the healthcare system in improving health outcomes, which depends on the licensing threshold through its impact on the number of patients seen (service rate), and on its impact on the value added quantity and quality of physicians as well as the distribution of characteristics of treated patients. We will focus on lives

saved as the ultimate health outcome in our empirical analysis. Thus, we will proxy per-patient treatment value added with the *decrease* in patients' mortality as a function of physicians' quantity and quality while also controlling for patients' case mix to account for heterogeneous treatment effects due to variations in patients' characteristics.

Given this objective function, we can approximate the elasticity of healthcare's impact with respect to the licensing threshold as the difference between the elasticity of the service rate and the elasticity of per-patient mortality risk, as follows:[21]

$$\eta_{\underline{s}}^{Y} \simeq \eta_{\underline{s}}^{\text{service rate}} - \eta_{\underline{s}}^{\text{mortality}}. \tag{6}$$

Thus, the licensing threshold may affect lives saved in two ways. First, it may affect access through the service rate. Second, it may affect treatment value added by changing patients' mortality. In the next section, we describe a general framework for estimating how service rate and mortality depend on the licensing threshold.

5 Empirical Model

This section augments the model of the previous section by including many hospitals and the corresponding endogenous sorting of physicians across them. We first outline the planner's objective as a function of hospitals' input and output elasticities. We then describe the empirical model used to estimate these elasticities. The model is flexible enough to incorporate policy effects over different time horizons, which is relevant in settings with exam retaking.

5.1 The Licensing Problem and the Time Frame for Policy Evaluation.

Consider a social planner who, in period $t_0 = 0$, determines the licensing threshold $\underline{s}$ considering its impact on outcome Y in a period $R \geq 0$, Y_R:

$$Y_R \equiv \prod_{j \in \mathcal{J}} y_{jR}^{p_j},$$

where p_j are hospital Pareto weights. Restating Equation (1) in the context of the functional form assumptions for the production function of Section 4, the elasticity of Y_R with respect to the

[21] Formally, $\eta_{\underline{s}}^{Y} = \eta_{\underline{s}}^{\text{service rate}} - \eta_{\underline{s}}^{\text{mortality}} - \eta_{\underline{s}}^{\text{service rate}} \eta_{\underline{s}}^{\text{mortality}}$. Our approximation ignores the cross-term. Empirically, we find that $\eta_{\underline{s}}^{\text{mortality}} \simeq 0$.

licensing threshold is given by:

$$\eta_{\underline{s}}^{Y_R} = \underbrace{\alpha_L \cdot \bar{\eta}_{\underline{s}}^{L,R}}_{\text{Licensing Quantity Effect}} + \underbrace{\alpha_\theta \cdot \bar{\tilde{\eta}}_{\underline{s}}^{\bar{\theta},R}}_{\text{Licensing Quality Effect}},$$

where $\bar{\eta}_{\underline{s}}^{L,R} = \sum_{j \in \mathcal{J}} p_j \cdot \eta_{\underline{s}}^{L_j,R}$, is the average elasticity of labor with respect to $\underline{s}$ in period R, and $\bar{\tilde{\eta}}_{\underline{s}}^{\bar{\theta},R} = \sum_{j \in \mathcal{J}} p_j \cdot \eta_{\underline{s}}^{\bar{\theta}_j,R}$, is the average semi-elasticity of quality with respect to $\underline{s}$ in period R. The hospital-specific elasticities of quantity and quality are functions of the density and mass of physicians at the licensing threshold, the baseline quantity and quality of each hospital, the precision of the signal, and physicians' matching probabilities across hospitals.

The possibility of exam retaking generates a distinction between the immediate and future impacts of a change in the licensing threshold, as test-takers in any period t' include retakers who failed the exam in a previous period $t < t'$. As such, lowering the threshold in a period t_0 not only impacts who passes in period t_0 but also the set of test takers in any period $t' > t_0$.

We define, therefore, two time windows for evaluating the effects of changing the licensing threshold:

(i) *Short-Run* ($R = 0$): Elasticities reflect the immediate effects of licensing policy changes.

(ii) *Long-Run* ($R > 0$): Elasticities incorporate the dynamic effects of the policy considering exam retaking.

The regime-specific formulation of Y_R and $\eta_{\underline{s}}^{Y_R}$ allows us to evaluate counterfactual scenarios and compare the immediate and dynamic impacts of licensing policy changes.

5.2 Input Elasticities: Scores and Labor Matching Model

We begin with the elasticity of inputs, which depend on the mass of test-takers at the threshold, the mapping between scores and quality, and the matching probabilities (see Equation 4). We recover these objects with a dynamic model of scores and a labor-matching model. Modeling the dynamics of scores serves two purposes. First, it allows us to infer physicians' latent quality by leveraging the entire history of their scores across attempts. Second, it allows us to predict the dynamic effects on the mass of test-takers when evaluating the long-run effects of changing the threshold. We complement the model of scores with a labor-matching model to estimate matching probabilities at the current and counterfactual thresholds.

Scores History Determination: Each physician i belongs to a type $\tau(i) \in \{N, F\}$ and is characterized by her latent quality θ_i. Physicians can retake the exam and change their test-taking ability over attempts.[22] We denote physician i's test-taking ability in attempt n by Γ_{in}. The score in attempt n, s_{in}, is a noisy measure of a physician's quality and test-taking ability, with

$$s_{in} = \theta_i + \Gamma_{in} + \epsilon_{in}. \tag{7}$$

In the data, average score gains over attempts are positive, decreasing, and convex (see Figure A.1). We assume, therefore, that test-taking ability improves with exponential decay, such that for any attempt number $n_i \geq 1$, test-taking ability is

$$\Gamma_{in} = \sum_{k=0}^{n_i-1} \gamma \cdot \exp(-\rho \cdot k) \tag{8}$$

where γ and ρ are parameters to be estimate. γ governs the average improvement in the first retake, while ρ governs the average rate at which improvements decrease over subsequent attempts.

Physicians who fail the exam in attempt n, retake it with a probability that is a function of the distance between their average past score and the passing threshold $\bar{s}_{in} - \underline{s}$, the number of attempts, n, physician's type, $\tau(i)$, and the licensing threshold, $\underline{s}$:

$$P(\text{retake}|\bar{s}_{in}, n_i, \tau(i)) = \frac{e^{\beta_{0,\tau(i)} + \beta_{n,\tau(i)} n + \beta_{s,\tau(i)}(\bar{s}_{in} - \underline{s})}}{1 + e^{\beta_{0,\tau(i)} + \beta_{n,\tau(i)} n_i + \beta_{s,\tau(i)}(\bar{s}_{in} - \underline{s})}}. \tag{9}$$

By allowing the retaking probability to depend on both the distance between an individual's average score and the licensing exam threshold, and the number of attempts (a sufficient statistic for predicting future scores and posterior quality), this specification captures the net benefits of retaking. These net benefits arise from two factors: (i) the probability of passing the threshold in subsequent attempts (determined by the gap between expected future scores and the threshold), and (ii) the expected value of the match conditional on passing the exam (which depends on physicians' type and posterior quality). In addition, explicitly incorporating the licensing threshold in the specification allows retaking behavior to change under counterfactual scenarios.

Assuming that θ and ϵ are normally distributed as described in Section 4, the posterior of quality

[22] We assume that quality is constant over time which implies that physicians cannot experience quality gains over attempts. To support this assumption, in Appendix D, we use regression discontinuity designs to show that physicians who retake the exam around the passing threshold do not experience gains on quality proxies.

for each physician given a sequence of scores over attempts $\{s_{i1}, s_{i2}, ..., s_{in}\}$ is equal to:

$$\mathbb{E}[\theta_i \mid s_{i0}, s_{i1}, \ldots, s_{in}] = \mu_{\theta,\tau(i)} + \frac{\sigma^2_{\theta,\tau(i)}}{\sigma^2_{\varepsilon,\tau(i)} + (n+1)\sigma^2_{\theta,\tau(i)}} \left(\sum_{t=0}^{n} (s_{it} \underbrace{-\Gamma_{t,\tau(i)}}_{\text{de-trending}} - \mu_{\theta,\tau(i)}) \right), \tag{10}$$

with

$$\theta_i = \mathbb{E}(\theta_i | s_i) + \nu_i. \tag{11}$$

Equations (10) and (11) are the basis for inferring physician's quality from their vector of scores.

Labor Market Matching: Physicians who pass the exam match with hospitals in a decentralized labor market. The main challenge in modeling this matching process is to capture how it changes in counterfactual scenarios with different licensing thresholds. In particular, relaxing the licensing threshold increases the number of (lower-quality) physicians seeking jobs, which may impact the equilibrium matching probabilities due to competition in the labor market. To capture this dimension of the problem, we specify matching probabilities that depend on the inflow of physicians who pass the exam.

Denote by $M_t(\underline{s})$ the mass of physicians who pass the licensing exam in period t when the threshold is $\underline{s}$, and let $\kappa_t = \{\kappa_{1t}, ..., \kappa_{|\mathcal{J}|t}\}$, the vector of posted vacancies in period t; which jointly determine the labor market tightness. We split physicians into disjoint quality ranges, and allow the matching probability of physician i with hospital j to depend on $M_t(\underline{s})$, κ_t, the quality range $r_{\hat{\theta}}(i)$ and physician's type $\tau(i)$. Matching probabilities also depend on a set of observables x_{ijt}. As such, conditional on passing the licensing exam in period t, each physician i matches with a hospital j or opts for their outside option, $\emptyset$, based on a conditional matching probability function denoted by $CMP(\cdot)$, with:

$$CMP_{ijt}(\underline{s}) = \frac{e^{v(x_{ijt}) + g(M_t(\underline{s}), \kappa_t | \tau, r_{\hat{\theta}}(i), j)}}{1 + \sum_{j'} e^{v(x_{ij't}) + g(M_t(\underline{s}), \kappa_t | \tau, r_{\hat{\theta}}(i), j')}}. \tag{12}$$

The function $v(\cdot)$ captures the determinants of matching probabilities based on physician's and hospital's preferences. In our empirical application it is a flexible function of physician's characteristics with j-specific coefficients.

The function $g(\cdot)$ captures the potential equilibrium effects driven by competition in the labor market; the key channel through which matching probabilities depend on the licensing threshold. For our empirical application, we specify the general equilibrium effects as a simple linear function

of labor market tightness:

$$g(M_t(\underline{s}), \kappa_t | \tau, r_{\hat{\theta}}(i), j) = \boldsymbol{\beta}_j \frac{M_{it}(\underline{s})}{\kappa_{jt}} \tag{13}$$

where $\boldsymbol{\beta}_j$ is a vector of hospital-specific coefficients and $M_{it}(\underline{s}) = [M^0_{it}(\underline{s}), M^+_{it}]$ is a vector composed by the mass of physicians in i's quality range; $M^0_{it}(\underline{s})$, and the mass of physicians above i's quality range; M^+_{it}.[23]

Our specification of the matching function captures key determinants of physicians' and hospitals' preferences, as well as market-level conditions that can affect sorting patterns and vary in the counterfactuals.[24] In Appendix G, we generalize and characterize how equilibrium effects can affect our counterfactual exercises, and provide an identification strategy to account for them by exploiting the variations driven by the migration wave.[25]

The labor-matching probabilities and the licensing policy determine hospital-specific inflows of physicians and their respective quality. For a physician $i \in \mathcal{I}$ with type $\tau \in \mathcal{T}$, exam score s, and a matrix of physician–hospital characteristics $X \in \mathbb{R}^{K \times |\mathcal{J}|}$ (whose jth column is the vector $\boldsymbol{x}_{ijt} \in \mathbb{R}^K$ for hospital $j \in \mathcal{J}$), in a market characterized by (M_t, κ_t) in period t, define:

$$CMP_j\big(X, s \,\big|\, \tau;\, M_t;\, \kappa_t;\, \underline{s}\big) \;:=\; CMP_{ijt}\Big(\big[\, x_{i1t}, \ldots, x_{i|\mathcal{J}|t} \,\big] = X,\; s_{it} = s,\; \tau(i) = \tau,\; M_t,\; \kappa_t,\; \underline{s}\Big).$$

This CMP_j is the conditional probability that such a physician matches with hospital $j \in \mathcal{J}$ in period t. Letting $h^\tau_t(s, X)$ be the type- and time-specific density of the joint distribution of

[23] Let m_t be the number of test takers in period t and $h_t(s, X)$ be the joint distribution of scores and characteristics in period t. The mass of physicians who pass the exam in year t and have expected quality within a range $r_{\hat{\theta}} \in \mathcal{R}$ is:

$$M_{r_{\hat{\theta}},t}(\underline{s}) \equiv m_t \int_X \int_{s > \underline{s}:\ \hat{\theta}(s) \in r_{\hat{\theta}}} h_t(s, X) ds dX. \tag{14}$$

The mass of physicians in i's quality range is $M^0_{it} = M_{\tau(i), r_{\hat{\theta}}(i), t}$ and the mass of physicians above i's quality range, $M^+_{it} = \sum_{r_{\hat{\theta}'} \succ r_{\hat{\theta}}(i)} M_{\tau(i), r_{\hat{\theta}'}, t}$. Only M^0_{it} depends on the licensing score as the licensing score only affects the mass at the bottom of the distribution.

[24] We do not specify the extent to which these conditional matching probabilities are separately influenced by the preferences of physicians and hospitals or by the labor market conditions. However, in Appendix K.5 we provide a microfoundation for the current model where matching probabilities arise endogenously and are affected by changes in the mass of physicians due to capacity constraints and sorting.

[25] In particular, we assume that equilibrium effects can affect the conditional matching probabilities of physicians with expected quality range $r_{\hat{\theta}}$ only through changes in the distribution of potential physicians in their own range and "upstream" in the order of expected quality ranges. In addition, we assume that equilibrium effects can be approximated by contiguous chained effects, where a change in the mass of physicians in a specific expected quality range can have a direct effect on the CMPs within that range, and can also induce a displacement effect on the expected quality range that immediately precedes it. This displacement effect influences the mass in that range and consequently affects the CMPs indirectly.

observables and scores, the labor inflow of type τ in hospital j in period t is given by:

$$\Delta L_{jt}^{\tau}(\underline{s}) \;=\; m_{\tau,t} \int_X \int_{s \geq \underline{s}} CMP_j\big(X, s \mid \tau;\, M_t;\, \kappa_t;\, \underline{s}\big)\, h_t^{\tau}(s, X)\, ds\, dX.$$

In addition, the average quality of physicians inflow of type τ in hospital j at time t is given by:

$$\Delta \bar{\theta}_{jt}^{\tau}(\underline{s}) \;=\; \frac{\displaystyle\int_X \int_{s \geq \underline{s}} CMP_j\big(X, s \mid \tau;\, M_t;\, \kappa_t;\, \underline{s}\big)\, \hat{\theta}(s, \tau)\, h_t^{\tau}(s, X)\, ds\, dX}{\displaystyle\int_X \int_{s \geq \underline{s}} CMP_j\big(X, s \mid \tau;\, M_t;\, \kappa_t;\, \underline{s}\big)\, h_t^{\tau}(s, X)\, ds\, dX}$$

The labor in hospital j at time t and its corresponding average quality are given by

$$L_{jt}(\underline{s}) = L_{j,t-1} + \sum_{\tau \in \mathcal{T}} \Delta L_{jt}^{\tau}(\underline{s}) \tag{15}$$

$$\bar{\theta}_{jt}(\underline{s}) = \frac{1}{L_{jt}} \left(\bar{\theta}_{j,t-1} L_{j,t-1} + \sum_{\tau \in \mathcal{T}} \Delta L_{jt}^{\tau}(\underline{s}) \cdot \Delta \bar{\theta}_{jt}^{\tau}(\underline{s}) \right) \tag{16}$$

The elasticity of quantity and semi-elasticity of quality with respect to the licensing threshold follow directly from the expressions above.

5.3 Output Elasticities: Production Function

In this subsection, we introduce the hospital production function for healthcare and discuss an instrumental variables approach to estimate the output elasticities.

In period t, each hospital j produces an outcome k that we denote by y_{jt}^k, by combining a quantity of physicians L_{jt} with quality index $Q(F_{\theta_{jt}})$, and other determinants of hospital output such as capital, patient case-mix, and productivity, collectively represented by A_{jt}. We assume the production function is a Cobb-Douglas, such that:

$$y_{jt} = A_{jt} L_{jt}^{\alpha_L} exp(Q\left(F_{\theta_{jt}}\right))^{\alpha_\theta}, \tag{17}$$

where $Q(F_{\theta_{jt}}) = \int q(\theta)\, f_{\theta_{jt}}(\theta)\, d\theta$ and $q(\cdot)$ is a *nondecreasing* function of θ. Intuitively, $Q(F_{\theta_{jt}})$ captures how the distribution of quality at hospital j in period t. For our empirical application, we adopt $q(\theta) = \theta$, which implies $Q(\theta_{jt})$ is simply the (unconditional) mean of the quality distribution in hospital j in period t.[26]

[26] In Appendix E, we show that an alternative specification—defining the quality index as the share of physicians

Using the posterior described in Equation (11), we can express the empirical analog of Equation (17) as:

$$\ln(y_{jt}^k) = \alpha_L^k \ln(L_{jt}) + \alpha_\theta^k \frac{1}{L_{jt}} \sum_{i \in J_t} E(\theta_i | \mathbf{s}_i) + \gamma_{f(j)t}^k + \rho_j^k + \beta^k X_{jt} + \underbrace{\omega_{jt}^k + \alpha_\theta^k \frac{1}{L_{jt}} \sum_{i \in J_t} \nu_{it} + \varepsilon_{jt}^k}_{\mu_{it}}. \quad (18)$$

Equation (18) is our estimating equation to recover α_L^k and α_θ^k, the output-specific elasticities with respect to quantity and quality, respectively. This specification implicitly models logged productivity as being influenced by time-invariant unobservable characteristics, which we capture using hospital fixed effects, ρ_j^k. These fixed effects also capture other time-invariant unobservables, such as the capital stock, and we further account for time-varying changes in capital by including the number of beds per patient in each HRR in the vector X_{jt}. Additionally, following Propper and Van Reenen (2010) and Gaynor et al. (2013), X_{jt} includes demographic controls to account for changes in patient composition that might influence hospital outcomes. Specifically, these case-mix controls include the shares of female inpatients, foreign inpatients, and inpatients across eight age bands (0–29, followed by 10-year increments up to 90+), as well as the shares of inpatients with different insurance types categorized by co-payment levels.

To account for potential differential time trends by hospital complexity, the specification also includes a vector of year-fixed effects that vary with hospital complexity, $\gamma_{f(j)t}^k$. Finally, the error term μ_{it} consists of three components: an unobserved productivity shock potentially known before input choices, ω_{jt}^k (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015); measurement error in quality, $\alpha_\theta^k \frac{1}{L_{jt}} \sum_{i \in J_t} \nu_{it}$; and an unobserved productivity shock that occurs after input decisions, ε_{jt}^k.

To address the problem of measurement error and the identification challenge that physicians' quantity and quality could be correlated with unobserved factors affecting hospital outcomes, we implement a two-stage least squares (2SLS) estimation strategy that uses two shift-share (or Bartik) instruments (Altonji and Card, 1989; Autor et al., 2013) to recover the *causal* impact of physician quantity and quality on hospital-level outcomes. Our instruments leverage the increase in the labor supply of physicians brought about by immigration flows from other countries and, to a lesser extent, by the expansion of medical schools in Chile. The instrument for physician quantity, Z_{jt}^L, is constructed by summing the percentage change in the number of physicians clearing the cutoff of

in hospital j during period t with quality below the median of the overall distribution—yields very similar empirical results. We also discuss the impact of physician quantity and quality on health outcomes using a Translog production function that includes a linear interaction between the two.

the licensing exam from each region of training c (i.e., the shift component ΔS_c), weighted by the percentage of physicians from that region who worked at hospital j the year before (i.e., the share component $\text{Share}_{i(c)jt-1} \equiv \frac{L_{cjt-1}}{\sum_c L_{jct-1}}$). Similarly, the instrument for physician quality, Z^{θ}_{jt}, sums the change in the average quality of eligible test-takers from each training region c, weighted by the percentage of physicians from that region who worked at hospital j the year before.

6 Estimation Results

6.1 Input elasticities: The impact of licensing on the quantity and quality of physicians

Latent quality, matching probabilities, and the mass of test-takers around the licensing threshold are the key ingredients to estimate the input elasticities with respect to the licensing threshold.

Latent Quality Table 1 presents the maximum likelihood estimation results for the retaking model specified in Equation (9). As expected, the probability of retaking decreases with the number of attempts and with the distance of the score to the cutoff.

Table 1: Retaking Model Estimates

	Foreign	Nationals
n_{it}	-0.231	-0.163
	(0.020)	(0.059)
$\bar{s} - s_{it}$	-0.036	-0.060
	(0.003)	(0.009)
Constant	2.592	1.595
	(0.077)	(0.139)
N	8,221	1,340

Notes: The table shows maximum likelihood estimates for the coefficients of the logit model for retaking as specified in Equation (9). Standard errors in parentheses.

Using the estimated retaking probabilities, we estimate the model of score gains via Simulated Method of Moments (SMM).[27] We match the following moments by physician type (national or foreign): the mean over attempts, the mean of gains over attempts, the covariance between attempts, and the variance of the first attempt. Table 2 shows the estimated coefficients by type. We observe that foreigners have larger variances for the estimated quality distribution and exam noise than nationals. In addition, the estimates for score gains predict for foreigners that exam gains

[27] This estimation strategy allows us to model the selection behavior in the retaking process.

decay relatively quickly at an exponential rate of 0.55. On the other hand, for nationals, score gains are imprecisely estimated due to the lack of data on retaking behavior.

With the estimated quality distribution and score gain parameters, and given the history of score realizations for each physician, we use Equation (10) to estimate individual posterior quality means and compute average posterior quality for every hospital in every period.[28]

Table 2: Score Gains and Latent Quality Estimates

	Natives	Foreigners	Common
$\hat{\mu}_\theta$	65.474	46.002	
	(0.107)	(0.864)	
$\hat{\sigma}_\theta$	8.679	14.723	
	(0.113)	(0.174)	
$\hat{\sigma}_\epsilon$	8.677	9.227	
	(0.072)	(0.190)	
SNR	0.500	0.718	
	(0.009)	(0.012)	
$\hat{\gamma}$			9.599
			(0.541)
$\hat{\rho}$			0.285
			(0.050)

Note: Coefficients are estimated via Simulated Method of Moments (SMM). Bootstrapped standard errors are in parentheses, computed using the empirical standard deviation of the estimates across 10 simulations.

Matching Probabilities We estimate the conditional matching probabilities by maximum likelihood following Equations (12) and (13). We specify $v(x_{ijt})$ as a function of the distance between the university of training and the centroid of location j (Distance_{ij}), the (lagged) share component of our instrument (Share_{ijt-1}). We also include alternative-specific time fixed effects, alternative-specific shifters of the matching probability based on physician's posterior quality ($\mathbb{E}(\theta_i)$), whether the physician is foreign (Foreign_i) and whether the physician is a specialist (Specialist_i):

$$\begin{aligned} v_{ijt} = \alpha^d \text{Distance}_{ij} + \alpha^h \text{Share}_{ijt-1} + \alpha_{jt} + \alpha_j^f \text{Foreign}_i \\ + \alpha_j^q \mathbb{E}(\theta_i) + \alpha_j^{fq} \mathbb{E}(\theta_i) \times \text{Foreign}_i + \alpha_j^s \text{Specialist}_i. \end{aligned} \tag{19}$$

The coefficients α_{jt} represent alternative-specific year fixed effects, and α_j^f, α_j^q and α_j^{fq} and α_j^s allow those mean effects to vary with physicians' characteristics. We normalize $v_{ijt} = 0$ for the outside

[28] Alternatively, we could use only data of initial scores, and leverage our instruments to correct for the associated measurement error, without the need to specify the model of scores (Agostinelli and Wiswall (2016)). However, specifying the model of scores allows us to perform the long-run counterfactuals, and thus we use it for the estimation of the returns to quality for the sake of parsimony.

option.

As specified in Equation 13, the matching probabilities depend on the labor market tightness, i.e. the mass of physicians who approve the licensing exam across different quality ranges over the vacancies in each location. We construct quality ranges to construct the vector of masses M_{it} using four quality quantiles. We proxy the number of vacancies κ_{jt} with the ratio of beds and the stock of physicians in the previous period, that is, $\tilde{\kappa}_{jt} = \frac{\text{Beds}_{jt}}{\text{Stock of Physicians}_{j,t-1}}$.

The results are presented in Table 3, where columns (1)-(3) vary how we incorporate the labor market tightness on the matching probabilities. Column (1) shows a specification where we specify the function $g()$ as depending only on other physicians with the same quality rage (M_{it}^0). Column (2) allows the function $g()$ to also depend on the mass of physicians with higher quality range (M_{it}^+). Column (3) allows the effects of these masses to vary across three different hospital-quality tiers; which we construct based on the average quality of their physicians. As a placebo check, in column (4) we show that the mass of physicians in a lower quality range (which we denote M_{it}^-) does not affect the matching probabilities.

Table 3: Conditional Matching Probabilities Estimates

	Alternative Models			Placebo
	(1)	(2)	(3)	(4)
Distance_{ij}	-0.228	-0.228	-0.228	-0.228
	(0.014)	(0.014)	(0.014)	(0.014)
Share_{ijt-1}	0.651	0.651	0.653	0.652
	(0.146)	(0.146)	(0.146)	(0.146)
$(M_{it}^0)/\kappa_{jt}$	-0.637	-0.676	-0.726	
	(0.152)	(0.159)	(0.186)	
$(M_{it}^+)/\kappa_{jt}$		0.017	0.050	
		(0.021)	(0.038)	
$(M_{it}^0)/\kappa_{jt} \times \mathbb{1}[r_j = 2]$			0.004	
			(0.097)	
$(M_{it}^0)/\kappa_{jt} \times \mathbb{1}[r_j = 3]$			0.115	
			(0.122)	
$(M_{it}^+)/\kappa_{jt} \times \mathbb{1}[r_j = 2]$			-0.037	
			(0.045)	
$(M_{it}^+)/\kappa_{jt} \times \mathbb{1}[r_j = 3]$			-0.067	
			(0.056)	
$(M_{it}^-)/\kappa_{jt}$				0.022
				(0.019)
Log likelihood	-15276.84	-15276.53	-15275.33	-15285.23

Notes: The table shows results from a multinomial logit model for the matching probabilities between physicians and hospital referral regions. The functions $\mathbb{1}[r_j = k]$ indicate the hospital's quality tier. As shown in Equation (19), all specifications include alternative-specific coefficients for the following variables: Year, Foreign indicator, physician's posterior quality, an interaction between Foreign indicator and posterior quality, and a Specialist indicator. We display only the estimates for the coefficients that do not depend on the alternative.

Input Elasticities The resulting quantity and quality elasticities are shown in Figure 1 (COMPLETE HERE).

We then investigate patterns of heterogeneity in the elasticities. We pool the results across years, and estimate a series of OLS regressions where we asses the relationship between the labor elasticity (Columns 1-4) or the quantity semi-elasticity (Columns 5-9) and a series of hospital observables: The variable "high phys/pat" indicates hospitals with above-the-median ratio of physicians per patients in the previous year, while "high average score" indicates hospitals with above-the-median score. north_j indicates hospitals at a latitude below the median.[29] In all specifications we include year fixed effects.

The labor elasticity is higher (in absolute terms) in hospitals with a low ratio of physicians per

[29]Latitudes in Chile are negative. Due to the particular geography of the country, latitude captures most of the location.

patient and in hospitals with a lower average score. As expected, the quality semi-elasticity displays an opposite pattern.

Table 4: Correlates of Elasticities

	Labor elasticity $\eta_{\underline{s}}^{L_{jt}}$				Quality Semi-elasticity $\eta_{\underline{s}}^{\bar{\theta}_{jt}}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
high (phys/pat)$_{j,t-1}$	0.019			0.023	-0.294			-0.416
	(0.007)			(0.007)	(0.133)			(0.138)
high average score$_{j,t-1}$		0.033		0.029		-0.236		-0.163
		(0.006)		(0.006)		(0.135)		(0.126)
north$_j$			-0.025	-0.028			0.557	0.630
			(0.007)	(0.007)			(0.139)	(0.143)
mean dep. var.	-0.072	-0.072	-0.072	-0.072	1.401	1.401	1.401	1.401
N	1086	1086	1086	1086	1086	1086	1086	1086

Notes: The table shows OLS regression coefficients relating the estimated elasticities quantity and quality elasticities to hospital observables. All specifications include year fixed effects.

As shown in condition 2, the ratio of the quantity elasticity and quality elasticity is a key object in determining the desirability of changing the licensing threshold.

6.2 Output Elasticities: The Impact of Physicians' Quantity and Quality on Health Outcomes

Table 5 presents the results from our two-stage least squares (2SLS) estimation, which examines the causal impact of physicians' quantity and quality on different hospital-level outcomes of interest. We present point estimates alongside exposure-robust standard errors clustered at the region of origin (i.e., the shock) level in brackets (Adao et al., 2019; Borusyak et al., 2022),[30] and we complement our analysis by showing the Anderson and Rubin (1949) p-values (Lee et al., 2022).

Panel A focuses on access. Column (1) reports the results for the hospital service rate, which is our main measure of access. We find an elasticity of service rate with respect to the number of physicians of 1. Column (2)-(4) show the impacts on additional measures of access. Column (2) focuses on the number of inpatient surgeries, for the subset of hospitals performing surgeries. We find a surgery elasticity of five. We also find that physicians' quality does not affect the service rate or surgeries. Columns (3) and (4) analyze the impact on the completion of wait-listed surgical procedures and specialist consultations, respectively. Column (3) shows that increasing the number of physicians leads to more exits from the surgical waiting list, with no effect from changes in physician quality.

[30]To obtain these standard errors—which are shown to be asymptotically valid (Adao et al., 2019)—we estimate the transformed regression proposed in Borusyak et al. (2022).

Similarly, Column (4) indicates that more physicians increase the number of patients exiting the specialist waiting list, while physician quality remains inconsequential.

Overall, our findings suggest that the quantity of physicians significantly influences access, consistent with the notion that physician scarcity is the primary binding constraint in expanding hospital capacity and addressing patient demand (e.g., Carrillo and Feres, 2019). Our results also show that the quality of physicians does not impact a hospital's ability to admit more patients, suggesting that the availability of physicians, rather than their expertise, is the primary determinant of hospital utilization rates.

Panel B of Table 5 focuses on quality, where our main measure is the in-hospital death rate. Column (1) shows the results. We find that: i) increasing the number of physicians by 1% decreases the in-hospital death rate by 0.8%, and ii) a one-point increase in the average quality of physicians—which corresponds to a 0.23 standard deviations increase—decreases death rates by 0.04%.

To address the concern that a potential correlation between increases in the number of physicians and the admission of healthier patients might be driving our results (i.e., inframarginal, previously non-admitted patients might be healthier), Column (2) shows the impact on a hospital death rate that is predicted based upon patients' characteristics.[31] Neither physician quantity nor quality significantly affects predicted mortality rates, suggesting that changes in patient composition are not driving our findings.

Columns (3) and (4) present the results for additional quality metrics. In Column (3), we use the 28-day mortality rate as the outcome and find effects consistent with those reported in Column (1). This suggests that the impact of physicians' quantity and quality remains robust even when accounting for out-of-hospital deaths among discharged patients. Finally, Column (4) focuses on the in-hospital complications rate. We define complications rate as the number of patients discharged from the hospital but later readmitted for inpatient care (at any hospital within 3-months) due to an ICD-10 code related to infections, hemorrhage, or other complications, divided by the total number of admissions. Consistent with the impacts on mortality, we find that physicians' quantity and quality help to reduce the complications rate.[32]

[31] We calculate the expected death rate by fitting a logit model for death outcomes at the inpatient level, controlling for patient demographics and diagnoses group, as per the enhanced Elixhauser comorbidity index (Elixhauser et al., 1998; Quan et al., 2005). The total number of *predicted deaths* at each hospital and year is then divided by the number of admissions.

[32] Several mechanisms could explain why quantity and quality affect health outcomes. On the one hand, more physicians can facilitate better patient monitoring and quicker responses to health complications, both of which can improve patient outcomes and reduce mortality. More physicians also mean that inpatients are less likely to experience delays in receiving necessary treatments, which is particularly critical in life-threatening situations. On the other hand, physicians of higher quality may possess greater skill in accurately diagnosing and treating complex cases, making timely decisions, and effectively applying evidence-based practices. This expertise can decrease complications

Identification using shift-share instruments is predicated upon the assumption that either the "shifts" or the "shares" components are as good as random and not correlated with factors that would affect the outcomes of interest (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Identification "from the shifts" can be understood as leveraging a shift-level natural experiment, while identification "from the shares" can be viewed as pooling together multiple difference-in-differences designs leveraging heterogeneous shock exposure (Borusyak et al., 2024). In Appendix F, we present evidence in favor of the exogeneity of shifts and shares components. First, we show that the quantity and quality shocks do not predict predetermined variables related to hospitals' workforce and patients' demographics, as it should be the case if shocks are as-good-as-randomly assigned. Second, to assuage concerns related to potential endogenous mechanisms affecting the composition of physicians from different origins within hospitals and hospital outcomes simultaneously, we show that differential exposures to common shocks (the "shares") are not correlated with changes in our outcomes of interest.

As additional robustness checks, in Appendix E, we examine the impact of physicians' quantity and quality on various hospital-level outcomes using variants of our preferred model. First, we obtain qualitatively similar results when the quality index is defined as the share of physicians in hospital j whose quality falls below the median of the overall quality distribution—instead of the average quality of the physicians working at the hospital. Also, the effects of physician quantity and quality on health outcomes also remain qualitatively similar when considering a translog production function—instead of a Cobb-Douglas—albeit the first stage is weaker in this case.[33]

and enhance patient survival by reducing misdiagnosis, treatment errors, and adverse health outcomes.

[33] In this case, we include the interaction between physicians' quantity and quality as an additional endogenous variable and the interaction of our shift-share instruments as an additional instrumental variable.

Table 5: Impact of Physicians' Quantity and Quality on Access and Quality of Care

Panel A: Access

	Ln service rate	Ln inpatient surgeries	Ln exits from waiting list	
			Surgical	Medical
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L^{\text{service}}$)	1.01	4.97	3.69	3.00
	[0.25]	[1.96]	[0.69]	[1.02]
Avg. Physicians' Quality ($\hat{\alpha}_\theta^{\text{service}}$)	0.01	0.11	-0.00	0.02
	[0.01]	[0.10]	[0.04]	[0.06]
Observations	1,402	744	738	942
Mean Dep. Var.	0.015	3,803	1,534	8,403
F-stat (First-stage)	22	12.3	9.9	15.9
Anderson-Rubin (χ^2)	0.000	0.000	0.000	0.000

Panel B: Quality

	Mortality			In-hospital
	In-Hospital		28-days	Complications
	Ln death rate	Pred. death rate	Ln death rate	Ln complications rate
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L^{\text{mortality}}$)	-0.83	0.13	-0.74	-0.58
	[0.19]	[0.05]	[0.20]	[0.23]
Avg. Physicians' Quality ($\hat{\alpha}_\theta^{\text{mortality}}$)	-0.04	-0.00	-0.04	-0.04
	[0.01]	[0.00]	[0.01]	[0.02]
Observations	1,402	1,402	1,402	1,402
Mean Dep. var.	3.284	3.494	5.075	3.272
F-stat (First-stage)	22	34.90	22	22
Anderson-Rubin (χ^2) p-value	0.00	0.02	0.00	0.01

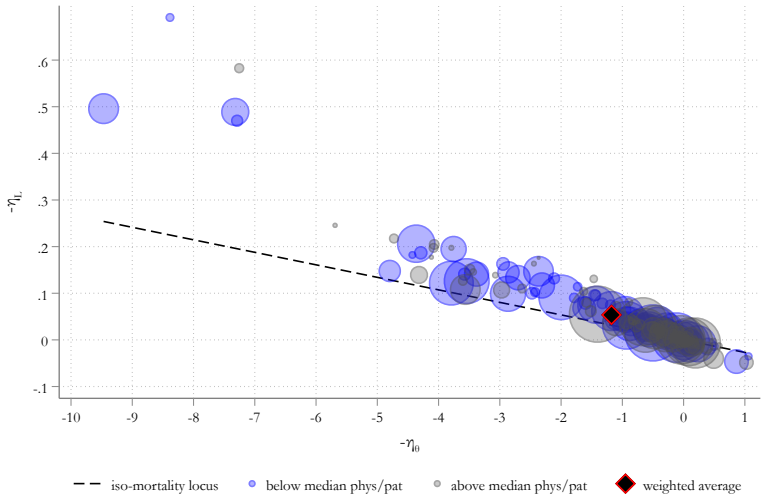
Notes: This table presents the impact of the quantity and quality of physicians on public hospital performance. Panel A focuses on utilization, which we proxy through the service rate, inpatient surgeries, and exits from the waiting list. Panel B focuses on patients' mortality and complications. Estimates come from the two-stage least squares estimation of Equation (18). We present the exposure-robust standard errors clustered at the region of origin (i.e., the shock) level in brackets (Adao et al., 2019; Borusyak et al., 2022).

6.3 Short-Run Impacts of Lowering the Licensing Threshold

The first set of statistics needed for evaluating the effects of changing the licensing threshold are the elasticity of the quantity and quality of physicians in each hospital with respect to the licensing threshold. We compute these elasticities numerically, by simulating the hospital-physician matches under the baseline licensing threshold $\underline{s}$ and under a counterfactual threshold $\underline{s}' = \underline{s} - \Delta\underline{s}$, and compute the resulting qualities and quantities using the expressions in Equation (15).[34]

Figure 2 summarizes our main results for the short-run elasticies in 2018. For ease of interpretation, we plot the *negative of* the elasticities to quantify the impact of a counterfactual *decrease* in the licensing threshold. The size of the marker is proportional to the number of patients in each hospital. The color of the market relates to scarcity; blue markers denote hospitals with physicians per patient below the median, whereas gray markers denote hospitals with physicians per patient above the median.

Figure 2: Short-run Elasticity of Quantity and Semi-elasticity of Quality by Hospital in 2018



Notes: This figure shows a scatter plot with the estimates for the (negative of) the elasticity of quantity and the semi-elasticity of quality with respect to the licensing threshold. Each dot represents a hospital. The size of the marker is proportional to the number of patients. Blue markers denote hospitals where the number of physicians per patient is below the median, whereas gray markers denote hospitals where the number of physicians per patient is above the median. Combinations of elasticities above the dashed line are such that patient's outcomes improve when the threshold is reduced.

There is generally a quantity-quality trade-off of lowering the licensing threshold as $-\eta_{\underline{s}}^{L_j} > 0$ and $-\eta_{\underline{s}}^{\bar{\theta}_j} < 0$, although there is ample heterogeneity across hospitals in the magnitudes of the elasticities.

[34] We provide more details on how we perform this calculation in Appendix L.

To evaluate the overall effects of lowering the licensing threshold, we contrast these elasticities with the quantity and quality output elasticities noting that, combining Equation (1) with Equation (6), the elasticity of hospital j's value added (lives saved) with respect to the licensing threshold is:

$$\eta_{\underline{s}}^{Y_j} = (\alpha_L^{\text{service}} - \alpha_L^{\text{mortality}}) \cdot \eta_{\underline{s}}^{L_j} + (\alpha_{\bar{\theta}}^{\text{service}} - \alpha_{\bar{\theta}}^{\text{mortality}}) \cdot \tilde{\eta}_{\underline{s}}^{\bar{\theta}_j}.$$

The dashed line in Figure 2 corresponds to the "iso-mortality curve", depicting the minimum quantity elasticity $\eta_{\underline{s}}^{*L}(\tilde{\eta}_{\underline{s}}^{\bar{\theta}})$ such that the elasticity of healthcare's value added is non-negative for a given quality semi-elasticity $\tilde{\eta}_{\underline{s}}^{\bar{\theta}}$.[35] For most hospitals we find that $-\eta_{\underline{s}}^{L_j} > -\eta_{\underline{s}}^{*L}(\tilde{\eta}_{\underline{s}}^{\bar{\theta}_j})$, which means that the increase in quantity more-than-compensates the decrease in quality when the threshold is reduced. The solid diamond shows the weighted averages of the quantity and quality elasticities; which also lies above the iso-mortality locus. On net, we find that healthcare's value added would increase in the short run with a policy that marginally decreases the licensing threshold.

Time series evolution of short-run impacts Given the large changes in market fundamentals, mostly resulting from the migration wage, we turn to analyze whether the policy effects found for 2018—5 years after the onset of the migration wave—differ from those in earlier years.

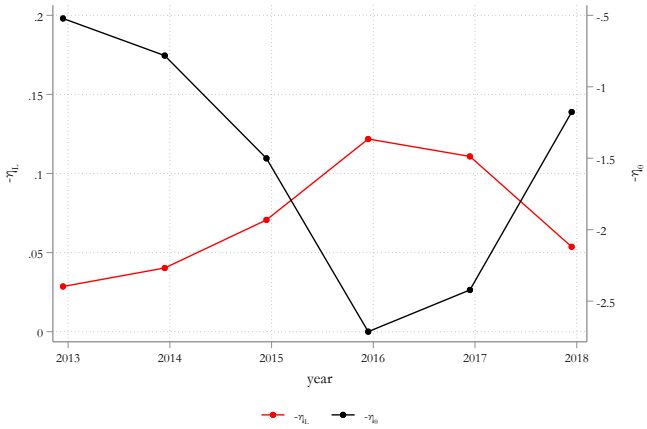
Figure 3-A shows the evolution of the short-run input elasticities over time. For the quantity elasticity (in red), we find an inverse U pattern. The quantity elasticity is the smallest in 2013 when there are few physicians at the margin of passing (see Table A.1). Over time, migration increases the number of marginal physicians, which increases the quantity elasticity. However, after 2016, the elasticity decreases. Even if the number of marginal physicians increases throughout the sample period, more physicians were already hired when the later cohorts arrived. This decreases the elasticity mechanically as the baseline is higher, but also through the lower capacity in the public sector which increases the share of physicians matching with the outside option as captured by the labor matching functions. Conversely and by the same arguments, the quality semi-elasticity has a U shape.

Figure 3-B shows the resulting elasticities of mortality, service rate, and total healthcare value added, that result in all years in our sample. The elasticity of mortality stays mostly flat over time, although it becomes slightly negative in 2016. Overall, per-patient mortality increases due to the quality reductions outweighing the quantity gains of lowering the threshold. However, the increase in the service rate more than compensates for this effect, and overall value added increases when

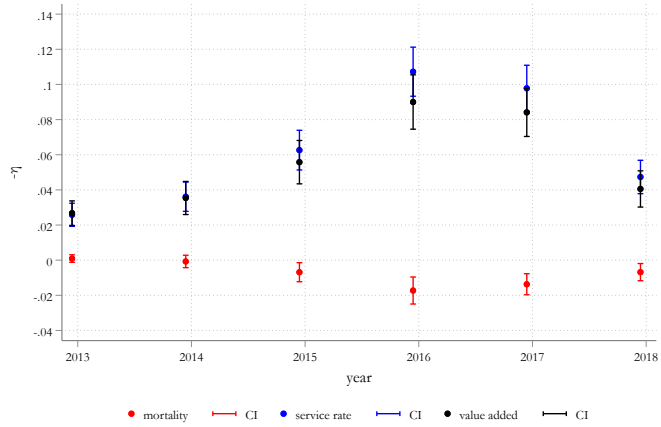
[35] That is, the iso-mortality curve is defined by the equation $\eta_{\underline{s}}^{*L}(x) \equiv -\frac{(\alpha_{\bar{\theta}}^{\text{service}} - \alpha_{\bar{\theta}}^{\text{mortality}})}{(\alpha_L^{\text{service}} - \alpha_L^{\text{mortality}})} \cdot x$.

the threshold is reduced.

Figure 3: Time Series of Short-Run Elasticities



A. Labor Quantity and Quality



B. Mortality, Access and Value Added

Notes: Panel A shows the evolution of the average short-run elasticities of quantity and quality of physicians with respect to the licensing threhold. Panel B shows the resulting average effects on patient's mortality, access, and over value added of the healthcare sector.

6.4 Long-Run Impacts of Lowering the Licensing Threshold

We now turn to analyze the dynamic effects of permanently changing the licensing threshold. The key mechanism we stress in this section is that retaking mitigates the relevance of the licensing threshold over time. For example, in our sample, 83% of test-takers who fail their first attempt in 2013 pass by 2018.

We quantify the dynamic effects of changing the threshold by simulating individual histories for

each cohort of test-takers —defined by the year they first take the exam— using the estimated model of scores and retaking from section 5. We use this simulated model to compute yearly elasticities with respect to the threshold that we set permanently lower in 2013.

To gain intuition for the results, Table 6 shows the simulated passing rates for cohort 2013, under the status-quo threshold ($\underline{s} = 51$), as well under a counterfactual policy with a threshold set permanently lower at $\underline{s}' = 41$. In the status quo, 86% of test takers pass in their first attempt (in 2013), compared to 94% under the counterfactual policy. The 8% gap in passing rates determines the short-run elasticities. However, the magnitude of the gap in passing rates across both scenarios shrinks over time. By 2018, almost 94.7% of physicians from the 2013 cohort pass under the status quo, compared to 98.5% under the counterfactual.

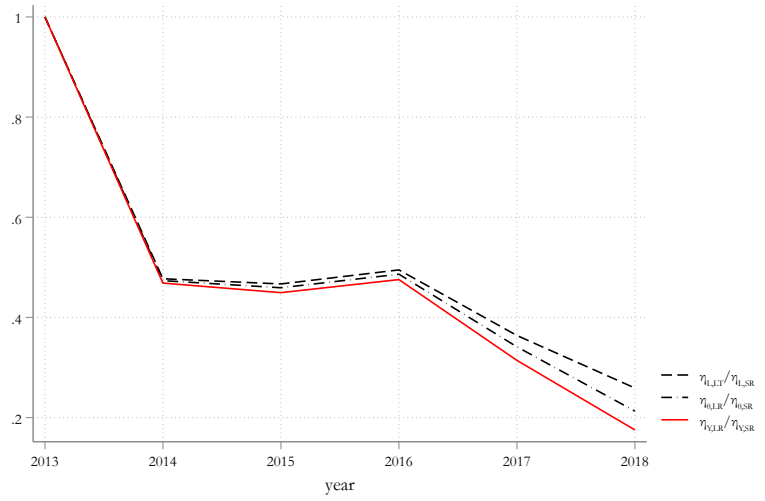
Table 6: Simulated Passing Year for 2013 Cohort

year	$\underline{s} = 51$		$\underline{s} = 41$	
	passing rate	cumulative passing rate	passing rate	cumulative passing rate
2013	86.0	86.0	94.0	94.0
2014	6.8	92.8	3.5	97.5
2015	1.4	94.2	0.7	98.2
2016	0.3	94.6	0.2	98.4
2017	0.1	94.6	0.0	98.4
2018	0.1	94.7	0.1	98.5

Notes: The table shows the simulated passing rates over time for the cohort of physicians that take the exam for the first time in 2013, under a (baseline) scenario where the threshold is kept at 51 points, and under a counterfactual scenario where the threshold is reduced to 41 points.

The ratio between the simulated short-run and long-run elasticities is shown in Figure 4. By definition, the short and long-run elasticities coincide for 2013 when the policy is implemented. For the following years, the long-run elasticities are smaller, as some of the marginal physicians who contribute to the short-run elasticities in any year $t > 2013$ are retakers who pass in a year $t' < t$ when the threshold is set permanently lower in 2013. By 2018, five years after the policy is implemented, the long-run elasticities are approximately 20% of the short-run elasticities. However, lowering the threshold in 2013 still generates positive outcomes by 2018.

Figure 4: Ratio of Simulated Short- and Long-Run Elasticities



Notes: The figure shows the ratio between the short- and long-run elasticities of mortality, service rate, and value added.

7 Conclusion

Occupational licensing is a widely used regulation in the labor market to ensure a minimum quality standard. However, it comes at the cost of reducing labor supply. This quantity-quality trade-off is particularly relevant in healthcare, where licensing is ubiquitous and could have first-order welfare implications. In this paper, we first analytically characterize this trade-off in an optimal licensing problem. We then propose and estimate an empirical model of physician licensing that allows us to quantify the quantity-quality trade-off in the context of physician licensing in Chile.

Our estimation is built around estimating two sets of sufficient statistics to evaluate the quantity-quality trade-off: The elasticities of inputs—the quantity and quality of labor—with respect to the threshold, and the elasticities of outputs—the quantity (access) and quality of healthcare—with respect to those inputs. To estimate the elasticities of inputs, we infer the latent quality of physicians using individual histories of exam scores and introduce a microfounded labor matching function to estimate the sorting of physicians with different quality levels into hospitals. We then estimate production functions to provide novel estimates of the elasticity of healthcare outcomes with respect to the quantity and quality of physicians. Key to our analysis, we leverage exogenous shocks to these inputs coming from a large migration wave of physicians.

We find that both the quantity and quality of physicians affect health outcomes. As a consequence,

lowering the licensing threshold generally entails a quantity-quality trade-off. Still, on net, population health would improve in the short run. Notably, this result is robust to the large changes in the labor market fundamentals coming from the migration wave. We also investigate the long-run policy effects, taking into account exam retaking. While retaking dampens the net effects of lowering the threshold over time, it would not have fully offset them five years later, had the policy been implemented at the start of our sample period.

Other policies can also be effective tools to address physician shortages. Expanding nurses' scope of practice, which involves similar trade-offs between increasing access and potentially affecting quality, may be preferable to lowering licensing thresholds for physicians. Additionally, improving access to medical education can help increase the supply of high-quality physicians. Comparing these alternative policies with the reduction in licensing thresholds presents an important avenue for future research.

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ONLINE APPENDIX

Physicians' Occupational Licensing and the Quantity-Quality Trade-off

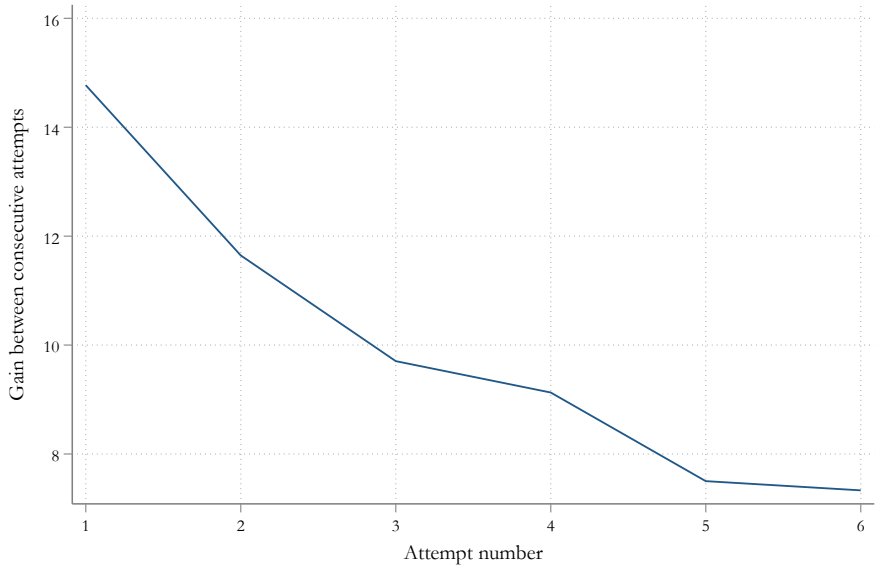
Juan Pablo Atal, Tomás Larroucau, Pablo Muñoz, and Cristóbal Otero

List of Figures

List of Tables

Additional Figures

Figure A.1: Score Gains Over Attempts



Notes: This figure presents the score gains after consecutive test-taking attempts by the same individual. It shows that on average score gains diminish with each additional attempt. Data come from ASOFAMECH (2019) and the figure includes the universe of test-takers between 2009 and 2018.

Additional Tables

Table A.1: Descriptive Statistics

Panel A: Health Outcomes

	Mean	Std. Dev.	Median (p50)	# of Obs.
	(1)	(2)	(3)	(4)
Patient Characteristics:				
% Female	0.57	0.08	0.58	1402
% Age $<$ 29	0.30	0.15	0.31	1402
% Age $\in$ (30,29)	0.10	0.04	0.10	1402
% Age $\in$ (40,49)	0.09	0.03	0.09	1402
% Age $\in$ (50,59)	0.11	0.03	0.11	1402
% Age $\in$ (60,69)	0.12	0.04	0.12	1402
% Age $\in$ (70,79)	0.14	0.06	0.13	1402
% Age $\in$ (80,89)	0.11	0.06	0.10	1402
% Age $>$ 89	0.03	0.02	0.02	1402
% Public Insurance	0.97	0.04	0.98	1402
Hospital Characteristics:				
In-hospital Death Rate	3.28	1.82	2.92	1,402
28-day Death Rate	5.07	2.71	4.51	1,402
Patients (# Admissions)	5,656	7,686	1,964	1,402
Service Rate (# Admissions/Beneficiaries)	0.02	0.02	0.01	1,402
Average Length of Stay	4.03	5.66	3.00	1,402
Complication Rate	11.41	4.25	11.05	1,402
Number of Surgeries	2,018	3,332	6.00	1,402
Physicians	77.64	119.64	20.00	1,402

Panel B: Test Scores

Year	Number Tests Takers	Average score	% Approved (score $\geq$ 51)	Average score if score $\geq$ 51	# Tests $\in [40-51)$
2009	1,389	71.8	92	74.3	87
2010	1,535	65.1	80	72.1	142
2011	1,748	66.6	81	73.3	160
2013	2,003	56.1	66	67.5	231
2014	2,557	55.8	65	67.5	335
2015	3,641	54.7	60	66.5	651
2016	4,999	53.0	54	66.9	1,012
2017	6,014	52.1	55	64.9	1,233
2018	7,121	53.9	58	65.0	1,552

Notes: This table presents descriptive statistics for the data used in the primary analysis. Panel A summarizes patient and hospital characteristics for all public hospitals included in the analysis. These data are derived from individual-level inpatient records reported by DEIS (2019) and restricted administrative records on public hospital employees from SIRH (2019). Panel B provides statistics on EUNACOM scores from 2009 to 2018. For cases where the exam was taken twice in the same year, all data are pooled. The dataset includes all records of test takers and come from ASOFAMECH (2019).

A Score Imputation

The EUNACOM exam was introduced in 2009. Before that, physicians were not required to take a standardized test to practice medicine. To account for the quality of physicians licensed before EUNACOM, we impute their hypothetical scores. This appendix outlines the imputation procedure.

Formally, let y_{ih} denote the licensing score of physician i in hospital h. Our baseline model for scores is:

$$y_{ih} = \mu_h + \alpha^h_{r(i)} + \varepsilon_{ih},$$

where μ_h represents the hospital-level mean, $\alpha^h_{r(i)}$ captures the region-of-origin effect (or "differential score") for physicians from region r working in hospital h, and ε_{ih} is an idiosyncratic error term with mean of zero.

To improve out-of-sample predictions, which is particularly important when hospitals have very few physicians from a particular region, we apply an empirical Bayes shrinkage procedure (Efron and Morris, 1973; Walters, 2024). Specifically, we regress scores on region-of-origin fixed effects for each hospital h using OLS with sum-to-zero constraints (i.e., $\sum_r \alpha^h_r = 0; \forall h$). We then treat each α^h_r and its standard error s_h as coming from a prior distribution centered at 0—reflecting the sum-to-zero constraint—with limiting variance s^2_h. Given the OLS estimate $\widehat{\alpha}^h_r$ and its sampling variance $\widehat{\mathrm{Var}}(\widehat{\alpha}^h_r)$, the empirical Bayes estimate (posterior mean) is a weighted average of the OLS estimate and the prior mean (zero). Specifically:

$$\widetilde{\alpha}^h_r \;=\; \underbrace{\frac{\widehat{\mathrm{Var}}(\widehat{\alpha}^h_r)}{\widehat{\mathrm{Var}}(\widehat{\alpha}^h_r) + s^2_h}}_{\text{shrinkage factor}} \widehat{\alpha}^h_r.$$

Since the shrinkage factor ranges between 0 and 1, each estimated effect is pulled ("shrunk") toward zero, with the degree of shrinkage increasing as the precision of $\widehat{\alpha}^h_r$ decreases.

Imputation of Missing Scores: For a physician i at hospital h from region $r(i)$ who does *not* have an observed licensing score, we impute her score using the empirical Bayes-adjusted model:

$$\widehat{y}_{ih} \;=\; \widehat{\mu}_h \;+\; \widetilde{\alpha}^h_{r(i)},$$

where $\widehat{\mu}_h$ is the average score of physicians working at hospital h. Thus, the imputed score is a combination of the grand mean for hospital h ($\widehat{\mu}_h$), and the "shrunk" region-of-origin differential at hospital h ($\widetilde{\alpha}^h_{r(i)}$).

In very few cases (1.6%), the data does not include a region of origin for the physician. In these cases, we predict the individual score using a LASSO model. This model incorporates hospital indicators as well as controls for physicians' age and gender.

A.1 Alternative Imputation Method:

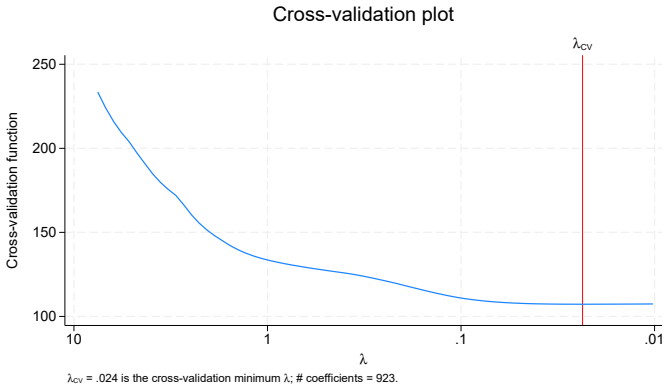
As an alternative to our Empirical Bayes approach to imputation, we also employ a Least Absolute Shrinkage and Selection Operator (LASSO) model for prediction (Tibshirani, 1996; Murdoch et al.,

2019). Specifically, we estimate a LASSO regression at the physician level to predict EUNACOM scores based on physicians' gender, age, age squared, and a full set of hospital by region-of-origin fixed effects.

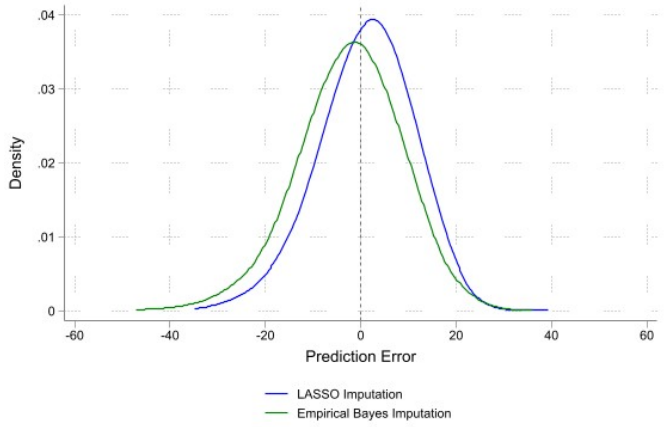
Panel A of Figure A.2 plots the mean cross-validation (CV) error against the regularization parameter λ. Each point represents the average error from k-fold CV for a specific value of λ. We highlight the λ that minimizes the CV error, denoted λ_{CV}, and use it to shrink coefficients toward zero, effectively performing variable selection. Panel B of Figure A.2 presents the density of prediction errors from each model. For this comparison, we focus on physicians whose EUNACOM scores we observe and contrast their actual scores with those predicted by both LASSO and our Empirical Bayes approach.

Finally, Table A.2 replicates the analysis presented in Table 5 in the main body of the paper but using the LASSO imputation method. We find quantitative and qualitative similar results, albeit with a weaker first stage.

Figure A.2: Alternative Imputation Methods



A. Cross-validation



B. Prediction Error

Notes: This figure shows statistics related to the imputation methods. Panel A shows the mean cross-validation (CV) error against the regularization parameter λ. Panel B shows the density of prediction errors from the LASSO and the Empirical Bayes imputation methods.

Table A.2: Impact of Physicians' Quantity and Quality: LASSO Imputation

Panel A: Access

	Ln service rate	Ln inpatient surgeries	Ln exits from waiting list	
			Surgical	Medical
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	1.06	6.90	3.62	3.24
	(0.40)	(3.54)	(3.05)	(2.20)
Avg. Physicians' Quality ($\hat{\alpha}_\theta$)	0.01	0.16	-0.01	0.02
	(0.02)	(0.15)	(0.12)	(0.09)
Observations	1,402	744	738	942
Mean Dep. Var.	0.015	3,803	1,534	8,403
F-stat (First-stage)	11.18	3.544	2.979	5.978
Anderson-Rubin (χ^2)	0.00	0.00	0.00	0.00

Panel B: Quality

	Mortality			In-hospital
	In-Hospital		28-days	Complications
	Ln death rate	Pred. death rate	Ln death rate	Ln complications rate
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	-1.21	0.10	-1.11	-1.44
	(0.47)	(0.11)	(0.42)	(0.43)
Avg. Physicians' Quality ($\hat{\alpha}_\theta$)	-0.05	-0.00	-0.04	-0.05
	(0.02)	(0.01)	(0.02)	(0.02)
Observations	1,402	1,402	1,402	1,373
Mean Dep. var.	3.28	3.51	5.08	11.65
F-stat (First-stage)	11.18	19.22	11.18	10.60
Anderson-Rubin (χ^2) p-value	0.00	0.03	0.00	0.00

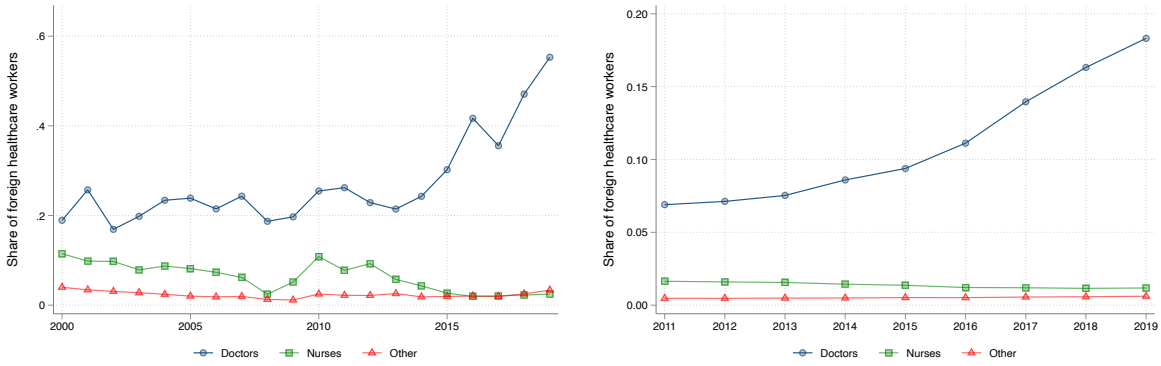
Notes: This table presents the impact of the quantity and quality of physicians on public hospital performance. Panel A focuses on utilization, which we proxy through the service rate, inpatient surgeries, and exist from the waiting list. Panel B focus on patients' mortality and complications. Estimates come from the two-stage least squares estimation of Equation (18), and we use a quality measure based on the scores imputation using LASSO.

B Other Labor Inputs

To work in a public hospital, foreign-trained healthcare professionals must validate their degree in Chile. This process is overseen by specific recognized Chilean universities and involves submitting academic credentials, with additional coursework or exams required in some cases. For physicians, passing the EUNACOM is also necessary, as it qualifies them to practice in public healthcare settings.[36] After validation, they must register with the National Registry of Individual Health Providers by providing their validated degree and other required personal documentation.

We observe the impact of the migration wave only in the introduction of foreign-trained physicians. As described in the main text, there is a significant increase in the share of foreign-trained physicians, both among those newly enrolled in the National Registry of Healthcare Providers and those working in public hospitals. However, we do not find similar effects for other healthcare workers. As shown in Panel A of Figure A.3, the share of newly registered healthcare workers in the National Registry of Individual Health Providers remained fairly stable between the 2000s and 2019, except for physicians. Panel B highlights the share of foreign-trained healthcare workers employed in public hospitals, and shows a significant increase for physicians—from 7% in 2011 to 18% in 2019. In contrast, there is no noticeable change in the share of foreign-trained workers in other healthcare categories.

Figure A.3: Migration Wave: Other Labor Inputs



A. Newly Registered Providers

B. Stock in Public Hospitals

Notes: This figure shows the evolution of the share of foreign-trained healthcare providers in Chile. Panel A examines trends from 2000 to 2019 using data from the National Registry of Healthcare Providers (RNPI, 2024). Panel B focuses on healthcare providers working in public hospitals from 2011 to 2019, based on data from SIRH (2019).

[36] Passing the EUNACOM simultaneously qualifies physicians to practice and validates their degree, which reduces the incentive to pursue a separate degree validation process before taking the EUNACOM.

C A mapping with Chetty (2009)

Chetty (2009) provides a framework to compute the welfare effects of policies from a set of sufficient statics rather than from the entire set of model primitives. Chetty's main framework provides a rubric of steps to derive the sufficient statics in the context of a static single-agent model; where the agent takes actions (e.g. decides consumption and leisure) to maximize utility subject to constraints that are affected by government policies (e.g. budget constraints affected by taxes and transfers). However Chetty (2009) also notes that assuming optimizing behavior is not needed to derive sufficient statistics, as long as one can directly estimate the objects determining the derivative of welfare with respect to the policy variable. We follow that approach in the paper.

For completeness, we discuss below how one could apply the optimization framework in our context. We recast our licensing problem by considering the problem of a representative hospital optimally choosing labor and quality subject to constraints that are affected by the licensing threshold. We follow the same rubric of steps as in Chetty (2009), and show how to use it to derive the sufficient statics formula (Equation 1 in the text).

Using the notation of Section 4 the structure of the model would be given by:

$$\begin{aligned} \max_{L,\bar{\theta}} \quad & F(L,\bar{\theta}) \\ \text{subject to} \quad & G_1(L,\underline{s}) \equiv L - m\int_{\underline{s}}^{\infty} h(s)\,p(s|\underline{s})\,ds = 0, \\ & G_2(\bar{\theta},L,\underline{s}) \equiv L\,\bar{\theta} - \int_{\underline{s}}^{\infty} \theta(s)\,h(s)\,p(s|\underline{s})\,ds = 0, \end{aligned}$$

where $F(L,\bar{\theta})$ is hospital's output as a function of quantity and quality of labor. $G_1(L,\underline{s})$ and $G_2(L,\underline{s})$ are the contraints linking quantity and quality with the licensing threshold. Note that these constraints include the matching functions. The constraints therefore result, in part, from the matching process.

In the paper we focus on the elasticity of hospital production with respect to the threshold, which is the planner's welfare criterion in Chetty's context. Welfare as a function of the licensing threshold is given by

$$Y(s) \equiv \max_{L,\bar{\theta}} F(L(s),\bar{\theta}(s)) + \lambda G_1(L,s) + \mu G_2(\bar{\theta},L,s).$$

As in Chetty (2009), we can use the envelope conditions and differentiate Y to get

$$\frac{dY}{ds} = \lambda\frac{\partial G_1}{\partial s} + \mu\frac{\partial G_2}{\partial s}. \tag{A.1}$$

In Chetty's framework, Lagrange multipliers are recovered from marginal utilities. In our framework, Lagrange multipliers are recovered from the output elasticities in the production function. Note that optimization implies that the marginal products of inputs are equated to linear combinations of the Lagrange multipliers:

$$\frac{\partial F}{\partial L} = \lambda\frac{\partial G_1}{\partial L} + \mu\frac{\partial G_2}{\partial L}, \tag{A.2}$$

and

$$\frac{\partial F}{\partial \bar{\theta}} = \mu \frac{\partial G_2}{\partial \bar{\theta}}. \tag{A.3}$$

Also, note that differentiating $G_1(L, s)$ with respect to s yields:

$$\frac{dL}{ds} = \frac{\partial G_1}{\partial s} \cdot \frac{1}{\frac{\partial G_1}{\partial L}}. \tag{A.4}$$

Similarly, differentiating $G_2(L, s, \bar{\theta})$ with respect to s yields:

$$\frac{d\bar{\theta}}{ds} = \frac{\partial G_2}{\partial s} \cdot \frac{1}{\frac{\partial G_2}{\partial \bar{\theta}}} - \frac{\partial G_2}{\partial L} \cdot \frac{1}{\frac{\partial G_2}{\partial \bar{\theta}}} \cdot \frac{\partial G_1}{\partial s} \cdot \frac{1}{\frac{\partial G_1}{\partial L}}. \tag{A.5}$$

Combining equations A.1-A.5 yields the sufficient statistic formula (Equation 1) in the text.

We also note that Chetty (2009) proposes to use the first order conditions to derive the marginal utilities from observed choices. In our context, it would entail to link the marginal product of inputs to hospital's input decisions (e.g. using factor shares). Instead, we rely on exogenous variation in inputs to estimate those parameters without imposing optimality.

D Quality Gains

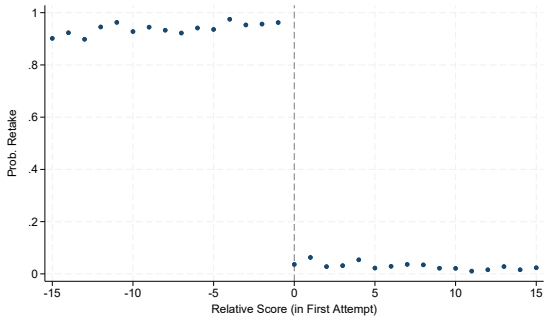
In general, our model could allow for scores to improve over attempts due to increased test-taking ability as well as due to improvements in quality. With data on scores alone, it is not possible to disentangle both mechanisms. In this section, we show that auxiliary data is consistent with no quality improvements over attempts. This justifies the assumption of no quality gains over attempts.

We leverage the discontinuity in retaking probability around the passing threshold to show that retaking does not improve labor-market outcomes that proxy for quality. Figure A.4-A shows the probability of ever retaking the test as a function of the distance to the score in the first attempt to the threshold. It shows that the retaking probability drops substantially around the cutoff. Figure A.4-B shows that the maximum achieved scored changes discontinuously around the threshold. Note that score gains in panel B are a combination of gains in test-taking ability, gains in quality, and selection around cutoff (Gilraine and Penney, 2023).

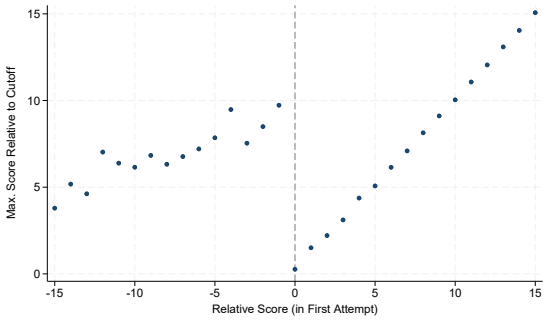
We investigate how two proxies of quality change around the threshold. Figure A.4-C shows that the probability of being appointed chief general practitioner increases substantially with the score in the first attempt. However, there are no discernible increases around the threshold. Similarly Figure A.4-D shows a (more modest) increase in the hours of contract with the score in the first attempt, with no discernible increases around the threshold. Together, we take this as evidence against the idea that there are quality improvements from retaking.

A key feature of the above framework is to assume that agents maximize utility although, as pointed out by Chetty (2009); it is not a necessary feature of the sufficient statistic framework as long as one can identify the relevant elasticities. However, a common challenge in identifying the elasticities without imposing maximization is that marginal utilities are unobserved. Imposing optimizing behavior allows researchers to recover marginal utilities from observed choices. One feature of our application is that we focus on an *observable* outcome (hospital production) and therefore can measure marginal utilities (the marginal products of labor and quality) directly from the data.

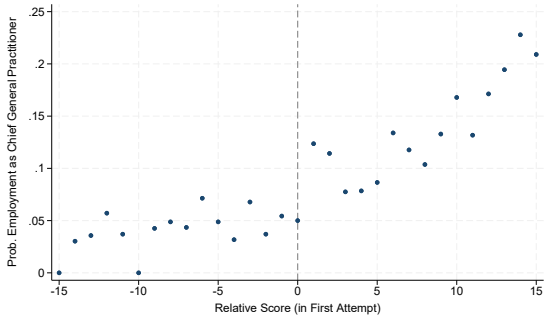
Figure A.4: Testing for Quality Gains



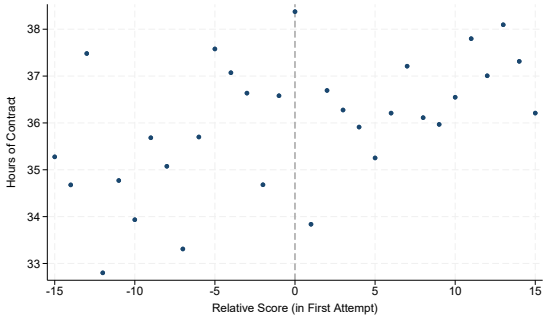
A. Retaking Probability



B. Maximum achieved score



C. Appointed Chief General Practitioner



D. Hours of Contract

Notes: This figure illustrates the effect of exam retaking on physician-quality improvements. Panel A depicts the probability of individuals retaking the exam based on whether they scored above the passing threshold on their first attempt. Panel B presents the maximum additional points individuals gained across all their retake attempts, relative to the passing threshold. The line on the right closely follows a 45-degree trajectory, consistent with the fact that individuals who pass the exam do not retake it. In contrast, the line on the left indicates that individuals just below the threshold improve their scores by approximately 10 points on average, with smaller improvements observed for those further below the threshold. Panel C examines the probability of becoming Chief General Practitioner as a proxy for physician quality. There is no visible discontinuity at the threshold on their first test-taking attempt, which is consistent with the absence of quality gains from repeated test-taking. Panel D use weekly working hours as an additional quality measure and similarly there is no visible effect at the threshold. Data on scores come from ASOFAMECH (2019). Panels A and B use the full sample of test-takers, while Panels C and D incorporate data from SIRH (2019), restricting the sample to physicians observed working in public hospitals.

E Production Function

Translog Production Function: Given its parsimony and tractability, we opt for the Cobb-Douglas specification in our main analysis. Table A.3 below assesses the impacts of physician quantity and quality on health outcomes when using a Translog production function, which allows for a linear interaction between physicians' quantity and quality. The table shows the results from the main model in columns (1) and (3) and the results from the alternative model in columns (2) and (4). At the bottom of the table, we present the overall effect of physicians' quantity and quality on access and mortality. The results are similar, but we obtain a weak first stage for the Translog model, an additional reason in favor of our preferred specification.

Table A.3: Impact of Physicians' Quantity and Quality: Translog Production Function

	Ln Death Rate		**Ln Service Rate**	
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	-0.83	0.43	1.01	1.08
	(0.31)	(1.64)	(0.29)	(1.34)
Avg. Physicians' Quality ($\hat{\alpha}_\theta$)	-0.04	0.07	0.01	0.01
	(0.02)	(0.15)	(0.02)	(0.12)
Interaction ($\hat{\alpha}_{L\theta}$)		-0.02		-0.00
		(0.03)		(0.03)
Observations	1,402	1,402	1,402	1,402
Model	2SLS	2SLS	2SLS	2SLS
Year FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Mean dep var	3.28	3.28	0.015	0.015
First-stage F-stat	22	2.332	22	2.332
Translog Quantity and Quality Impacts:				
Quantity Impact		-1.280		0.987
		(0.460)		(0.309)
Quality Impact		-0.010		0.008
		(0.002)		(0.001)

Notes: This table presents the impact of the quantity and quality of physicians on public hospital performance. Columns (1) and (2) focus on utilization, which we proxy through the service. Columns (3) and (4) focus on health outcomes, which we proxy with in-hospital deaths. Estimates in columns (1) and (3) come from the two-stage least squares estimation of Equation (18). Estimates in columns (2) and (4) come from alternative models that include the interaction between physicians' quantity and quality as an additional endogenous variable and the interaction of our shift-share instruments as an additional instrumental variable.

Alternative Quality Index:

Table A.4 presents estimates of the health production function using an alternative specification. In this specification, the quality index is defined as the share of physicians in the hospital j during period t whose quality falls below the median of the overall distribution. Encouragingly, the results remain qualitatively similar: quality does not affect access, and worse quality is associated with

poorer health outcomes.

Table A.4: Impact of Physicians' Quantity and Quality: Alternative Quality Index

Panel A: Access

	Ln service rate	Ln inpatient surgeries	Ln exits from waiting list	
			Surgical	Medical
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	0.98	4.36	3.71	2.94
	(0.25)	(1.29)	(1.32)	(1.19)
% Low Quality Physicians ($\hat{\alpha}_\theta$)	-0.05	-1.00	0.05	-0.17
	(0.18)	(0.80)	(0.78)	(0.82)
Observations	1,376	740	736	934
Mean Dep. Var.	0.0155	3,819	1,537	8,467
F-stat (First-stage)	16.25	10.33	9.29	9.96
Anderson-Rubin (χ^2)	0.00	0.00	0.00	0.00

Panel B: Quality

	Mortality			In-hospital
	In-Hospital		28-days	Complications
	Ln death rate	Pred. death rate	Ln death rate	Ln complications rate
	(1)	(2)	(3)	(4)
Ln Physicians ($\hat{\alpha}_L$)	-0.68	0.13	-0.61	-0.45
	(0.28)	(0.07)	(0.25)	(0.27)
% Low Quality Physicians ($\hat{\alpha}_\theta$)	0.49	0.03	0.48	0.48
	(0.20)	(0.06)	(0.18)	(0.19)
Observations	1,376	1,376	1,376	1,376
Mean Dep. var.	3.30	3.50	5.09	11.65
F-stat (First-stage)	16.25	21.57	16.25	15.46
Anderson-Rubin (χ^2) p-value	0.00	0.03	0.00	0.00

Notes: This table presents the impact of the quantity and quality of physicians on public hospital performance. Panel A focuses on utilization, which we proxy through the service rate, inpatient surgeries, and exist from the waiting list. Panel B focuses on patients' mortality and complications. Estimates come from the two-stage least squares estimation of Equation (18), where we use the share of physicians in each hospital and time with quality below the median of the entire distribution as quality index. For this exercise, we only consider physicians with EUNACOM scores.

F Shift-share Instruments

To assess the robustness of our instrumental variables approach, we build on a recent econometric literature which suggests two distinct paths to identification. One path, developed by Borusyak and Jaravel (2017) and Adao et al. (2019), leverages many exogenous shifts while making no assumption on the exogeneity of the shares. The second path, proposed by Goldsmith-Pinkham et al. (2020), instead focuses on share exogeneity. As pointed out in Borusyak et al. (2024), identification "from the shifts" can be understood as leveraging a shift-level natural experiment, while identification "from the shares" can be viewed as pooling together multiple difference-in-differences designs leveraging heterogeneous shock exposure. In this appendix, we present different robustness checks assessing the exogeneity of our shifts and shares.

F.1 Identification "from the shifts"

Shift-based identification stems from the observation that a share-weighted average of random shifts is itself as-good-as-random (Borusyak et al., 2024). This is true even if the shares are econometrically endogenous, in the sense that units with different shares may have systematically different unobservables. Indeed, Borusyak et al. (2022) shows that classical shift-share IV regression coefficients are numerically equivalent to those obtained from a regression where the outcome and treatment variables are first averaged, using exposure shares as weights, and the shocks are directly used as instrument for the aggregated treatment.

The fact that shift-share estimates can be equivalently obtained by a shock-level IV procedure suggests ways to establishing their consistency. Following Borusyak et al. (2022), we begin by showing statistics of the shocks. Table A.5 shows the distribution of the quantity and quality shocks. As shown by columns (1) and (3), the distribution of the quantity shocks has an average of 3.0, a standard deviation of 7.6, and an interquartile range of 1.8; while the distribution of the quality shocks has an average of -0.5, a standard deviation of 2.2, and an interquartile range of 3.9. Columns (2) and (4) show that there is residual shock variation even conditional on period fixed effects. The inverse HHI of the exposure shares is 28.8 across region by period cells. The largest shock weights are 6% across region-by-periods.

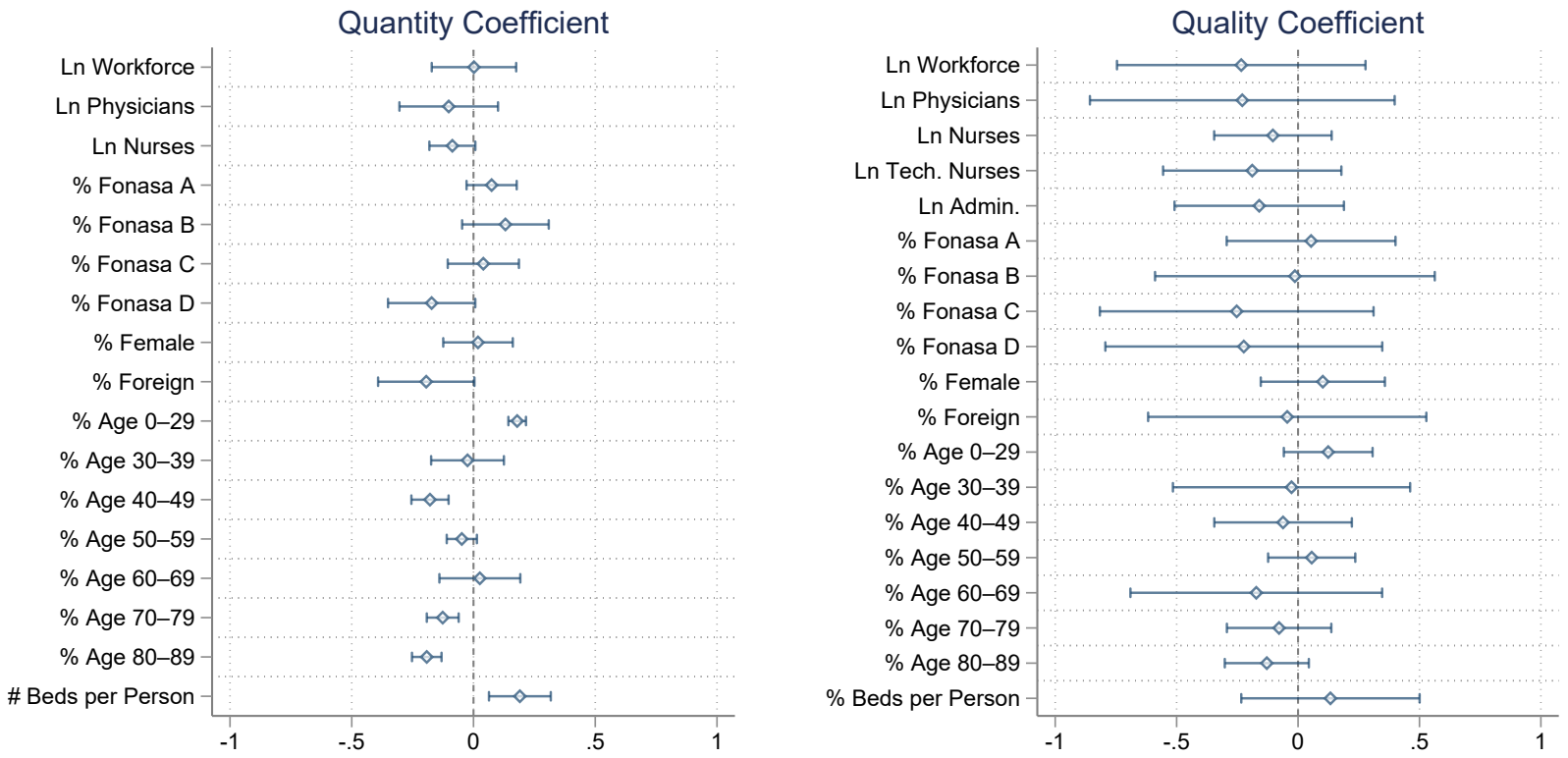
To corroborate the plausibility of the conditional quasi-random shock assignment we perform a shock balance test. If the migration shocks are as-good-as-randomly assigned, we expect them to not predict predetermined variables related to hospitals' workforce and patients' demographics. Figure A.5 reports the results of our balance tests on potential confounders. Panel A focuses on the quantity shocks and Panel B on the quality shocks. Reassuringly, we find that there is no statistically significant relationship between most variables and the shocks. There is some evidence of unbalance between the quantity shock and a few patient and hospital characteristics. Nonetheless, these are variables we control for in our main analysis.

Table A.5: Shock Summary Statistics

	Quantity Shock		Quality Shock	
	(1)	(2)	(3)	(4)
Mean	3.0	0.0	-0.5	0.0
Standard deviation	7.6	7.5	2.2	1.3
Interquartile range	1.8	1.2	3.9	1.3
Residualizing on period FE	No	Yes	No	Yes
Effective sample size ($1/HHI$ of s_{nt} weights)	28.83	28.83	28.83	28.83
Largest s_{nt} weight	0.06	0.06	0.06	0.06
No. of regions-period shocks	126	126	126	126
No. of regions	16	16	16	16

Notes: This table summarizes the distribution of migration shocks across regions of origin and periods. Quantity shocks are measured as the percentage change in the number of physicians from each region of origin clearing the cutoff of the licensing exam. Similarly, quality shocks are measured as the change in the average quality of eligible test-takers from different regions of origin. All statistics are weighted by the region of origin exposure shares. Columns (1) and (2) consider the quantity shocks and columns (3) and (4) consider the quality shocks. Columns (2) and (4) residualize the migration shocks on period indicators. As in Borusyak et al. (2022), we also report the effective sample size (the inverse re-normalized Herfindahl index of the weights) as well as the largest shares.

Figure A.5: Shocks Balance Test



Notes: These figures assess the plausibility of the conditional quasi-random assignment of shocks. Panels A and B show the point estimate and confidence interval obtained from separate regressions of predetermined variables (as of 2012) on the quantity and quality shocks, respectively. All variables are standardized to have a mean of zero and a standard deviation of one.

F.2 Identification "from the shares"

Share-based identification stems from the work by Goldsmith-Pinkham et al. (2020) showing that the Bartik 2SLS estimator can be decomposed into a weighted sum of the just-identified instrumental variable estimators that use each entity-specific share as a separate instrument.

The fact that the exogeneity of the shift-share instruments might also rely on the exogeneity of the shares implies that for our empirical strategy to be valid, we require the differential exposures to common immigration shocks (the "shares") to be independent of differential changes in our outcome of interest during the pre-period. In our case, this would not be the case if there are endogenous mechanisms affecting both the composition of immigrants within hospitals and patients' outcomes.

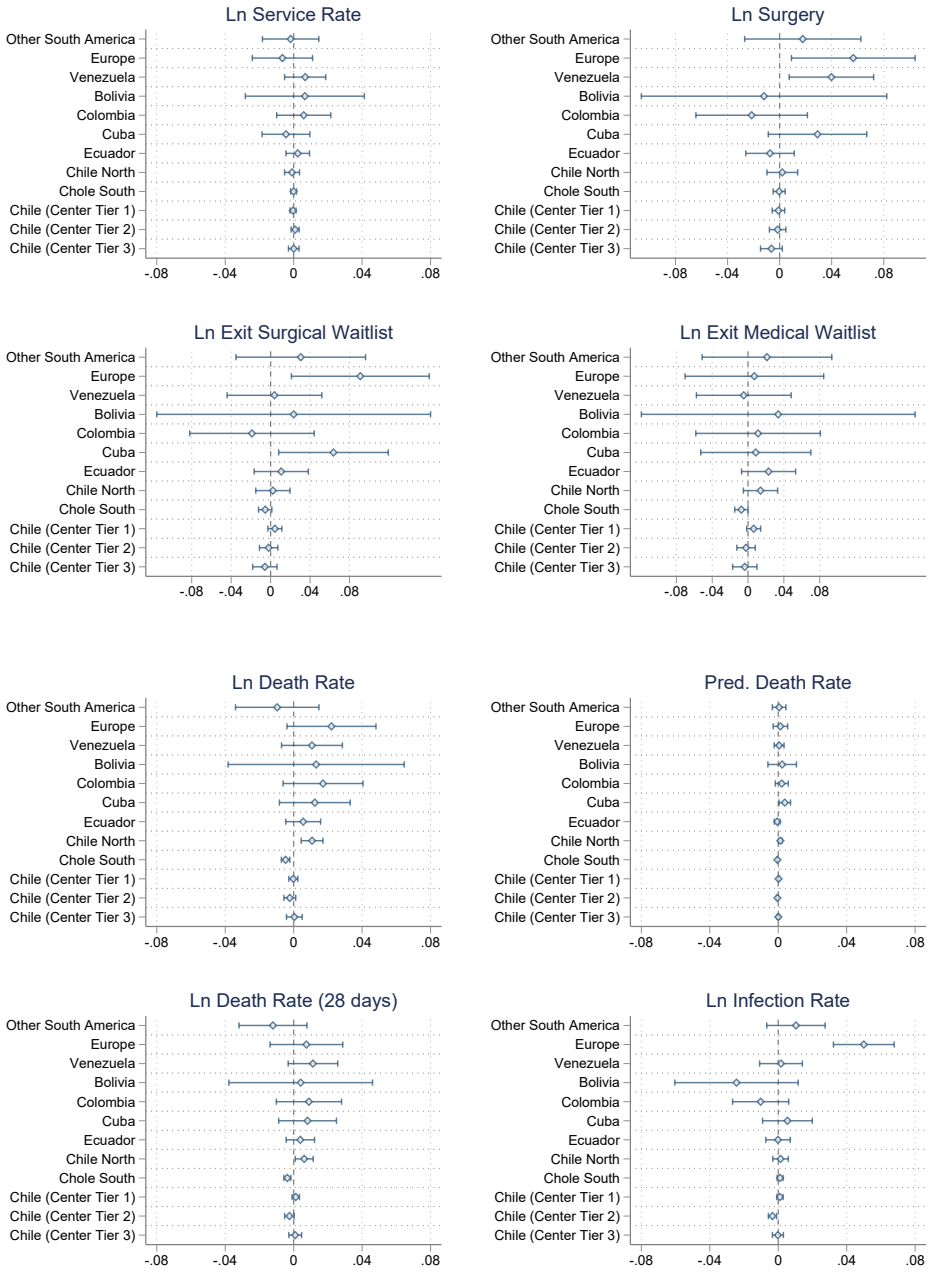
To assess the plausibility of the identification assumption we follow Goldsmith-Pinkham et al. (2020) and proceed in two steps. First, we compute the Rotemberg weights for each country-specific instrument. Rotemberg weights indicate which country-specific exposure gets a larger weight in the overall Bartik-2SLS estimate, and thus which nationality-share effects are more important for testing. In our data, Ecuador has the highest weight (0.585), followed by Colombia (0.262), mid and low tier universities in the central region of Chile (0.22), and Cuba (0.182). Second, we test for "parallel trends". Table A.6 presents our results on the relationship between differential exposures to common immigration shocks (the "shares") and differential changes in our outcome of interest during the pre-period. Specifically, we assess "pre-trends" by regressing the outcome of interest against the region of origin-shares during the (pre) period 2012-2015, controlling by hospital and year fixed effects as well our main battery of control variables. Generally, we find that the differential exposure to immigrants from different regions do not statistically or economically predict differential utilization or health outcomes. An exception is the share of European physicians, which seem to be statistically associated with surgeries and infection rates. However, the Rotemberg weight of Europe is among the smallest (0.007). Figure A.6 complements our analysis by visually showing the point estimate and confidence interval associated to each share, for all our outcomes of interest.

Table A.6: Rotemberg Weights and Pre-trends

Region of Origin											
Other S. America	Europe	Venezuela	Bolivia	Colombia	Cuba	Ecuador	Chile (north)	Chile (south)	Chile (tier 1)	Chile (tier 2)	Chile (tier 3)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln Service Rate											
-0.002	-0.007	0.007	0.007	0.006	-0.004	0.002	-0.001	-0.000	-0.000	0.001	0.000
(0.008)	(0.009)	(0.006)	(0.018)	(0.008)	(0.007)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Ln Surgery											
0.018	0.057	0.040	-0.012	-0.021	0.029	-0.007	0.002	-0.000	-0.001	-0.002	-0.006
(0.023)	(0.024)	(0.017)	(0.048)	(0.022)	(0.019)	(0.009)	(0.006)	(0.002)	(0.002)	(0.003)	(0.004)
Ln Exit Surgical Waitist											
0.031	0.091	0.004	0.023	-0.019	0.064	0.011	0.002	-0.005	0.004	-0.002	-0.006
(0.033)	(0.036)	(0.024)	(0.071)	(0.032)	(0.028)	(0.014)	(0.009)	(0.003)	(0.004)	(0.005)	(0.006)
Ln Exit Medical Waitist											
0.021	0.007	-0.005	0.034	0.011	0.009	0.023	0.014	-0.007	0.006	-0.002	-0.004
(0.037)	(0.039)	(0.027)	(0.078)	(0.035)	(0.031)	(0.015)	(0.010)	(0.004)	(0.004)	(0.005)	(0.007)
Ln Death Rate											
-0.010	0.022	0.011	0.013	0.017	0.012	0.006	0.011	-0.005	-0.000	-0.002	0.000
(0.012)	(0.013)	(0.009)	(0.026)	(0.012)	(0.011)	(0.005)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Ln Death Rate (28-days)											
-0.012	0.007	0.011	0.004	0.009	0.008	0.004	0.006	-0.004	0.001	-0.002	0.001
(0.010)	(0.011)	(0.007)	(0.021)	(0.010)	(0.009)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Ln Infection Rate											
0.010	0.050	0.002	-0.024	-0.010	0.005	-0.000	0.001	0.001	0.001	-0.003	-0.000
(0.009)	(0.009)	(0.006)	(0.018)	(0.008)	(0.007)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)

Notes: This table presents robustness checks in the spirit of Goldsmith-Pinkham et al. (2020). Panel A shows the Rotemberg weights associated to each region of origin. Panel B assesses pre-trends by regressing each of the outcomes of interest against the region of origin shares in the (pre) period 2012-2015. Point estimates reflect the differential effect of region-specific shares on the dependent variable.

Figure A.6: Share Balance Test



Notes: These figures show the results from regressing the outcome of interest against the region of origin-shares during the (pre) period 2012-2015, controlling by hospital and year fixed effects as well our main battery of control variables.

G Equilibrium Effects

In this section, we generalize how equilibrium effects can affect the conditional matching probabilities. We choose the following linear function:

$$g_{eq}(M|\tau, r_{\hat{\theta}}, j) = \sum_{\tau' \in \mathcal{T}} \sum_{r'_{\hat{\theta}}} M_{\tau', r'_{\hat{\theta}}} \beta^{\tau, r_{\hat{\theta}}}_{\tau', r'_{\hat{\theta}}, j}, \tag{A.6}$$

where $\beta^{\tau, r_{\hat{\theta}}}_{\tau', r'_{\hat{\theta}}, j} \in \mathbb{R}$ is a parameter capturing the marginal effect of a change in the mass of physicians of type τ' in range $r'_{\hat{\theta}}$, on the conditional match probability of physicians of type τ in range $r_{\hat{\theta}}$ to match with hospital j.

We introduce some definitions and assumptions to characterize how equilibrium effects can affect our counterfactual exercises. We define an order, denoted as $\succ$, over the expected quality ranges in $\mathcal{R}$. Specifically, for any expected quality ranges $r_{\hat{\theta}}$ and $r'_{\hat{\theta}}$ in $\mathcal{R}$, we say that $r'_{\hat{\theta}} \succ r_{\hat{\theta}}$ if the expected qualities in the range $r'_{\hat{\theta}}$ are strictly higher than those in $r_{\hat{\theta}}$. Furthermore, we index quality ranges in increasing order by $r_k \in \mathcal{R} \quad \forall k \in \{1, ..., K\}$, with $K = |\mathcal{R}|$. We introduce the following simplifying assumptions:

Assumption 1.

$$\beta^{\tau, r_k}_{\tau', r_l, j} = 0, \quad \forall r_k, r_l \in \mathcal{R} : k > l, \tau \in \mathcal{T}, j \in \mathcal{J} \tag{A.7}$$

Under Assumption 1, equilibrium effects can affect the conditional matching probabilities of physicians in expected quality range r_k only through changes in the distribution of potential physicians in their own range and "upstream" in the order of expected quality ranges.

We further assume that equilibrium effects can be approximated by contiguous chained effects, where a change in the mass of physicians in a specific expected quality range can have a direct effect on the CMPs within that range, and can also induce a displacement effect on the expected quality range that immediately precedes it. This displacement effect influences the mass in that range and consequently affects the CMPs indirectly. The effect on the predecessor range's CMP is given by the product of its direct effect and the indirect effects from each succeeding range in the chain, thereby chaining these effects downstream and reducing the number of parameters that need to be identified and estimated. We formalize the structure of chain effects in the following assumption:

Assumption 2.

$$\beta^{\tau, r_k}_{\tau', r_l, j} = \begin{cases} \beta^{\tau, r_k}_{\tau', j} & \text{if } l = k \\ \beta^{\tau, r_k}_{N, j} \left(\delta^N_{\tau', r_l} \prod_{i=k+1}^{l-1} \delta^N_{N, r_i} \right), & \text{if } K \geq l > k, \\ 0 & o.w. \end{cases} \tag{A.8}$$

Where $\delta^N_{\tau', r_l} \in \mathbb{R}, \quad \forall \tau' \in \mathcal{T}, K \geq l > k$, are parameters capturing the contiguous displacement effect of a change in the mass of physicians of type τ' in range r_l into an equivalent mass of Nationals in the immediate range below, i.e., r_{l-1}. Notice that under Assumption 2, the number of parameters that specify how changes in the distribution of potential physicians, M, affect the conditional matching probabilities, is vastly reduced. Indeed, we only need to identify the direct effects, β, and the contiguous displacement effects, δ, to identify the effects of any change in the distribution.[37] The previous assumptions lead to the following corollary:

[37] We expect the contiguous displacement effect parameters, δ, to be non-negative, and the direct effect parameters,

Corollary 1. *Under Assumptions 1 and 2, the general equilibrium effects are given by:*

$$g(M|\tau, r_{\hat{\theta}} = r_k, j) = \beta_{N,j}^{\tau,r_k} \tilde{M}_{N,r_k} + \beta_{F,j}^{\tau,r_k} M_{F,r_k}, \quad \forall k \in \{1, ..., K\}, \tag{A.9}$$

with

$$\tilde{M}_{N,r_k} = \begin{cases} M_{N,r_k} + \delta_{N,r_{k+1}}^{N} \tilde{M}_{N,r_{k+1}} + \delta_{F,r_{k+1}}^{N} M_{F,r_{k+1}} & \text{if } k < K \\ M_{N,k} & \text{if } k = K. \end{cases} \tag{A.10}$$

We can now introduce the propositions that will allow us to characterize the equilibrium effects in the counterfactual exercises, i.e., with marginal changes of the physician migration wave, m_F, and marginal changes of the licensing threshold, $\underline{s}$.

Proposition 1. *Under Assumptions 1 and 2, the equilibrium effects of a marginal change on the physician migration wave, m_F, on the conditional matching probabilities, is given by:*

$$\frac{\partial}{\partial m_F} CMP_j = CMP_j \left(\frac{\partial}{\partial m_F} g_{eq}(M|\tau, r_{\hat{\theta}}, j) - \sum_{j'} CMP_{j'} \frac{\partial}{\partial m_F} g_{eq}(M|\tau, r_{\hat{\theta}}, j') \right) \tag{A.11}$$

where

$$\frac{\partial}{\partial m_F} g_{eq}(M|\tau, r_{\hat{\theta}} = r_k, j) = \begin{cases} \underbrace{\beta_{F,j}^{\tau,r_k} \int_{\hat{\theta}(s,F) \in r_k} f^F(s) ds}_{\textit{Direct effect}} + \underbrace{\sum_{r_l \succ r_k} \left[\beta_{N,j}^{\tau,r_k} \left(\delta_{\tau',r_l}^{N} \prod_{i=k+1}^{l-1} \delta_{N,r_i}^{N} \right) \int_{\hat{\theta}(s,F) \in r_l} f^F(s) ds \right]}_{\textit{Indirect Displacement effect}} & \text{if } k < K \\ \underbrace{\beta_{F,j}^{\tau,r_k} \int_{\hat{\theta}(s,F) \in r_k} f^F(s) ds}_{\textit{Direct effect}} & \text{o.w.} \end{cases} \tag{A.12}$$

Proposition 1 gives us intuition on how the physicians' migration wave might affect the matching probabilities of different hospitals. If the direct effect parameters, β, are non-positive, and the displacement effect parameters, δ, are non-negative, a marginal increase in the physicians' migration wave will lower the conditional matching probability of matching with a hospital j if the sum of its direct and indirect effects, i.e., $\frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_{\hat{\theta}} = r_k, j)$, are larger in magnitude than the weighted average of these effects over every hospital, weighted by their conditional matching probabilities. Finally, Proposition 1 also states that the physicians' migration wave will be negligible for physicians of a given type at hospitals that are not already exposed to that type, i.e., if $CMP_j \approx 0$.

Proposition 2. *Under Assumption 1, the equilibrium effects of a marginal change on the licensing threshold, $\underline{s}$, on the conditional matching probabilities, is given by:*

$$\frac{\partial}{\partial \underline{s}} CMP_j = CMP_j \left(\frac{\partial}{\partial \underline{s}} g_{eq}(M|\tau, r_{\hat{\theta}}, j) - \sum_{j'} CMP_{j'} \frac{\partial}{\partial \underline{s}} g_{eq}(M|\tau, r_{\hat{\theta}}, j') \right) \tag{A.13}$$

β, to be non-positive.

where

$$\frac{\partial}{\partial \underline{s}} g_{eq}(M|\tau, r_{\hat{\theta}} = r_k, j) = \begin{cases} \underbrace{-\sum_{\tau \in \mathcal{T}} \beta_{\tau,j}^{\tau, r_k} m_\tau f^\tau(\underline{s})}_{Direct\ effect} & if\ k = 1 \\ 0 & o.w. \end{cases} \tag{A.14}$$

Proposition 2 shows that under Assumption 1, a marginal increase in the licensing threshold has only a direct effect on matching probabilities for physicians at the bottom of the expected quality ranges. In addition, the overall effect on each hospital depends again on the relative magnitude of the direct effects–which are non-negative if the direct effect parameters β are non-positive–and the relative weights given by the conditional matching probabilities across hospitals. Finally, if physicians at the lowest quality range have negligible matching probabilities with respect to highly competitive hospitals, i.e., $CMP_j \approx 0$, a change in the licensing threshold will have no effects on their matching probabilities to these hospitals, revealing a strong vertical sorting of physicians across hospitals.

G.1 Identification strategy

To show identification of the the parameters governing the CMPs, we can take log-odds over $y_j := CMP_j/CMP_\emptyset$. Then, fixing a market, i.e., fixing time t, cross-sectional variation identifies the parameters up to a fixed effect of the combination of $(\tau, r_{\hat{\theta}}, j)$. To separately identify β_j^τ from the parameters within the function g, we need to exploit variation over markets. The mean effect for a given type τ and hospital j will be captured by β_j^τ, because it is fixed over markets, and variation over M across time identifies the parameters within g.

To formalize this identification strategy, we can write in matrix form the direct and indirect effects from the accumulated displacement effects by type of mass. For simplicity of exposition, we omit the indices τ, j, and t. Let M_N and M_F be the vectors of masses for nationals and foreigners respectively from range r_k upwards. These vectors can be represented as:

$$M_{\tau'} = \begin{bmatrix} M_{\tau', r_K} \\ M_{\tau', r_{K-1}} \\ M_{\tau', r_{K-2}} \\ \vdots \\ M_{\tau', r_k} \end{bmatrix}, \quad \forall \tau' \in \mathcal{T}$$

and let B_N and B_F be diagonal matrices of the direct effect parameters for nationals and foreigners respectively:

$$B_{\tau'} = \begin{bmatrix} \beta_{\tau'}^{r_K} & 0 & 0 & \cdots & 0 \\ 0 & \beta_{\tau'}^{r_{K-1}} & 0 & \cdots & 0 \\ 0 & 0 & \beta_{\tau'}^{r_{K-2}} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \beta_{\tau'}^{r_k} \end{bmatrix}, \quad \forall \tau' \in \mathcal{T}$$

In addition, let by D_N the matrix containing the displacement effects from masses of nationals:

$$D_N = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ \delta^N_{N,r_K} & 0 & 0 & \cdots & 0 \\ \delta^N_{N,r_K}\delta^N_{N,r_{K-1}} & \delta^N_{N,r_{K-1}} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \delta^N_{N,r_K}\prod_{i=k+1}^{K-1}\delta^N_{N,r_i} & \delta^N_{N,r_{K-1}}\prod_{i=k+1}^{K-2}\delta^N_{N,r_i} & \cdots & \delta^N_{N,r_{k+1}} & 0 \end{bmatrix}$$

and let by D^F the matrix containing the displacement effects from masses of foreigners:

$$D_F = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ \delta^N_{F,r_K} & 0 & 0 & \cdots & 0 \\ \delta^N_{F,r_K}\delta^N_{N,r_{K-1}} & \delta^N_{F,r_{K-1}} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \delta^N_{F,r_K}\prod_{i=k+1}^{K-1}\delta^N_{N,r_i} & \delta^N_{F,r_{K-1}}\prod_{i=k+1}^{K-2}\delta^N_{N,r_i} & \cdots & \delta^N_{F,r_{k+1}} & 0 \end{bmatrix}$$

The total direct and indirect effects on Y from both nationals and foreigners can be represented as the sum of the effects from each group. This is given by:

$$Y = \underbrace{B_N M_N + B_F M_F}_{\text{Direct effects}} + \underbrace{B_N(D_N M_N + D_F M_F)}_{\text{Indirect effects}}$$

Due to the cumulative and diagonal structure of the displacement (chain) effects, it is clear that variation of masses at the top, M_{τ',r_K}, will identify the direct effect at the top, $\beta^{r_K}_{\tau'}$, and variation on the mass at the immediate predecessor range, $M_{\tau',r_{K-1}}$, together with variation at the successor range, M_{τ',r_K}, helps us to separately identify both the direct effect from range r_{K-1}, $\beta^{r_K-1}_{\tau'}$, from the displacement effect of its immediate successor, δ^N_{τ',r_K-1}. This argument can be applied by moving downward in the order of ranges until we reach the bottom range r_1. To see this more clearly, we can exploit the structure of our Corollary 1:

$$g(M|\tau, r_{\hat{\theta}} = r_k, j) = \beta^{\tau,r_k}_{N,j}\tilde{M}_{N,r_k} + \beta^{\tau,r_k}_{F,j}M_{F,r_k}, \quad \forall k \in \{1, ..., K\},$$

with

$$\tilde{M}_{N,r_k} = \begin{cases} M_{N,r_k} + \delta^N_{N,r_{k+1}}\tilde{M}_{N,r_{k+1}} + \delta^N_{F,r_{k+1}}M_{F,r_{k+1}} & \text{if } k < K \\ M_{N,k} & \text{if } k = K. \end{cases}$$

thus, for $k < K$ we get:

$$g(M|\tau, r_{\hat{\theta}} = r_k, j) = \beta^{\tau,r_k}_{N,j}M_{N,r_k} + \beta^{\tau,r_k}_{N,j}\delta^N_{N,r_{k+1}}\tilde{M}_{N,r_{k+1}} + \beta^{\tau,r_k}_{N,j}\delta^N_{F,r_{k+1}}M_{F,r_{k+1}} + \beta^{\tau,r_k}_{F,j}M_{F,r_k}, \quad \forall k \in \{1, ..., K\} \tag{A.15}$$

Notice that conditional on having identified the upstream displacement parameters, variation over the displaced mass of equivalent nationals over range $k+1$, $\tilde{M}_{\tau,r_{k+1}}$, together with variation over the masses from k, M_{τ,r_k}, identifies each of the parameters up to range r_k.

G.2 Likelihood

The previous identification strategy suggests that we can estimate the CMPs by Maximum likelihood, where the individual log-likelihood is given in a recursive manner:

CMPs Log-likelihood. For all $i \in \mathcal{I}$ with $\hat{\theta}(s,\tau,t) \in r_k$, let the individual log-likelihood to be defined recursively by:

$$l\left(\beta,\delta|i\in\mu(j);\tau,s,X,M,t\right)=\log\left(\frac{e^{\beta_j^\tau+X_{j\cdot,t}\beta_x^\tau+g(M_t|\tau,r_k,j)+\beta_{\hat{\theta}}^\tau\hat{\theta}(s,\tau,t)}}{1+\sum_{j'}e^{\beta_{j'}^\tau+X_{j'\cdot,t}\beta_x^\tau+g(M_t|\tau,r_k,j')+\beta_{\hat{\theta}}^\tau\hat{\theta}(s,\tau,t)}}\right),\forall j\in\mathcal{J} \quad \text{(A.16)}$$

with

$$g(M|\tau,r_k,j)=\beta_{N,j}^{\tau,r_k}\tilde{M}_{N,r_k}+\beta_{F,j}^{\tau,r_k}M_{F,r_k},\quad \forall k\in\{1,...,K\},$$

with

$$\tilde{M}_{N,r_k}=\begin{cases}M_{N,r_k}+\delta_{N,r_{k+1}}^N\tilde{M}_{N,r_{k+1}}+\delta_{F,r_{k+1}}^N M_{F,r_{k+1}} & \text{if } k<K\\ M_{N,k} & \text{if } k=K.\end{cases}$$

H Proof of corollary 1

By the matrix definitions of the total effects we have:

$$Y = B_N M_N + B_F M_F + B_N(D_N M_N + D_F M_F)$$

Calculating each of the terms we have:

$$B_N \times M_N = \begin{bmatrix} \beta_N^{r_K} M_{N,r_K} \\ \beta_N^{r_{K-1}} M_{N,r_{K-1}} \\ \vdots \\ \beta_N^{r_k} M_{N,r_k} \end{bmatrix}$$

$$B_F \times M_F = \begin{bmatrix} \beta_F^{r_K} M_{F,r_K} \\ \beta_F^{r_{K-1}} M_{F,r_{K-1}} \\ \vdots \\ \beta_F^{r_k} M_{F,r_k} \end{bmatrix}$$

$$D_N \times M_N = \begin{bmatrix} 0 \\ \delta^N_{N,r_K} M_{N,r_K} \\ \delta^N_{N,r_K}\delta^N_{N,r_{K-1}} M_{N,r_K} + \delta^N_{N,r_{K-1}} M_{N,r_{K-1}} \\ \vdots \\ \delta^N_{N,r_K}\prod_{i=k+1}^{K-1}\delta^N_{N,r_i} M_{N,r_K} + \delta^N_{N,r_{K-1}}\prod_{i=k+1}^{K-2}\delta^N_{N,r_i} M_{N,r_{K-1}} \cdots + \delta^N_{N,r_{k+1}} M_{N,r_{k+1}} + 0 \end{bmatrix}$$

$$D_F \times M_F = \begin{bmatrix} 0 \\ \delta^N_{F,r_K} M_{F,r_K} \\ \delta^N_{F,r_K}\delta^N_{N,r_{K-1}} M_{F,r_K} + \delta^N_{F,r_{K-1}} M_{F,r_{K-1}} \\ \vdots \\ \delta^N_{F,r_K}\prod_{i=k+1}^{K-1}\delta^N_{N,r_i} M_{F,r_K} + \delta^N_{F,r_{K-1}}\prod_{i=k+1}^{K-2}\delta^N_{N,r_i} M_{F,r_{K-1}} \cdots + \delta^N_{F,r_{k+1}} M_{F,r_{k+1}} + 0 \end{bmatrix}$$

$$B_N(D_N M_N + D_F M_F) = \begin{bmatrix} 0 \\ \beta_N^{r_{K-1}}(\delta^N_{N,r_K} M_{N,r_K} + \delta^N_{F,r_K} M_{F,r_K}) \\ \beta_{N,j}^{r_{K-2}}\left(\delta^N_{N,r_K}\delta^N_{N,r_{K-1}} M_{N,r_K} + \delta^N_{N,r_{K-1}} M_{N,r_{K-1}} + \delta^N_{F,r_K}\delta^N_{N,r_{K-1}} M_{F,r_K} + \delta^N_{F,r_{K-1}} M_{F,r_{K-1}}\right) \\ \vdots \end{bmatrix}$$

With this we can write the effect when $k = K$ as:

$$g(M|\tau, r_K, j) = \beta_{N,j}^{\tau,r_K} M_{N,r_K} + \beta_{F,j}^{\tau,r_K} M_{F,r_K}$$

Now for $K-1$ we have:

$$\begin{aligned} g(M|\tau, r_{K-1}, j) &= \beta_{N,j}^{\tau,r_{K-1}} M_{N,r_{K-1}} + \beta_{F,j}^{\tau,r_{K-1}} M_{F,r_{K-1}} + \beta_{N,j}^{r_{K-1}} M_{N,r_{K-1}}(\delta^N_{N,r_K} M_{N,r_K} + \delta^N_{F,r_K} M_{F,r_K}) \\ &= \beta_{N,j}^{\tau,r_{K-1}}\left(M_{N,r_{K-1}} + \delta^N_{N,r_K} M_{N,r_K} + \delta^N_{F,r_K} M_{F,r_K}\right) + \beta_{F,j}^{\tau,r_{K-1}} M_{F,r_{K-1}} \end{aligned}$$

For $K-2$ we have:

$$\begin{aligned}
g(M|\tau, r_{K-2}, j) &= \beta_{N,j}^{\tau,r_{K-2}} M_{N,r_{K-2}} + \beta_{F,j}^{\tau,r_{K-2}} M_{F,r_{K-2}} \\
&+ \beta_{N,j}^{r_{K-2}} \left(\delta_{N,r_K}^N \delta_{N,r_{K-1}}^N M_{N,r_K} + \delta_{N,r_{K-1}}^N M_{N,r_{K-1}} + \delta_{F,r_K}^N \delta_{N,r_{K-1}}^N M_{F,r_K} + \delta_{F,r_{K-1}}^N M_{F,r_{K-1}} \right) \\
&= \beta_{N,j}^{\tau,r_{K-2}} \left(M_{N,r_{K-2}} + \delta_{N,r_K}^N \delta_{N,r_{K-1}}^N M_{N,r_K} + \delta_{N,r_{K-1}}^N M_{N,r_{K-1}} + \delta_{F,r_K}^N \delta_{N,r_{K-1}}^N M_{F,r_K} + \delta_{F,r_{K-1}}^N M_{F,r_{K-1}} \right) \\
&+ \beta_{F,j}^{\tau,r_{K-2}} M_{F,r_{K-2}}
\end{aligned}$$

Defining

$$\tilde{M}_{N,r_k} = \begin{cases} M_{N,r_k} + \delta_{N,r_{k+1}}^N \tilde{M}_{N,r_{k+1}} + \delta_{F,r_{k+1}}^N M_{F,r_{k+1}} & \text{if } k < K \\ M_{N,k} & \text{if } k = K. \end{cases}$$

we can write the case $K-1$ as:

$$g(M|\tau, r_{K-1}, j) = \beta_{N,j}^{\tau,r_{K-1}} \tilde{M}_{N,r_{K-1}} + \beta_{F,j}^{\tau,r_{K-1}} M_{F,r_{K-1}}$$

Because of the definition we have that:

$$\tilde{M}_{N,r_{K-1}} = M_{N,r_{K-1}} + \delta_{N,r_K}^N M_{N,r_K} + \delta_{F,r_K}^N M_{F,r_K}$$

Wich is equal to the original expression:

$$g(M|\tau, r_{K-1}, j) = \beta_{N,j}^{\tau,r_{K-1}} \left(M_{N,r_{K-1}} + \delta_{N,r_K}^N M_{N,r_K} + \delta_{F,r_K}^N M_{F,r_K} \right) + \beta_{F,j}^{\tau,r_{K-1}} M_{F,r_{K-1}}$$

Now for the case of $K-2$ we can write it as:

$$g(M|\tau, r_{K-2}, j) = \beta_{N,j}^{\tau,r_{K-2}} \tilde{M}_{N,r_{K-2}} + \beta_{F,j}^{\tau,r_{K-2}} M_{F,r_{K-2}}$$

Now we have:

$$\tilde{M}_{N,r_{K-2}} = M_{N,r_{K-2}} + \delta_{N,r_{K-1}}^N \tilde{M}_{N,r_{K-1}} + \delta_{F,r_{K-1}}^N M_{F,r_{K-1}}$$

From before we have that:

$$\tilde{M}_{N,r_{K-1}} = M_{N,r_{K-1}} + \delta_{N,r_K}^N M_{N,r_K} + \delta_{F,r_K}^N M_{F,r_K}$$

Now combining the two previous expressions we have:

$$\tilde{M}_{N,r_{K-2}} = M_{N,r_{K-2}} + \delta_{N,r_{K-1}}^N \left(M_{N,r_{K-1}} + \delta_{N,r_K}^N M_{N,r_K} + \delta_{F,r_K}^N M_{F,r_K} \right) + \delta_{F,r_{K-1}}^N M_{F,r_{K-1}}$$

Replacing in the original expression for $K-2$, yields the same result:

$$\begin{aligned}
g(M|\tau, r_{K-2}, j) &= \beta_{N,j}^{\tau,r_{K-2}} M_{N,r_{K-2}} + \beta_{F,j}^{\tau,r_{K-2}} M_{F,r_{K-2}} \\
&+ \beta_{N,j}^{r_{K-2}} \left(\delta_{N,r_K}^N \delta_{N,r_{K-1}}^N M_{N,r_K} + \delta_{N,r_{K-1}}^N M_{N,r_{K-1}} + \delta_{F,r_K}^N \delta_{N,r_{K-1}}^N M_{F,r_K} + \delta_{F,r_{K-1}}^N M_{F,r_{K-1}} \right)
\end{aligned}$$

In conclusion, the general equilibrium effect is defined recursively by:

$$g(M|\tau, r_k, j) = \beta_{N,j}^{\tau,r_k} \tilde{M}_{N,r_k} + \beta_{F,j}^{\tau,r_k} M_{F,r_k}, \quad \forall k \in \{1, ..., K\},$$

with

$$\tilde{M}_{N,r_k} = \begin{cases} M_{N,r_k} + \delta^N_{N,r_{k+1}} \tilde{M}_{N,r_{k+1}} + \delta^N_{F,r_{k+1}} M_{F,r_{k+1}} & \text{if } k < K \\ M_{N,k} & \text{if } k = K. \end{cases}$$

□

I Proof of Proposition 1

Differentiating **??** with respect to m_F, and noting that we have a quotient rule, and that m_F has an effect through Equation (A.6):

$$\frac{\partial}{\partial m_F} CMP_j(\tau, s, X, M) =$$
$$\frac{e^{\beta^\tau_j + X_j.\beta^\tau_x + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) + \beta^\tau_{\hat{\theta}} \hat{\theta}(s,\tau)} \cdot \frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) \cdot \left(1 + \sum_{j'} e^{\beta^\tau_{j'} + X_{j'}.\beta^\tau_x + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') + \beta^\tau_{\hat{\theta}} \hat{\theta}(s,\tau)}\right)}{\left(1 + \sum_{j'} e^{\beta^\tau_{j'} + X_{j'}.\beta^\tau_x + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') + \beta^\tau_{\hat{\theta}} \hat{\theta}(s,\tau)}\right)^2}$$
$$- \frac{e^{\beta^\tau_j + X_j.\beta^\tau_x + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) + \beta^\tau_{\hat{\theta}} \hat{\theta}(s,\tau)} \cdot \left(\sum_{j'} e^{\beta^\tau_{j'} + X_{j'}.\beta^\tau_x + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') + \beta^\tau_{\hat{\theta}} \hat{\theta}(s,\tau)} \cdot \frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j')\right)}{\left(1 + \sum_{j'} e^{\beta^\tau_{j'} + X_{j'}.\beta^\tau_x + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') + \beta^\tau_{\hat{\theta}} \hat{\theta}(s,\tau)}\right)^2}$$

This can be rearranged, note that we recover the CMP_j terms

$$\frac{\partial}{\partial m_F} CMP_j(\tau, s, X, M) = CMP_j \frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) - CMP_j \cdot \frac{\sum_{j'} e^{\beta^\tau_{j'} + X_{j'}.\beta^\tau_x + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') + \beta^\tau_{\hat{\theta}} \hat{\theta}(s,\tau)} \cdot \frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j')}{1 + \sum_{j'} e^{\beta^\tau_{j'} + X_{j'}.\beta^\tau_x + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') + \beta^\tau_{\hat{\theta}} \hat{\theta}(s,\tau)}}$$
$$= CMP_j \left(\frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) - \sum_{j'} CMP_{j'} \frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j')\right)$$

Note that the sign will depend on the sign of the parenthesis. Now we must calculate the effect of m_F through the channel of the general equilibrium effect, Equation (A.6). Because of assumption 1, we will have different cases (if we are in the final range, theres only a direct effect). When $r_{\hat{\theta}} = r_{\bar{\hat{\theta}}}$

$$g(M|\tau, r_k, j) = \sum_{\tau' \in \mathcal{T}} \sum_{r_l} M_{\tau', r_l} \beta^{\tau, r_k}_{\tau', r_l, j}$$
$$= \sum_{\tau' \in \mathcal{T}} M_{\tau, r_l} \beta^{\tau', r_k}_{\tau, j}$$

Recall that $M_{\tau, r_{\hat{\theta}}}$ is defined by Equation (14), so the previous expression becomes:

$$g(M|\tau, r_k, j) = \beta^{\tau, r_k}_{F,j} m_F \int_{s:\ \hat{\theta}(s,F) \in r_k} f^F(s) ds + \beta^{\tau, r_k}_{N,j} m_N \int_{s:\ \hat{\theta}(s,N) \in r_k} f^N(s) ds$$

Differentiating with respect to m_F, we have:

$$\frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_k, j) = \beta_{F,j}^{\tau,r_k} \int_{s:\ \hat{\theta}(s,F)\in r} f^F(s)ds$$

Now for the case that $r \neq \bar{r}$, the expression becomes:

$$\begin{aligned} g(M|\tau, r_{\hat{\theta}}, j) &= \sum_{\tau'\in\mathcal{T}} \sum_{r_l} M_{\tau',r_l} \beta_{\tau',r_l,j}^{\tau,r_k} \\ &= \sum_{\tau'\in\mathcal{T}} \sum_{r_l} m_{\tau'} \int_{s:\ \hat{\theta}(s,\tau')\in r_l} f^{\tau'}(s)ds\beta_{\tau',r_l,j}^{\tau,r_k} \\ &= \sum_{\tau'\in\mathcal{T}} m_{\tau'} \sum_{r_l} \int_{s:\ \hat{\theta}(s,\tau')\in r_l} f^{\tau'}(s)ds\beta_{\tau',r_l,j}^{\tau,r_k} \end{aligned}$$

Differentiating with respect to m_F, and taking in consideration the definition of $\beta_{\tau',r_l,j}^{\tau,r_k}$

$$\begin{aligned} \frac{\partial}{\partial m_F} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) &= \sum_{r_l} \int_{s:\ \hat{\theta}(s,F)\in r_l} f^F(s)ds\beta_{F,r_l,j}^{\tau,r_k} \\ &= \int_{s:\ \hat{\theta}(s,F)\in r_k} f^F(s)ds\beta_{F,j}^{\tau,r_k} + \sum_{r_l \succ r_k} \int_{s:\ \hat{\theta}(s,F)\in r_l} f^F(s)ds\beta_{F,j}^{\tau,r_k} \left(\delta_{\tau',r_l}^N \prod_{i=k+1}^{l-1} \delta_{N,r_i}^N\right) \end{aligned}$$

■

J Proof of Proposition 2

Now in this case we must differentiate $CMP_j(\underline{s})$ with respect to $\underline{s}$. Just as before, the CMP_j has an effect from $\underline{s}$ through general equilibrium effect A.6 so the derivative is the same as before, the only change is the derivative of Equation A.6.

$$\begin{aligned} &\frac{\partial}{\partial \underline{s}} CMP_j(\tau, s, X, M) = \\ &\frac{CMP_j}{1 + \sum_{j'} e^{\beta_{j'}^{\tau} + X_{j'}.\beta_x^{\tau} + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') + \beta_{\hat{\theta}}^{\tau}\hat{\theta}(s,\tau)}} \\ &\cdot \left(\frac{\partial}{\partial \underline{s}} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) + \sum_{j'} e^{\beta_{j'}^{\tau} + X_{j'}.\beta_x^{\tau} + g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') + \beta_{\hat{\theta}}^{\tau}\hat{\theta}(s,\tau)} \cdot \left(\frac{\partial}{\partial \underline{s}} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) - \frac{\partial}{\partial \underline{s}} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') \right) \right) \end{aligned}$$

is equal to:

$$\frac{\partial}{\partial \underline{s}} CMP_j = CMP_j \left(\frac{\partial}{\partial \underline{s}} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) - \sum_{j'} CMP_{j'} \frac{\partial}{\partial \underline{s}} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j') \right) \tag{A.17}$$

Now the derivative of Equation (A.6) is (please note that the threshold only affects the first range $r_k = r_1$), so we have:

$$\begin{aligned} g(M|\tau, r_k, j) &= \sum_{\tau' \in \mathcal{T}} \sum_{r_l} M_{\tau', r_l} \beta^{\tau, r_k}_{\tau', r_l, j} \\ &= \sum_{\tau' \in \mathcal{T}} M_{\tau', r_k} \beta^{\tau, r_k}_{\tau', j} \\ &= \sum_{\tau' \in \mathcal{T}} m_{\tau'} \int_{s:\ \hat{\theta}(s,\tau') \in r_k} f^{\tau'}(s) ds \beta^{\tau, r_k}_{\tau', j} \end{aligned}$$

Differentiating, and taking in consideration leibnitz rule of integration, we have:(note that the integrand and the upper bound are both independent of $\underline{s}$, but the lower bound is $\underline{s}$

$$\frac{\partial}{\partial \underline{s}} g_{\text{eq}}(M|\tau, r_{\hat{\theta}}, j) = -\sum_{\tau' \in \mathcal{T}} m_{\tau'} f^{\tau'}(\underline{s}) \beta^{\tau, r_k}_{\tau', j}$$

K Microfoundation of CMPs

We now provide a microfoundation for the CMPs in a simplified environment.

K.1 Physicians' preferences

Consider a continuum of physicians indexed by i. Each physician i belongs to a type $\tau(i) \in \{N, F\}$, with total mass m_τ for each type τ. The physician's indirect utility from matching with hospital j is given by

$$u_{ij} \;=\; X_{\tau(i)j}\,\beta \;+\; \gamma_j\, s_i \;+\; \varepsilon_{ij}, \tag{A.18}$$

where $X_{\tau(i)j}$ represents observable characteristics (e.g., hospital attributes), s_i is physician i's licensing score, γ_j is a hospital-specific coefficient on that score, and ε_{ij} are i.i.d. Type-I Extreme Value shocks.

K.2 Hospitals' preferences

Let $\mathcal{J}$ be a finite set of hospitals, each indexed by j, and suppose hospital j is endowed with κ_j vacancies, where $\kappa_j \in \mathcal{K}$. Hospitals maximize an objective function that is strictly increasing in the expected quality $\hat{\theta}$ of the physicians they match with. Strict monotonicity in $\hat{\theta}$ implies that if hospital j can replace a physician of lower expected quality with one of higher expected quality, it will strictly prefer to do so.

K.3 Equilibrium

An equilibrium allocation satisfies pairwise stability: no hospital–physician pair can profitably deviate and match with each other, given the matches of all other agents. Following Azevedo and Leshno (2016), the equilibrium can be characterized by a system of expected quality cutoffs. In particular, each hospital j admits any physician i with $\hat{\theta}_i$ above the relevant cutoff $\bar{\theta}_j$, while each

physician i chooses the hospital that maximizes her indirect utility among those that would admit her.

K.4 Example with two vertically sorted hospitals.

Assume there are two hospitals, i.e., $\mathcal{J} = \{U, R\}$ with capacities κ_U and κ_R respectively. Then, the equilibrium expected quality cutoffs are characterized by the following set of equations:

Assuming the Urban hospital is more selective than the Rural hospital, we get that the Urban hospital cutoff is characterized by:

$$\kappa_U = \sum_{\tau} m_\tau \int_{\hat{\theta}(s) \geq \underline{\hat{\theta}}_U} \frac{e^{X_{\tau U}\beta + \gamma_U s}}{1 + \sum_j e^{X_{\tau j}\beta + \gamma_j s}} f^\tau(s)\, ds \tag{A.19}$$

The Rural hospital cutoff must then satisfy the following equation:

$$\kappa_R = \sum_{\tau} m_\tau \int_{\hat{\theta}(s) \geq \underline{\hat{\theta}}_R} \frac{e^{X_{\tau R}\beta + \gamma_R s}}{1 + \sum_j e^{X_{\tau j}\beta + \gamma_j s}} f^\tau(s)\, ds + \sum_{\tau} m_\tau \int_{\underline{\hat{\theta}}_R \leq \hat{\theta}(s) \leq \underline{\hat{\theta}}_U} \left(\frac{e^{X_{\tau U}\beta + \gamma_U s}}{1 + \sum_j e^{X_{\tau j}\beta + \gamma_j s}} \right) \cdot \left(\frac{e^{X_{\tau R}\beta + \gamma_R s}}{1 + e^{X_{\tau R}\beta + \gamma_R s}} \right) f^\tau(s)\, ds, \tag{A.20}$$

where the terms inside the integrals represent the probability of an individual of type τ with score s choosing a particular hospital, following an exploded logit model.

K.5 Microfounded CMPs

Following Fack et al. (2019), in a continuum model the microfounded Conditional Matching Probability (CMP) for a physician i of type $\tau(i)$ and hospital j is:

$$CMP^m\big(i \in \mu(j)\big) \;=\; \frac{\exp\big(X_{\tau(i)j}\beta + \gamma_j s_i\big)\, \mathbf{1}\{\hat{\theta}(s_i) \geq \underline{\hat{\theta}}_j\}}{1 \;+\; \sum_{j'} \exp\big(X_{\tau(i)j'}\beta + \gamma_{j'} s_i\big)\, \mathbf{1}\{\hat{\theta}(s_i) \geq \underline{\hat{\theta}}_{j'}\}}. \tag{A.21}$$

The indicator $\mathbf{1}\{\hat{\theta}(s_i) \geq \underline{\hat{\theta}}_j\}$ enforces that j only matches with physicians whose expected quality $\hat{\theta}(s_i)$ exceeds the relevant threshold.

By contrast, our reduced-form CMPs for this simplified model, would be given by:

$$CMP^r\big(i \in \mu(j)\big) \;=\; \frac{\exp\big(X_{\tau(i)j}\,\tilde{\beta} + \tilde{\gamma}_j\, s_i - geq_j\big(M_{\hat{\theta}_i}\big)\big)}{1 \;+\; \sum_{j'} \exp\big(X_{\tau(i)j'}\,\tilde{\beta} + \tilde{\gamma}_{j'}\, s_i - geq_{j'}\big(M_{\hat{\theta}_i}\big)\big)}\,. \tag{A.22}$$

Equivalence between (A.22) and the microfounded CMP arises if:

$$\exp\Big(-\big[\, geq_j\big(M_{\hat{\theta}_i}\big) - X_{\tau(i)j}\,\beta_{eq} + \gamma_{eqj}\, s_i\big]\Big) \;\approx\; \mathbf{1}\{\hat{\theta}(s_i) \geq \underline{\hat{\theta}}_j\} \quad \forall j \in \mathcal{J}, \tag{A.23}$$

where $\beta_{eq} \equiv \tilde{\beta} - \beta$ and $\gamma_{eqj} \equiv \tilde{\gamma}_j - \gamma_j$.

A smooth approximation of the indicator can be obtained using the Gompertz function,

$$e^{-e^{-\lambda\left(\hat{\theta}_i-\underline{\hat{\theta}}_j\right)}},$$

which converges to an indicator as $\lambda \to \infty$. Thus, under a suitable parameterization of $geq_j(\cdot)$, our reduced-form CMPs can approximate the microfounded counterparts if

$$geq_j\left(M_{\hat{\theta}_i}\right) - X_{\tau(i)j}\,\beta_{eq} + \gamma_{eqj}\,s_i \approx e^{-\lambda\left(\hat{\theta}_i-\underline{\hat{\theta}}_j\right)}. \tag{A.24}$$

Finally, notice that the function $geq_j(\cdot)$ depends in principle on the vector mass of physicians by quality (which can vary in the counterfactuals). We make this modeling choice such that we can capture changes in equilibrium quality cutoffs, which are themselves a function of preferences, the mass of physicians by quality, and hospital vacancies. To see this, in the next Subsection, we derive expressions for the two-hospital example that make explicit this dependency.

K.5.1 Approximating the two-hospital choice set

For simplicity, assume that physicians' preferences are independent of their scores, i.e., $\gamma_j = 0, \quad \forall j \in \mathcal{J}$. Under this assumption, the equilibrium cutoff for the Urban hospital is given by:

$$1 = \sum_{\tau} \frac{e^{X_{\tau U}\beta}}{1+\sum_j e^{X_{\tau j}\beta}} \left[\frac{m_\tau\left(1-F^\tau(\underline{\hat{\theta}}_U)\right)}{\kappa_U}\right] \tag{A.25}$$

The first term shows the dependency of the equilibrium cutoff on physicians' preferences while the second term makes it explicit the dependency on the stratified market tightness, i.e., the mass of test takers by type who are above a given quality $\hat{\theta}$, divided by the number of posted vacancies.

To get a closed-form expression for the Urban hospital cutoff, we can further assume for simplicity that there is one type τ. Under this assumption, the previous equation gets to:

$$\underline{\hat{\theta}}_U = F^{-1}\left(1 - \frac{\kappa_U}{m\frac{e^{X_U\beta}}{1+\sum_j e^{X_j\beta}}}\right). \tag{A.26}$$

Using the logistic approximation to the inverse CDF, the previous expression becomes:

$$\underline{\hat{\theta}}_U \approx \hat{\mu}_\theta + \hat{\sigma}_\theta\left(\frac{\pi}{\sqrt{3}}\ln\left(\frac{m\frac{e^{X_U\beta}}{1+\sum_j e^{X_j\beta}} - \kappa_U}{\kappa_U}\right)\right), \tag{A.27}$$

thus, we can write the Gompertz fcn as:

$$
\begin{aligned}
e^{-e^{-\lambda(\hat{\theta}_i - \underline{\hat{\theta}}_U)}} &= \exp\left(-\exp\left(-\lambda(\hat{\theta}_i - \hat{\mu}_\theta)\right) \left(\underbrace{\frac{m}{\kappa_U}\left(\frac{e^{X_U\beta}}{1+\sum_j e^{X_j\beta}}\right)}_{\text{Preference-adjusted market tightness}} - 1 \right)^{\lambda\hat{\sigma}_\theta \frac{\pi}{\sqrt{3}}} \right) \\
&= \exp\left(-\exp\left(-\lambda(\hat{\theta}_i - \hat{\mu}_\theta)\right) \left(\alpha_U \left(\frac{M}{\kappa_U}\right) - 1 \right)^{\lambda\hat{\sigma}_\theta \frac{\pi}{\sqrt{3}}} \right)
\end{aligned}
$$

The previous equation suggests that the matching probability for a hospital at the top of the quality distribution, depends on the share of physicians of high quality that prefer this hospital as their top preference, divided by the number of vacancies for this hospital.

To approximate the Rural hospital choice set, we can further assume that physicians have common preferences over hospitals. Under this assumption, the original equation for the Rural equilibrium cutoff can be written as:

$$
\kappa_R = m\left(\frac{e^{X_U\beta}}{1+\sum_j e^{X_j\beta}}\right) \cdot \left(\frac{e^{X_R\beta}}{1+e^{X_R\beta}}\right)\left(F(\underline{\hat{\theta}}_U) - F(\underline{\hat{\theta}}_R)\right) \tag{A.28}
$$

Thus, the quality cutoff gets:

$$
\underline{\hat{\theta}}_R = F^{-1}\left(\underbrace{\left(1 - \frac{\kappa_U}{m\frac{e^{X_U\beta}}{1+\sum_j e^{X_j\beta}}}\right)}_{P_U} - \underbrace{\frac{\kappa_R}{m\left(\frac{e^{X_U\beta}}{1+\sum_j e^{X_j\beta}}\right)\cdot\left(\frac{e^{X_R\beta}}{1+e^{X_R\beta}}\right)}}_{P_R} \right) \tag{A.29}
$$

Doing similar steps than before, we can approximate the Gompertz function with the following expression:

$$
e^{-e^{-\lambda(\hat{\theta}_i - \underline{\hat{\theta}}_R)}} = \exp\left(-\exp\left(-\lambda(\hat{\theta}_i - \hat{\mu}_\theta)\right) \cdot \left(\frac{P}{1-P}\right)^{\lambda\hat{\sigma}_\theta \frac{\pi}{\sqrt{3}}} \right)
$$

where $P = P_U - P_R$ which is a function of the stratified preference-adjusted market tightness for each of the two hospitals.

The previous expression makes explicit that for the Rural hospital, matching probabilities can be affected by a direct effect, through the term P_R, and an indirect (displacement) effect, through the

term P_U.

The derivations from our simplified microfounded model, suggest that under reasonable assumptions, the true CMPs can be approximated with multinomial logit probabilities, where the equilibrium effects are a function of physicians' preferences and the stratified market tightness. Therefore, in our empirical application, we allow equilibrium effects to be affected by the market tightness of physicians (of each type) in their own quality range, and the market tightness of physicians ranked above their own quality range.

L Computation of numerical elasticities

To compute the elasticity of labor and quality, we simulate $R = 100$ draws for the EV1 shocks in the estimated CMPs, and compute the resulting matches for physicians who take the test in year t and have a score above the corresponding threshold. If $\Delta^r L_{jt}(\underline{s})$ physicians of average quality $\Delta^r \theta_{jt}(\underline{s})$ match with hospital j in simulation r; we compute the resulting quantity and quality of each hospital by adding the marginal physicians that match with hospital j in year t to the stock of physicians of the hospital j in year $t-1$. That is, the resulting simulated physicians is $L^r_{jt}(\underline{s}) = L_{jt-1} + \Delta^r L_{jt}(\underline{s})$ and the resulting simulated average quality is $\bar{\theta}^r_{jt}(\underline{s}) = \frac{(\bar{\theta}_{jt-1} L_{jt-1} + \Delta^r L_{jt} \Delta^r \theta_{jt}(\underline{s}))}{L^r_{jt}(\underline{s})}$.

We compute the quantity elasticity numerically as

$$\eta^r_{L_{jt},\underline{s}} \approx -\frac{\left(L^r_{jt}(\underline{s} + \Delta\underline{s}) - L^r_{jt}(\underline{s})\right)}{\Delta\underline{s}} \cdot \frac{\underline{s}}{L^r_{jt}(\underline{s})}$$

and the quality semi-elasticity as

$$\tilde{\eta}^r_{\bar{\theta}_{jt},\underline{s}} \approx -\frac{\left(\bar{\theta}^r_{jt}(\underline{s} + \Delta\underline{s}) - \bar{\theta}^r_{jt}(\underline{s})\right)}{\Delta\underline{s}} \cdot \underline{s}$$

.

We then compute the estimated elasticities by averaging out across simulations.