Quality and Location Choice of Immigrant Doctors

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Abstract

Doctor shortages are a widespread and growing concern in the healthcare systems of many developed countries, including in the United States. Allowing for immigration of working doctors is a commonly proposed policy to expand doctor supply. In the US, however, licensing requirements that impede immigrants with medical training from working as doctors are commonly justified on the grounds of ensuring their quality. I study the quality of domestically trained and immigrant doctors in the US, focusing on a setting with strong identification and measurement – Medicare patients and hospital emergency rooms. I find quality *premiums* associated with care provided by immigrant doctors, both within a given hospital and across the entire distribution of emergency room doctors. Notably, I do not find such quality premiums for US citizen medical students educated abroad. I also find immigrant doctors are significantly more likely to work in designated health professional shortage areas. Estimates from a structural matching model of the doctor labor market reveal that neither mobility preferences nor vertical sorting can fully explain this geographic pattern, suggesting immigrants have a greater preference towards working in these areas. These results show the important role of immigrant doctors in providing quality healthcare in the areas of greatest need in the US.

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1 Introduction and Setting

In the United States, as in many other developed countries with aging populations, growing demand for healthcare requires increasing the capacity of the healthcare system. Expanding the supply of doctors will be a key factor for maintaining patient access to treatment and controlling costs. However, current policy estimates suggest the number of doctors working in the United States is insufficient and that this shortage of doctors will only grow in the coming years, especially in rural and otherwise underserved areas (AAMC [2021]).

Immigrant doctors offer a potential way to fill the gap.[1] In the U.S., immigrants' share of the doctor workforce is significant and growing, but lags behind other countries with large immigrant populations (OECD [2021]). One potential reason is that immigrant doctors face barriers to practice medicine in the United States, such as licensing, residency training, and visa requirements (Mansell and Esterline [2025]).[2] These requirements apply even in the case of immigrants who have already completed training and potentially have substantial work experience in their home country.[3] The limited number of U.S. residency slots and relatively low placement rate of immigrants who are international medical graduates (IMGs) constrains the number of immigrants admitted as doctors into the U.S. health system (see Table 1).[4] There is a significant pool of immigrant IMGs (as well as U.S. citizen IMGs) who are willing and technically qualified to practice medicine in the United States but are constrained by a residency bottleneck.[5][6]

Some US states have proposed programs to tap the pool of immigrant doctors to address

[1]Immigrant doctors and nurses are ubiquitous in many developed countries, including the United Kingdom (BBC [2023]) and Canada (Government of Canada [2022]).

[2]In many aspects, these barriers are greater in the U.S. than in other countries. For example, unlike in the U.K. or Australia, doctors in the United States generally must complete a 2-4 year post-graduate residency training program within the country to become licensed to practice medicine.

[3]Canadian doctors are among the few exceptions, as Canadian residencies are recognized by American accrediting institutions

[4]Table 1 also shows residency placement rates for U.S. citizens who attend medical school abroad and thus are also IMGs. These doctors mostly attend specific schools in the Caribbean which are specifically targeted towards educating U.S. citizens with the aim of returning to practice in the U.S. medical system (van Zanten and Boulet [2008]). Additionally, immigrants who attend medical school within the United States would be categorized as a U.S. medical graduates. However, the share of international students at U.S. medical schools is extremely small.

[5]The share of immigrants admitted as residents has trended upwards in recent years, but Figure 1 shows that when the number of residency slots was increased in 2013 under the Affordable Care Act, these slots were primarily filled by IMGs, implying the marginal rejected applicants were IMGs.

[6]In this paper, I primarily identify immigrant doctors by their medical education background. I will refer to the general group of doctors educated outside the United States as "IMGs". I further distinguish "immigrant IMGs" from "US citizen IMGs" who are educated at international medical schools that primarily serve U.S. citizens going abroad. I will occasionally refer to the group of immigrant IMGs as just "immigrant doctors" for brevity.

shortages. The likely effects of policies that aim to lower barriers to practice for immigrant doctors depend on the performance of immigrant doctors on the job, as the benefit from increased doctor *quantity* may be offset if immigrants are of lower *quality*. Immigrant doctors are not trained under the same educational system as domestic doctors and are possibly less tailored to working in the U.S. medical context. This motivates the main question I address in this paper: how does on-the-job performance compare between domestic and immigrant doctors in the United States?

Policies to expand immigrant doctor supply are often specifically targeted towards alleviating shortages in specific areas. Health professional shortage areas (HPSAs), as defined by the federal government, do not tend to be locations with a high proportion of well-educated immigrants. Even by restricting initial employment location to such areas, these policies may not be effective if immigrants choose to move away at their first opportunity. This motivates the question driving the second half of the paper: Do immigrant doctors increase the number of doctors working in shortage areas?

This paper sheds light on these questions and concerns surrounding immigrant doctors (as well as U.S. citizen doctors educated internationally) in the context of doctors working in U.S. emergency rooms. I collect information on the medical educational background of the near-universe of emergency medicine doctors working in the United States. I estimate the relative performance of immigrant doctors in hospital emergency rooms when treating a comprehensive nationwide sample of Medicare patients. To account for possible selection of patients to immigrant doctors, I adapt the ER provider assignment instrument implemented in Chan and Chen [2022] to identify the effect on patient health outcomes of being assigned an immigrant doctor due to plausibly-exogenous variation in ER daily staffing schedules. I find that treatment by an immigrant doctor results in slightly *better* outcomes. I find no such quality premium for doctors trained in the Caribbean, who are highly likely to be U.S. citizens educated abroad.[7]

My instrumental variable estimates credibly compare doctors within the same ER, but cannot estimate the average difference in quality between immigrant and domestic doctors if the two groups match differently to ER employers. To estimate the relative quality of immigrants more broadly,

[7] This result for Caribbean-trained U.S. citizen doctor is not surprising, as Caribbean medical schools targeted at American students model their curriculum after U.S. medical schools, but are generally less selective than medical schools located in the US. It is, perhaps, surprising that I do not find a larger or statistically significant negative quality discount for them relative to domestically-educated doctors.

I exploit the large number of doctor movers across ERs in my sample to estimate a two-way fixed effects model to identify doctor quality and hospital $\times$ patient population fixed effects (Abowd et al. [1999]).[8] I find an immigrant quality premium across the distribution of doctor fixed effects, independent of hospital workplace. I also find that immigrants tend to work in worse hospitals as estimated by the hospital fixed effect.

I also find that immigrants, in particular, and to a lesser extent all IMGs, tend to work disproportionately in HPSAs. These location choices are not fully explained by differences in residency training locations (their initial entry point into the physician work force), or by the ranking of the residency in which they were trained. To gain a better understanding of doctors' location preferences, I estimate a structural model of the physician labor market using doctor movers and emergency room hires. To overcome difficulties in the identification of preferences in a two-sided labor market, I specifically estimate a matching model of doctors and hospitals with transferable utility. I find strong complementarity between immigrant doctors and shortage area emergency rooms, ruling out vertical sorting and differential mobility across distance as the full explanations of the geographic distribution. This leaves open the possibility that true differences in preferences induce immigrant doctors to be more willing to work in underserved areas.

Taking stock of my results, I find no evidence that immigrant doctors in the emergency room perform worse than domestic doctors. In fact, I find better patient outcomes when treated by immigrant doctors, and that this quality premium is independent of labor-market sorting of doctors into emergency rooms. Additionally, immigrant doctors do appear to be more likely to work in hospitals with worse health outcomes, and they provide labor supply to the locations of greatest need.

I contribute to a recent literature regarding the labor supply of immigrant doctors and the opportunity this group offers the U.S. healthcare system. This paper is most similar in subject to Braga et al. [2023], which finds that a visa relaxation policy (Conrad 30 waivers) for immigrant doctors increased the supply of immigrant doctors, particularly in physician shortage areas. My results are also consistent with the finding in Lo Sasso [2021] that restricting immigrant admissions through tightened immigration enforcement resulted in fewer new physicians choosing to work in

[8] Abowd et al. [1999] and other papers utilizing a movers design estimate employee and employer fixed effects in the set of matches connected by employee movers across employers.

underserved areas, implying immigrants have the strongest preference towards working in shortage areas. As far as I am aware, my paper is the first to look at the quality of immigrant doctors within the U.S. (see Atal et al. [2025] for a study of immigrant doctors in Chile).

This paper also relates to a larger literature which seeks to study individual physician performance and its determinants both in the emergency room (Van Parys [2016], Silver [2021], Chan et al. [2022], Gowrisankaran et al. [2023]) and more generally (Doyle et al. [2010], Johnson [2011], Kolstad [2013], Ginja et al. [2025]). Relatively few papers in this literature specifically study educational background as a source of doctor variation (exceptions include Currie et al. [2016] and Chan and Chen [2022]).

Part of this paper aims to understand the geographic distribution of immigrant doctors through modeling the physician labor market. Important for motivating and supplementing this exercise are the results of Gottlieb et al. [2023] in describing the earnings distribution of doctors in the US. Among other results, they find that location matters for the earnings of doctors, with a geographic pattern distinctive relative to other highly paid professionals, with earnings highest in smaller metropolitan areas and more remote practice areas. Some recent work similarly models the location choices of physicians outside the U.S. (Costa et al. [2024])

This paper offers guidance on the design of policies that aim to draw on the pool of immigrant doctors. For example, Minnesota began its International Medical Graduate Program in 2015, which funds and reserves residency slots in shortage areas for IMGs.[9] The results I find in this paper suggest that these types of policies should focus on immigrant IMGs as they are appear to be of higher quality than U.S. citizen IMGs. My results also suggest that restricting the location of these residencies to shortage areas may be unnecessary to induce immigrant physician supply in shortage areas. This is important for informing policy design as previous residency expansion experiences have found it difficult to expand residencies in shortage locations (Chen et al. [2013]).

More recently, states have allowed for alternative licensing requirements in order to bypass the residency bottleneck for IMGs.[10][11] This paper does not directly speak to the effects of removing

[9]See: https://www.health.state.mn.us/facilities/ruralhealth/img/index.html

[10]In 2025, as an example, Arkansas passed SB 601 allowing IMGs with prior work experience to practice medicine without requiring domestic residency training, provided they work in a shortage area for 2 years under a provisional license

[11]As most of these new pathways have come into being only in the past couple years, it is unclear they are even effective in increasing the number of immigrant doctors. Doctors who obtain these types of state-specific provisional licenses may face challenges with aligning with hospital credentialing standards and some specialty board certification,

training requirements, and future work will be required to study the specific effects of these policy changes, as well as the general effects of different medical education and training on doctor quality.

This paper is organized as follows. Section 2 describes my collection of data on doctor education backgrounds and the construction of the data set used in my empirical analysis. Section 3 explains the rationale for focusing on emergency medicine and provides descriptive statistics for my sample of emergency room cases. Section 4 examines differences in patient outcomes across doctors working in the same hospital using an instrumental variables strategy. Section 5 examines the quality distribution of doctors across hospitals by leveraging a two-way fixed effects with physician movers. Section 6 describes the geographic distribution of immigrant doctors and their likelihood to work in HPSAs. Section 7 describes and reports the results from a matching estimator which decomposes doctor location choice from other drivers of location sorting in the labor market. Section 8 concludes.

2 Data

In this paper, I assemble data on doctors, their educational background, and the outcomes of their patients. This section describes the various data sources I utilize to construct these data.

2.1 Patient Data

I use administrative data on Medicare enrollees' treatment by physicians and subsequent health outcomes. I obtain a set of beneficiary-level Medicare insurance claims data provided by Centers for Medicare and Medicaid Services (CMS). The data set is a random 20% sample of beneficiaries enrolled in Traditional Medicare from the period of 2010 to 2019.[12] I observe information on all health care services billed to a Medicare insurance claim for each enrolled beneficiary (patient) in the sample time period.[13] The generally elderly population of Medicare beneficiaries make it

and these policies also cannot resolve difficulties obtaining federal immigration status.

[12]The set of Traditional Medicare (Fee-For-Service) enrollees does not cover the universe of Medicare beneficiaries. More than one-third of Medicare beneficiaries are instead enrolled in Medicare Advantage programs which are administered by private insurers. Unlike fee-for-service Medicare, CMS does not directly observe individual claims for Medicare Advantage beneficiaries to the same level of detail. Furthermore, some Traditional Medicare enrollees are not enrolled in both Part B coverage, and for these, I will not observe outpatient claims.

[13]I make use of four distinct claims data files in order to bring together information on patients, medical treatment, and assignment to doctors. Patient demographic and insurance status information is sourced from the Master Beneficiary Summary File. This includes information on the age, sex, race, and comorbidities for individual patients. This file also includes the date of death for beneficiaries who die within the time period covered by the data set.

well-suited to observe short-term acute negative outcomes which can be associated with individual doctor treatment.

2.2 Physician Data

I obtain information on individual physician characteristics via publicly available data provided by the Centers for Medicare and Medicaid Services (CMS). The Doctors and Clinicians National Downloadable File (NDF) is a public data set of Medicare-enrolled doctors (and other healthcare providers) released annually. I use archived NDF data going back to 2016, and supplement this with information from online physician profiles.[14] These data contain detailed demographic, educational, and professional characteristics of physicians, and are indexed by the National Provider Identifier (NPI). The file contains graduation year for all physicians, but the medical school name field is missing for *all* international medical schools, as well as for many U.S. medical schools. Therefore, it is not possible to identify internationally educated doctors solely using this data file. However, a variety of online physician look-up tools exist which display individual profiles for active doctors.

To recover medical school information missing in the NDF, I scrape the WebMD and USNews physician profile websites and match these doctors by NPI to entries in the NDF physician data. I also obtain data on residency in USNews profiles, which is not available in either the NDF or through WebMD. Details about the web-scraping procedure are provided in Appendix A.1. Combining the school information in the NDF with the data I collect online, I obtain school names for 97% of doctors in the NDF dataset.

Because medical school information is gathered from three different data sources, medical school names must be standardized in the combined physician data set. I take the standardized names of 4,288 active (as of 2024) medical schools from the World Directory of Medical Schools (WDOMS) database (which also includes their country location), and match them with the school names in the physician data set using a large language model. Details of this fuzzy matching procedure are described in Appendix A.2, as well as a validation exercise in which I manually check a random

Hospital and other facility claims are found in the Inpatient and Outpatient data files and include date-of-service information, as well as diagnosis and treatment procedure codes for a given medical event. Physician services are generally billed separately from the facility and are found in the Carrier file, and it is from these claims that I will identify the doctor who performs treatment for a medical event observed in a patient's claims data.

[14] I download the archived datasets from 2016-2023 and remove duplicate doctors. As retired doctors are not immediately removed from the dataset, this is sufficient to match 95% of doctors in the Medicare claims data from 2010-2019.

sample of school name matches.

The overall physician dataset includes 944,768 physicians, of which 74.3% are US-educated, 22.6% are educated in another country, 3.1% are missing medical school names, and .3% have medical school names that are unmatched. The results reported throughout this paper proceed by assigning all missing medical school countries as domestic, but results are robust to dropping them from the analysis.

I have no direct access to any information on the citizenship or immigration status of doctors in my data. This is of limited concern in identifying immigrants who attend domestic medical schools, as non-U.S. citizens/permanent residents make up an extremely small share of U.S. medical students (Muthukumar et al. [2025]). However, there exists a population of U.S. citizens who attend medical school abroad, the vast majority of which attend medical school in a Caribbean country, and such U.S. citizens also make up the majority of medical graduates from Caribbean countries who practice in the United States (Arja and Chundru [2025], Young et al. [2023]).

Table 2 reports the medical school country share of IMGs in the sample. India is the most common non-US medical school country of origin, whereas other IMGs originate from a variety of Caribbean and non-Caribbean countries. I use Caribbean medical school attendance as a proxy for non-immigrant IMG in my analysis, and consider other doctors educated in other countries to be immigrant IMGs.[15] Due to common mutual recognition in training and licensing requirements, Canadian doctors do not face the same barriers to practice in the United States, and as such, this paper will classify Canadian medical school-educated physicians as domestic for all further analysis.[16]

3 Emergency Medicine Data Sample

To ensure comparability across doctors in the analysis, I restrict attention to one particular specialty and role: emergency medicine. The emergency room setting is particularly amenable to observing differences in doctor performance as it involves relatively straightforward assignment of doctors to individual medical cases. Emergency room cases involve short-term care, the resolution

[15] I define Caribbean narrowly here as both a country located in the Caribbean and which contains a U.S. targeting medical school. The majority of medical students in these countries are U.S. citizens (van Zanten and Boulet [2008]). The set of Caribbean medical schools observed in the data is listed in Appendix A.3.

[16] Canadian-educated doctors make up .6% of the sample.

of which results in easily observed patient outcomes (death, inpatient hospitalization, and ER readmittance) for which negative outcomes appear in a short time frame. The unpredictable nature of emergency room admissions and lack of discretion in doctor-to-patient assignment also facilitates the identification of the quality measure of individual doctors, independent of the characteristics of the patients they happen to treat.

Table 3 compares the doctors in my physicians data listed with an emergency medicine specialty to the overall population of doctors. While IMGs do not make up as large a share of emergency medicine doctors as they do primary care specialties, it is still a large specialty with a significant share of IMGs. The more recent average graduation year of emergency medicine reflects the well-documented high attrition rate of doctors working in emergency medicine; thus, ensuring a sufficient flow of new doctors into the specialty is important for maintaining the workforce. Recent declines in interest among domestic medical graduates for emergency medicine also imply that IMGs will become more important in supplying emergency medicine doctors in the future (Sheng et al. [2024]). Emergency care also cannot be deferred across time and space. The localized nature of emergency care has meant that the maintenance of ER services is prioritized in rural areas even as other hospital and specialist services close, requiring a greater share of doctors to work in less desirable areas (Schaefer et al. [2023]). As I will show, IMGs and immigrants in particular play a central role in the doctor workforce in rural and shortage areas.

3.1 Identifying Emergency Room Events

I construct the sample of emergency room physicians working in the U.S. from 2010 to 2019, matched to the emergency room cases of Medicare patients they treat.[17] Emergency department cases are identified through Carrier claims where the treating doctor has an emergency medicine specialty and the claim line lists ER as the place of service. As the Carrier claims data set does not list the hospital/emergency room in which the beneficiary was admitted, I match emergency medicine physician claims in the Carrier data with hospital-specific facility claims (Inpatient or Outpatient) with the same admission date. The vast majority of ER cases are associated with a

[17] I restrict to claims for Traditional Medicare beneficiaries with both Medicare Part A and Part B coverage as I will need to observe both outpatient (Part B) and inpatient (Part A) claims to construct my outcome measure. The vast majority (92%) of traditional Medicare enrollees are enrolled in both programs.

unique emergency medicine physician.[18] These physicians are matched by the NPI listed on the Carrier claim to the physician dataset constructed as above.[19]

ER Case Resolution Indicator: To assess the performance of a doctor, I evaluate the outcome of each emergency room case to which he or she is associated. I define the resolution or outcome of a case as an indicator. I assign the ER case outcome indicator as 0 (negative outcome) if any of the following are observed: 5-day readmittance to an ER, 6 to 60-day inpatient hospitalization, or death within 60 days. Otherwise, I assign the indicator 1 as a positive case outcome.

Conceptually, each individual outcome measure captures a possible negative result of poor quality care during the original ER event and has been utilized previously to measure doctor quality in the emergency room setting (Gowrisankaran et al. [2023]). I collapse these outcomes into a single indicator variable to avoid potential difficulties arising from non-monotonic relationships between these measures and doctor quality (e.g., sufficiently poor care resulting in death, which precludes hospitalization).[20] Inpatient hospitalization associated with the case itself or subsequent non-emergency outpatient care is not considered a negative case outcome, as this may reflect optimal treatment or routine follow-up care. ER events which are readmits from ER cases within the prior 5 days are not considered a distinct case and are dropped from the sample. I drop cases in the last two months of 2019 due to my 60-day outcome measure.

3.2 Analysis Sample

With the dataset of patient emergency room events merged with the physician data, I have my final analysis sample. Table 4 reports a summary of key measures in this sample which comprises 29 million distinct emergency room admissions over 10 years. Note that the observed number of

[18] Almost all patients only have one facility claim on a given date of admission. The small number of cases that overlap with a claim from another facility on the same date are dropped.

[19] Venkatesh et al. [2017] describe in detail how the identification of emergency department visits in Medicare claims data can be ambiguous and depend on the exact data files and variables used to define an individual visit. In this paper, I mostly follow their preferred definition of cases utilizing both facility (inpatient and outpatient) and physician carrier claims data and relying on the place-of-service code to identify treatment in the emergency room. However, my ER event sample is more conservative than their definition, taking the intersection of events found in the facility and carrier claims rather than the union. I do this to exclude care received (or otherwise associated) with the emergency room, but that does not involve an ER doctor providing care. This approach also likely excludes emergency care in settings other than hospital emergency rooms, such as some urgent care clinics.

[20] Generally, results in this paper are robust to considering re-hospitalization and mortality alone or together but excluding ER readmission. ER readmission alone are a rare outcome.

doctors is slightly lower (and the share of IMGs slightly higher) than that found among emergency medicine specialists in the overall CMS doctors data set, likely due to the presence of doctors who have stopped practicing emergency medicine but have not been dropped (or had their specialty updated) by CMS. 74% of cases are observed to have a positive outcome, implying that 26% have a negative outcome.

I am particularly interested in doctors working in shortage areas or the areas in which the number of working doctors is low relative to the health needs of the patients in the area. The Health Resources and Services Administration designates counties with a shortage of medical providers as geographic Health Professional Shortage Areas (HPSAs).[21] Based on the hospitals observed in the analysis sample, I can observe the geographic distribution of the emergency room workplaces of doctors. Mapping the zip codes of the workplaces of the ER physicians I observe in the sample to counties, I find that IMGs appear to make up a disproportionately high share of the workforce in HPSAs, as seen in Figure 2. This pattern is similarly reproduced for hospitals located in rural zip codes, as designated by the U.S. Census by their RUCA code.

4 Instrumental Variable Research Design

I begin my analysis of doctor quality by examining differences in average patient outcomes for doctors working in the same ER. This allows me to test for differences in performance between immigrant and domestic doctors, holding workplace and patient population fixed.

I begin with the following baseline regression framework to define doctor quality. For an ER event involving patient i on day t at hospital h, let y_{it} be the ER case resolution indicator described above. The OLS regression equation is

$$y_{it} = \xi X_{it} + \eta H_{ht} + \beta \mathrm{IMG}_{it} + \epsilon_{iht} \tag{1}$$

where H_{ht} are hospital-timing fixed effects: hospital $\times$ year $\times$ month, hospital $\times$ year $\times$ day-of-week. IMG_{it} is an indicator denoting treatment by immigrant doctor. This can be a coarse indicator

[21] Geographic HPSAs are primarily designated at the county-level when the ratio of providers falls under a coarse measure of population healthcare needs. HPSA status is used to determine the target locations of many federal policies intended to address location-specific healthcare provider shortages, such as Medicare bonus payments and J-1 visa waivers.

of IMG status, or a 2×1 vector separately indicating U.S. citizen (Caribbean-educated) IMGs and non-US citizen (non-Caribbean) IMGs. Patient characteristics are captured in X_{it}. These include race, gender, age, and condition/diagnosis code. To prevent small variation in diagnosis or coding behavior from affecting the analysis, I take the ICD-9 and ICD-10 codes associated with each claim and group them into broader condition codes as defined by the Agency for Healthcare Research and Quality's Clinical Classifications Software codes, which group fine-grained diagnosis codes into broader clinically relevant categories.[22][23] T_h are hospital-timing fixed effects: hospital $\times$ year $\times$ month, hospital $\times$ year $\times$ day-of-week. IMG_h is an indicator denoting treatment by an IMG doctor. The control variables account for observable differences in patient and case severity, as well as seasonality and time-trend differences in case severity that may interact with the distribution of IMG doctors in ERs.

4.1 Instrumental Variable

The baseline doctor quality estimation does not account for possible selection in patient assignment by physician quality/educational background. The scope for patient-doctor selection in the ER is limited compared to other healthcare settings. Patients are assigned doctors and cannot select one at their discretion. ER doctors with the same formal credentials are relatively undifferentiated, having the same role and specialty within a given workplace. Many emergency rooms conduct patient assignment using an automated or otherwise deterministic system, removing scope for doctor discretion altogether(Hodgson and Traub [2020]). However, it is not clear that these patient assignment mechanisms are universal, especially in smaller emergency rooms with fewer doctors and patients. Another major source of possible patient variation comes from differences in patients across shifts. I do not observe time-of-day (shift) in my data, and it is possible that different physicians are more likely to work different shifts.

The identification concept is as follows: doctors in the emergency room work in time-specific shifts during which the team of doctors on duty attempt to treat every patient who arrives. Shifts are assigned ahead of time, and cannot take into account variation in the population of patients

[22] The time period of my sample spans the transition from the usage of the ICD-9 to the ICD-10 diagnosis code systems. The claims data is organized into annual data files, and within each file year, all diagnosis codes conform to one of the coding systems. All analysis will include year fixed effects.

[23] ICD-9 and ICD-10 have different CCS coding systems. I use AHRQ [2015] for ICD-9 and AHRQ [2020] for ICD-10 codes.

who arrive except for foreseeable patterns in patient demand. While patient-case assignment may not be random within an ER shift, replacing a doctor of one type on a shift with a doctor of the other type must result in some patients assigned a doctor of the first type to instead be assigned one of the second, assuming they treat any patients at all. The share of IMG doctors on a given shift can be used as an instrument for assignment to an IMG doctor, controlling for the foreseeable aspects of shift timing. This argument can be extended from individual shifts to individual days, assuming the number of shifts is fixed across days.

I use plausibly exogenous variation in the share of IMGs on duty on a given day to construct an instrument for IMG doctor assignment to a given case. This instrumental variable strategy for doctor quality estimation in the emergency room draws from the instrumental variables strategy employed by Chan et al. [2022] in their analysis of the performance of nurse practitioners in the ER setting. I define the variable for all cases observed at a hospital h on a given day t:

$$Z_{ht} = \frac{\text{Unique \# of IMGs }_{ht}}{\text{Unique\# of Doctors}_{ht}} \tag{2}$$

is the share observed doctors working in that ER on that day who are IMGs. Alternatively, Z_{ht} can be a vector which records shares of immigrants and non-immigrants separately.

The two-stage least squares regression equation is as follows. For an ER event involving patient i at hospital h on day t, let y_{it} be the ER outcome measure.

$$\text{IMG}_{it} = \psi X_{it} + \omega H_{ht} + \chi Z_{ht} + \nu_{iht} \tag{3}$$

$$y_{it} = \xi X_{it} + \eta H_{ht} + \beta \text{IMG}_{it} + \epsilon_{iht} \tag{4}$$

As in the baseline quality estimation, X_{it} is patient race, gender, age and CCS code, H_{ht} are hospital $\times$ year $\times$ month and hospital $\times$ year $\times$ day-of-week fixed effects and IMG_{it} is the treatment variable of interest: treatment by IMG doctor. The instrument Z_{ht} is the share of observed doctors working in that ER on that day who are IMGs, with the predictable timing components controlled for in H_{ht}. β is the coefficient of interest and is an estimate of the local average treatment effect (LATE) on the outcome from being assigned an IMG physician relative to a domestic-educated physician.

Staffing of the emergency room is determined by shifts, and shifts are assigned to doctors ahead of time. Patients are assigned to a doctor on duty at the time they arrive. The nature of the emergency room means that patient flow should not be predictable outside of broad seasonal and otherwise regular timing patterns. Generally, ERs are open 24/7 and must be staffed constantly, which means shifts are constant across days. An increase in IMG share of doctors on staff on a day implies an increase in IMG share on some shift, increasing the proportion of patients treated by an IMG on that shift. Thus, the instrument can be used to estimate a local average treatment effect of IMG treatment for some patient population weighted across shifts.

4.2 Results

OLS Results: Table 5 depicts the OLS regression coefficients with of the baseline doctor quality estimation. Standard errors are clustered two-ways at the hospital and the year level. Columns 1 and 2 report statistically significant and large negative coefficients, showing IMG treatment is associated with worse patient outcomes. Specifically, the share of positive case outcomes is .27% percentage points lower on average when treated by an IMG, controlling for patient-case characteristics. However, in columns 3 and 4, these coefficients are positive once hospital and timing fixed effects are included as controls, implying a .09% percentage point premium in case outcome (statistically significant at the 10% level) associated with IMG treatment. This suggests that IMGs work on a patient population worse average health outcomes. Table 6 separately estimates coefficients on treatment by U.S. citizen IMG and immigrant IMG. The pattern showing negative patient outcomes without accounting for hospital-timing fixed effects remains for both groups. However, I find that the positive patient outcomes associated with IMG treatment is driven solely by immigrant IMG treatment, as I estimate a negative but statistically insignificant coefficient on U.S. citizen IMG treatment but a positive coefficient of .17 percentage points associated with immigrant IMG treatment. This immigrant quality premium is estimated to be highly statistically significant.

IV Relevance and Balances: Table 7 depicts balance tests for the instrument on patient characteristics. Each row reports the coefficient for hospital-day IMG share in a regression of a different dependent variable, controlling for hospital-timing. The reported coefficients are all extremely small (less than .2 percentage points) on demographic indicators, which each make up 20-80% of the patient case population. The first column in Table 8 reports the coefficient on the first stage of IMG share on IMG assignment. The estimated coefficient of .97 is extremely close to one, implying patients have a very similar probability of being assigned any doctor on duty, and is highly significant, demonstrating the relevance of the instrument.

Tables 8 and 9 report the results of the 2SLS regression estimates. As in the OLS results, I find quality premiums attributed to IMG treatment, and these premia are driven entirely treatment by an immigrant IMG. The estimated coefficient on immigrant IMG (.0017) is highly statistically significant and equivalent to a .65% decrease in negative case outcomes relative to the sample mean. This estimated effect is objectively fairly small, but this is consistent with other studies which show a relatively small role of physician quality in determining patient outcomes in the ER (Gowrisankaran et al. [2023]). The significant and positive estimated result does, however, demonstrate that there is no evidence of a quality penalty associated with immigrant doctors relative to domestic doctors working in the same ER. The estimated coefficient on immigrant treatment is also remarkably similar between the baseline and instrumented quality estimations, suggesting that selection on unobserved patient characteristics does not appear to affect doctor quality estimates along the dimension of immigrant status.

5 Two-Way Fixed Effects with Movers

The results I find above in the analysis using within-hospital variation in doctor assignment imply that treatment by an immigrant results in slightly better patient outcomes within the same workplace. The small difference between the OLS and IV coefficients also suggests that there are not large differences in selection to domestic and immigrant doctors on unobservable patient characteristics within emergency rooms. However, a limitation of the doctor daily scheduling instrument design is that I compare doctors working in the same hospital, and it is possible my estimates are driven by doctor sorting across hospitals. For example, if hospitals prefer to employ a domestic doctor over an immigrant at a given level of doctor quality, I may observe higher quality immigrant doctors within the same hospital as a compensating differential, but this would not be informative of the overall quality difference of immigrants.

To speak to the differences between IMGs and domestic doctors across the full distribution of emergency medicine doctors across hospitals requires a different research design. I separately identify physician and ER fixed effects within the analysis sample by leveraging movers across ERs (Abowd et al. [1999], Badinski et al. [2023]). Emergency medicine doctors are highly mobile, with around 40% of the doctors moving to another hospital within the 10-year sample. There also exists a group of doctors who work in multiple ERs concurrently (multi-homers). To exclude extremely short employment relationships, I restrict the sample to doctor-hospital employment pairs of at least 3 concurrent months and drop cases that occur in a hospital assigned to a doctor without an established relationship. [24] The doctor and hospital fixed effects are only identified for the set of hospitals connected by movers or multi-homers. The coverage of the largest connected set encompasses 98% of doctors, 90% of hospitals, and 96% of cases in the sample. All further analysis will proceed using this restricted sample on the connected set.

The assumptions under which the two-way fixed effects model is identified are as follows: movement across hospitals must be uncorrelated with time-varying unobservable determinants of quality (exogenous movers), and the individual doctor effect on the outcome measure is linearly separable from the hospital effect (additivity). Appendix B.1 shows an event study of the average patient outcomes for doctor movers before and after their move, and finds no discernible pre-trends or post-trends. This event study does not control for the hospital fixed effect, so the change in average outcomes at the time of the move reflects the average change in hospital quality. Appendix B.2 reports evidence that the doctor and hospital effects on outcomes are roughly linear and separable.

The two-way fixed effect regression model with estimated ER events on day t involving patient i treated by j physician at h hospital on the connected set doctor-hospital sample is as follows:

$$y_{it} = \beta X_{it} + \eta T_t + \omega_j + \gamma_h + \epsilon_{iht} \tag{5}$$

where y_h is the outcome indicator, X_{it} are patient-case characteristics (condition and demographics), T_t are time fixed effects (year, month, day-of-week) and ω_j is the doctor fixed effect and γ_h is the hospital fixed effect.

Table 10 reports the relationship between the estimated doctor and hospital fixed effects and IMG status. As standard errors in two-way fixed effect regressions generally suffer from limited mobility bias, the standard errors in this table are debiased using the method described in Kline

[24] Therefore, I also drop the last 3 months of the sample (October, November, and December of 2019) for all doctors, as I will not be able to verify that these cases occur in a durable employment relationship.

et al. [2020].[25]

I find a similar improved average patient outcome associated with average IMG doctor fixed effects as found in the IV estimation. This premium again only appears to be driven by immigrant doctors in particular, as I estimate immigrant IMG fixed effects .0015 higher than domestic doctors. U.S. citizen IMG fixed effects, on the other hand, are estimated to be .0001 lower. I conclude that differences in hospital employment standards do not induce the positive patient outcomes observed for immigrant treatment. Immigrant doctors appear to have a quality premium over domestic doctors on average. I also find that both immigrant and U.S. citizen IMGs tend to be observed working in worse-performing hospitals as measured by the hospital fixed effect. As emergency rooms do not move, the hospital fixed effects also reflect differences in patient population. The assignment of immigrant doctors to hospital-location workplaces will be the focus of the rest of the analysis in this paper.

6 Residency Geography and Mobility

A stated motivation for policies expanding immigrant doctor supply is to alleviate doctor shortages in areas of greatest need. In the prior analysis, I find that immigrant doctors work in hospitals and locations with worse average health outcomes. In Figure 2, I see that IMGs, and in particular immigrant IMGs, are disproportionately likely to work in rural areas and HPSA. Possible explanations for this geographic pattern include differences in initial location during residency training, differences in tendency to move, and different probabilities of moving to a health professional shortage area, possibly due to different location preferences between IMGs and non-IMGs.

I begin to disentangle these potential explanations with data about the location of residencies of doctors in the sample. While I do not have data on residencies for all doctors in the sample, this information is available for nearly all doctors with a profile on USNews. However, similarly to the web profile medical school data, the residency program information is only available as a raw text name. I match these program names by hand to currently active (as of 2025) emergency medicine programs as listed by the Accreditation Council for Graduate Medical Education (ACGME).[26]

[25] Actual estimation was performed using the Julia package developed by Paul Courcera at: https://github.com/HighDimensionalEconLab/VarianceComponentsHDFE.jl?tab=readme-ov-file

[26] https://apps.acgme.org/ads/Public/Reports/Report/1

Table 11 shows summary statistics of the subsample of USNews-listed doctors. One measure of the mobility of doctors across locations is whether their residency and first workplace are located in the same state i.e. concordance. In the sample, the residency to first workplace state-level concordance rate is 45%, implying that residency location may matter for future practice location.

I consider how the relationship between a doctor's residency location and the location of their first workplace may differ by doctors' IMG status (see Table 12). I find that IMGs are significantly less likely to work in the same state in which they trained. Importantly, this pattern holds even when controlling for the number of years out of residency in which I observe them at their first job. Immigrants appear to be more mobile than U.S. citizen IMGs.

Table 13 reports the relative likelihood of IMGs working or training in an HPSA. IMGs are overrepresented in both HPSA residencies and HPSA workplaces. Immigrants are again relatively more likely to work in shortage areas than U.S. citizen doctors. This pattern holds even when fully controlling for residency fixed effects. Table 14 reports the relative likelihood of working in an HPSA separately for those who trained in an HPSA and a non-HPSA. I see that immigrants appear to be relatively more likely to work in a shortage area regardless of whether they trained in one, though the number of doctors' residencies overall located in shortage areas is fairly small.

Taken together, these descriptive statistics show that the overrepresentation of immigrants in shortage areas cannot be completely explained by differences in initial training area. Differences in mobility can drive increased diffusion of immigrants from the relatively fewer residencies in shortage areas towards workplaces in those locations. Immigrants appear to be both more mobile and more likely to move to shortage areas to practice medicine professionally. However, this descriptive evidence cannot distinguish between differences in doctor preferences (more willing to move) and differences in choice set (less able to stay or move to desirable locations).

To attempt to disentangle some portion of the competing effects of supply-side (physician location choice) preferences and demand-side selection (hospital recruiting choice), I construct a residency ranking index on the conjecture that hospitals select workers based on this highly observable signal of quality. As no readily available ranking of residency programs exists, I construct this index by using the average school ranking of the medical schools of domestic MD-holding doctors I observe having trained in the program. This resulting program rank is highly negatively correlated with the share of IMGs attending these programs. Table A2 reports the share of doctors working in geographic HPSAs by IMG status and residency rank. Those trained in the lowest-ranked tercile of residencies tend to be more likely to work in a shortage area. However, at every level, IMGs are more likely to work in a shortage area than their domestic counterparts. At every level, the share of immigrant doctors, in particular, working in a shortage area exceeds the highest share group of domestic doctors.

Overall, while IMGs are more likely to train in a health shortage area, and to train in lower-ranked programs which disproportionately send alumni to work in shortage areas, these factors do not appear sufficient to explain the excess of IMGs and immigrants working in shortage areas. There is a substantive possibility that immigrants have a greater willingness to work in shortage locations and that these preferences matter in shaping the geographic distribution of doctors.

7 Matching Estimator for Physician Movers

One major remaining possible mechanism to generate the observed sorting of immigrant doctors to shortage areas is vertical sorting in the labor market. If immigrant doctors and shortage area hospitals are each uniformly less desirable to the other side in the labor market, it is possible that this is sufficient to explain the geographic distribution of immigrant doctors. In this case, expanding immigrant doctor supply would not necessarily expand physician supply in shortage areas any more than other sources of additional doctor workers. However, if immigrant doctors have a greater preference for shortage location characteristics (or shortage area hospital characteristics), increased immigrant doctor supply may more effectively allocate additional supply to the areas for which it is most needed. Differences in mobility propensity can likewise be due to lower costs of moving for immigrant doctors, or for greater preference to work in locations that just happen to be further away.

In order to explore the possible complementarity of matching between immigrant doctors and shortage area hospitals, I estimate a matching model of the physician labor market in which an assumption of transferable utility takes the place of explicit information on wages and non-pecuniary forms of compensation by hospitals to doctors.[27] I estimate this model using a semi-parametric maximum score estimator of the kind described in Fox [2010] and Fox [2018]. Maximum score

[27]Data on the true earnings of individual doctors is hard to come by. The exact formal employment relationship between a doctor and a hospital can take diverse forms.

estimators of matching models of this type have been previously used in the labor market context to analyze the matching of senior executives to firms (Pan [2017]) and university researchers to spin-off firms (Mindruta [2013]), among others.

Doctor-Hospital Matching Model with Transferable Utility: The model of doctor-hospital matching is characterized as follows: for a given two-sided labor market, there is a finite set of doctors $\{d_1, d_2, ..., d_n\}$ and a finite set of hospitals/workplaces $\{h_1, h_2, ..., h_m\}$. Pairs of doctors and hospitals match in a one-to-one manner in such a way as to maximize their individual utilities. There are no search or information frictions in the model; doctors and hospitals can perfectly observe each other's characteristics, and all doctors can in principle be matched to any hospital in the market if the match is utility maximizing. For doctor d_i matched with hospital h_a, the doctor's utility is

$$U_{d_i,h_a} = D(d_i, h_a) + t_{d_i,h_a} \tag{6}$$

and the hospital utility is

$$V_{d_i,h_a} = H(d_i, h_a) - t_{d_i,h_a} \tag{7}$$

where t_{d_i,h_a} is a freely set and possibly negative utility value of transfers from hospital to doctor. Thus, utility is assumed to be freely transferable within a doctor-hospital match. Define the total match utility generated for this match as

$$M_{d_i,h_a} = U_{d_i,h_a} + V_{d_i,h_a} = D(d_i, h_a) + H(d_i, h_a)$$

As in Fox [2010], I take the equilibrium concept for this matching game to be pairwise stability. In the transferable utility model, this gives rise to the local production maximization inequality: the total utility generated by any two equilibrium matches should be greater than the utility generated if the partners were exchanged between the two matches. Written in the previous notation, for any two equilibrium doctor-hospital matches (d_i, h_a) and (d_j, h_b), the following inequality should hold:

$$M(d_i, h_a) + M(d_j, h_b) \geq M(d_i, h_b) + M(d_j, h_a) \tag{8}$$

Local production maximization gives rise to a system of inequalities which can be used to identify the match utility function.

I use the following maximum score estimator (Manski [1975]):

$$\max_{M} \frac{1}{N}\{\Sigma_{(i,j,a,b)\in X_n}(1[M(d_i,h_a)+M(d_j,h_b)\geq M(d_i,h_b)+M(d_j,h_a)])\} \tag{9}$$

in which 1[.] is the indicator function, N is the number of distinct markets in the data, and X_h is the set of distinct pairs of realized matches observed in market n.

Under the maximum score estimator, only the contribution of interaction terms between doctors and hospital characteristics are identified, as the sole doctor and hospital fixed effects are differenced out in the inequalities. Also, the doctor's utility function D and the hospital's utility function H cannot be separately identified, only their sum.

I parameterize the match utility function as

$$M(d_i,h_a) = \beta(X_{d_i} \times [p_{d_i,h_a} + X_{h_a}]) + \epsilon_{d_i,h_a} \tag{10}$$

in which p_{d_i,h_a} is the distance from prior workplace. Doctor characteristics X_i include: IMG status, immigrant status, and doctor quality fixed effect as estimated above. Hospital characteristics include the hospital fixed effect as well as HPSA status.

I define 8 separate labor markets in which each year from 2011 to 2018 is a single and distinct labor market. The set of doctors in the labor market is all non-multihoming physician movers between hospitals in that year. The set of hospitals in the labor market is all hospitals that one of these movers moves to within that year. I estimate using differential evolution optimization.

Table 15 reports results of the estimated coefficients using the matching estimator. I find no evidence of positive immigrant mobility preferences. The estimated coefficient on distance is the effect of higher distance between the former and subsequent workplace on the total surplus of the post-move employment relationship. I interpret this as primarily reflecting the doctor-side preference or cost towards mobility, as the costs of relocation seem irrelevant to the post-move employer. While, as expected, further distance is estimated to be costly, the cost is not very different between immigrants and non-immigrants. A caveat to this result is that it speaks solely to distaste towards the distance of move. The estimator is estimated on the sample of doctors who have all made the decision to move.

Instead, I find high complementarity on surplus of immigrant doctors specifically matching to HPSA hospitals. What mechanisms are left that can explain this affinity? One possible explanation is that immigrants, having recently entered the country, lack prior locational attachment and simply do not have stronger preferences for other locations against these areas. Visa requirements that mandate immigrants work in shortage areas may play a role; however, in this sample of physician movers, the destination workplaces are at least second workplaces, and visa location restrictions generally only apply for the first few years of work. Preferences over compensation are a compelling possible explanation that I do not separately examine in this analysis. Amin and Uyar [2021] find that foreign-born doctors begin to have higher incomes on average than domestic doctors after 5 years of working and Gottlieb et al. [2023] find that underserved areas exhibit a wage premium for doctors. A higher immigrant doctor wage elasticity provides a possible explanation for these two facts.

8 Discussion and Conclusion

The analysis above uncovers no evidence that immigrant doctors perform worse in the context of emergency medicine. On the contrary, I find that treatment by an immigrant doctor is associated with better patient outcomes, both within a given ER-location context as well as over all hospitals. This suggests that there may not be a significant quality-quantity trade-off induced by policies that fill doctor shortages with immigrants. I find that immigrants are more likely to work in areas of health professional shortage, and while the specific mechanism driving this preference is unclear, it is not explained by simple labor market sorting patterns. This leaves room for a variety of mechanisms that include immigrants being more willing to work in these areas, which would imply immigrant doctors are more effective in addressing location-specific doctor shortages than domestic doctors. These results show that immigrants already play an important role in providing quality healthcare to underserved areas.

Therefore, this paper takes a step towards attenuating concerns that policies which further draw on the pool of immigrant doctors would result in a quality-quantity tradeoff of doctors or result in geographic misallocation. Concerns may remain that the marginal immigrant doctor induced by such policies are not similar in quality or preferences to those observed. For certain types of such policies lifting immigration restrictions, such as expanding visa availability, this seems unlikely to be the case as these reduce barriers that exclude doctors without explicit consideration of quality (in fact, prior policies such as the Conrad 30 waivers appear to be a policy lever to further incentivize work in shortage areas). Other more significant policy reforms, such as allowing immigrant doctors to work in the U.S. without undergoing domestic residency training, may not only heavily select on less qualified immigrants, but would change the overall training experience of these immigrant admits. Future work will be needed to understand the characteristics of the marginal immigrant doctor as well as the effects of different types of medical training more broadly.

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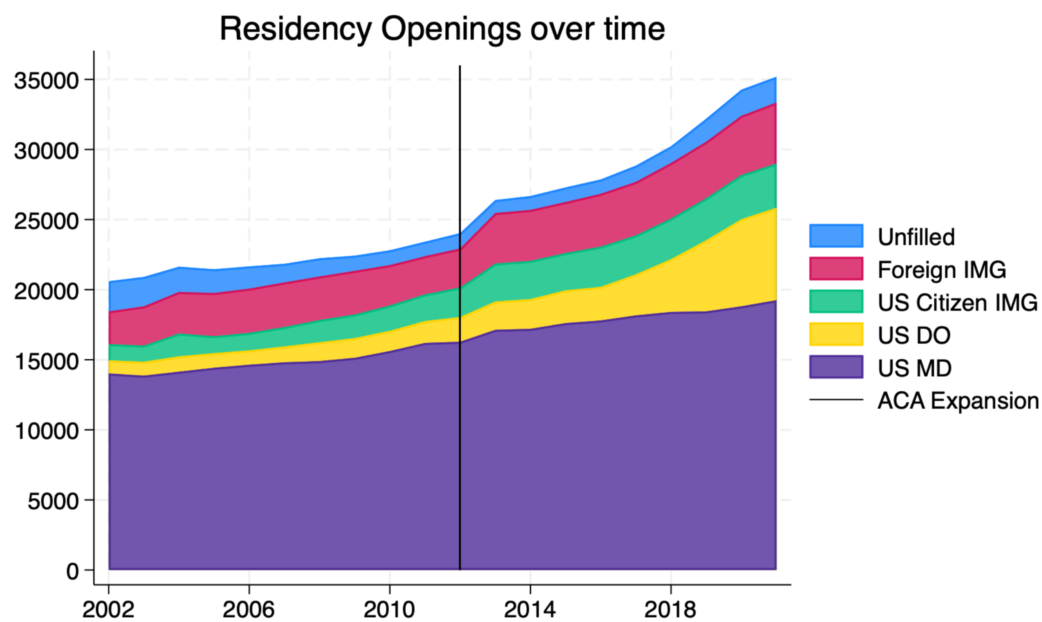
9 Figures

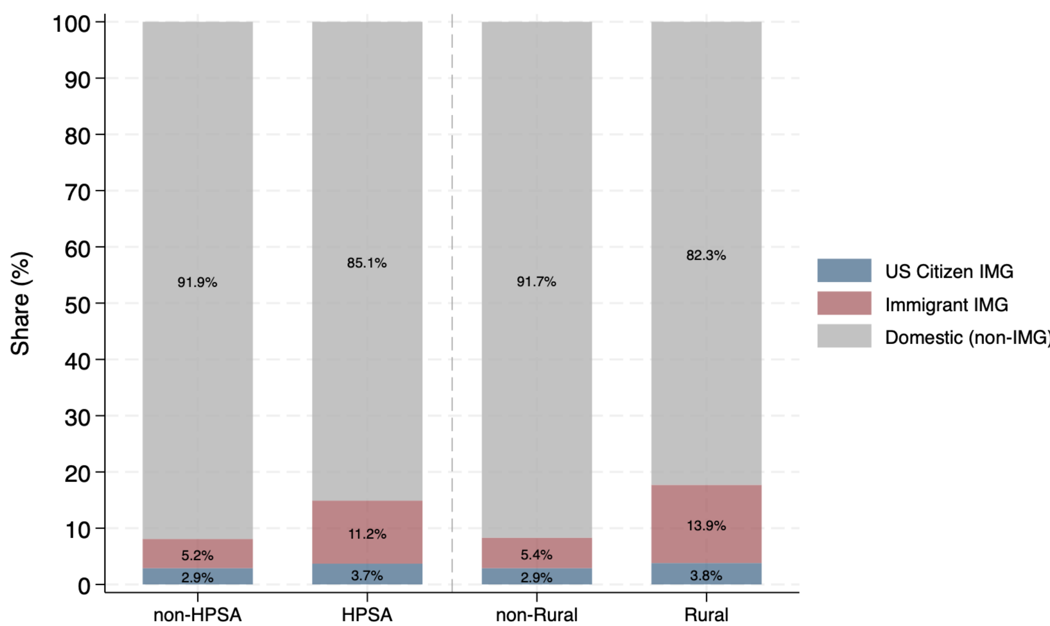
Figure 1: Distribution of filled residency positions after expansion



Notes: This figure depicts the results of the National Residency Matching Program from 2002 to 2020. Placements are split by the type of applicants or if a program is unfilled. A one-time expansion in the number as a result of increased funding from the Affordable Care Act in 2013 is shown to primarily increase the number of immigrant IMGs and US citizen IMGs placed into a residency program. Data sourced from the NRMP website. [28]

[28] https://www.nrmp.org/match-data/

Figure 2: Geographic Distribution of ER Physicians



Notes: This figure depicts the distribution of ER physicians across geography. A significantly greater share of doctors working in ERs located in designated health professional shortage areas and in rural areas are US citizen IMGs and immigrant IMGs.

10 Tables

Table 1: Distribution of filled residency positions

Applicant Type	# Applicants	Placement Rate
U.S. Medical Graduates	28,141	98.0%
U.S. Citizen IMGs	3,108	73.5%
Immigrant IMGs	6,653	60.3%

Notes: While most residency applicants are graduates of domestic medical schools, the placement rate of IMG applicants into any residency is significantly lower than that of domestic applicants. In 2025, Immigrant IMGs make up 66% of unplaced applicants among first-time applicants. Data sourced from the 2025 NRMP match data.

Table 2: Distribution of Medical School Origin Country

Non-Caribbean	Overall Share	IMG Share	**Caribbean**	Overall Share	IMG Share
India	4.1%	18.3%	Barbados	1.1%	4.9%
Pakistan	1.2%	5.3%	Grenada	1.1%	4.9%
Philippines	.95%	4.3%	Dominican Republic	.52%	2.3%
Mexico	.84%	3.8%	Sint Maarten	.46%	2.1%

Notes: This table depicts the share of medical school country both as a percentage of the educational background of all doctors as well as just among IMGs, as found in my sample data. Shares are calculated in the overall sample of doctors, not just among emergency medicine doctors.

Table 3: Comparison Statistics of Specialties

Specialty	Number	IMG Share	Avg. Grad. Year	Share HPSA
All CMS Doctors	912,339	22.3%	1997	2.6%
Internal Medicine	130,549	37.0%	1998	2.4%
Family Practice	87,841	20.1%	1998	4.9%
Emergency Medicine	**57,957**	**7.5%**	**2003**	**4.8%**
Radiology	41,150	11.9%	1996	3.1%
Opthamology	23,406	6.7%	1994	1.9%
Orthopedic Surgery	29,889	4.9%	1995	2.7%
Dermatology	16,096	4.1%	1997	1.5%

Notes: Descriptive statistics of emergency medicine specialists as compared with all doctors in the CMS data set as well as compared to other selected specialties. EM has a lower representation of IMGs compared to the overall population of doctors as well as primary care specialties, however represent a greater share than in highly competitive specialties such as dermatology. EM doctors in the sample on average have a more recent graduation year than other specialties and a higher proportion of them work in health professional shortage areas compared to non-primary care specialties.

Table 4: Summary Statistics of Analysis Sample

Statistic	**Value**
Years	2010-2019
# of ER events	29 million
# of Unique Hospitals	5,162
# of Unique Doctors	57,140
Share Treated by IMG	8%
Average 30 Day Mortality	4%
Proportion Positive Case Resolution	74%

Notes: Table displays summary statistics for the data sample used for analysis. Cases in the last 2 months of 2019 are excluded due to non-observability of the 60-day outcome measure. A small number of emergency medicine doctors in the CMS data are not observed working in the time period of the claims data.

Table 5: OLS Regression Results

	Positive Case Resolution			
	(1)	(2)	(3)	(4)
IMG	$-.0015^{***}$	$-.0027^{***}$	$.0019^{***}$	$.0009^{*}$
	(.0004)	(.0004)	(.0005)	(.0005)
Hospital × Timing FE			✓	✓
Patient-Case Mix Controls		✓		✓
R^2	.001	.06	.01	.07
N (millions)	29	29	29	29

Notes: Table reports the estimated coefficient (with standard errors in parentheses) on IMG treatment as estimated by equation 1. Hospital-timing controls are hospital by year, month, and day of week. Patient-case mix controls are patient race, sex, condition codes, and binned patient ages. Standard errors are two-way clustered at the hospital and year level. Positive coefficients imply a larger share of positive case resolution therefore higher doctor quality. Statistical significance at the 10%, 5% and 1% level are denoted by *, **, and *** respectively in the table.

Table 6: Immigrant OLS Results

	Positive Case Resolution			
	(1)	(2)	(3)	(4)
US Citizen IMG	$-.004^{***}$	$-.004^{***}$	$-.0001$	-.0003
	(.0006)	(.0006)	(.0005)	(.0004)
Immigrant IMG	$-.0004$	$-.0019^{***}$	$.0031^{***}$	$.0017^{***}$
	(.0005)	(.0005)	(.0007)	(.0006)
Hospital × Timing FE			✓	✓
Patient-Case Mix Controls		✓		✓
R^2	.001	.06	.01	.07
N (millions)	29	29	29	29

Notes: Table reports the estimated coefficients (with standard errors in parentheses) on immigrant IMG treatment and US citizen treatment as estimated by equation 1. Hospital-timing controls are hospital by year, month, and day of week. Patient-case mix controls are patient race, sex, condition codes, and binned patient ages. Standard errors are two-way clustered at the hospital and year level. Statistical significance at the 10%, 5% and 1% level are denoted by *, **, and *** respectively in the table.

Table 7: Instrument Balance Regressions

Dependent Variable	**Coefficient**	**Standard Error**	**t-stat**
White	.001	.0004	2.65
Black	-.0009	.0004	-2.58
Hispanic	-.0001	.0002	-0.56
Male	.0006	.0006	0.97
Age <40	.00007	.0006	0.26
Age 40-65	-.0006	.0004	1.40
Age 65-70	-.00002	.0004	0.05
Age 70-80	-.0005	.0005	-1.01
Age 80-90	-.00098	.0004	-2.02

Notes: Table reports the results of instrument balance regressions of the form $X_{it} = \omega H_{ht} + \chi Z_{ht} + e_{iht}$ for a variety of patient demographic indicators regressed on the instrument defined in equation 2. The table reports the estimated coefficient χ in each regression and standard errors and t-statistic.

Table 8: 2SLS Regression Results

	Positive Case Resolution		
	First-Stage	(1)	(2)
IMG Share	0.997***		
	(0.0002)		
IMG		0.0015**	0.0009*
		(0.0005)	(0.0005)
Hospital × Timing FE	✓	✓	✓
Patient-Case Mix Controls	✓		✓

Notes: The first column of the table reports the first stage of the IV regression as defined in 3. The other columns report estimated coefficients (with standard errors in parentheses) on IMG treatment as estimated in the 2SLS equation. Hospital-timing controls are hospital by year, month, and day of week. Patient-case mix controls are patient race, sex, condition codes, and binned patient ages. Standard errors are two-way clustered at the hospital and year level. Statistical significance at the 10%, 5% and 1% level are denoted by *, **, and *** respectively in the table.

Table 9: Immigrant 2SLS Results

	Positive Case Resolution	
	(1)	(2)
US Citizen IMG	.0005	−.0006
	(.0008)	(0008)
Immigrant IMG	.0025***	.0017**
	(.0007)	(.0007)
Hospital × Timing FE	✓	✓
Patient-Case Mix Controls		✓

Notes: The table reports estimated coefficients (with standard errors in parentheses) on US Citizen IMG treatment and Immigrant IMG treatment as estimated in the 2SLS equation 4. Separate instruments are defined for Immigrant IMG share and US Citizen IMG share at a hospital on a given day. Hospital-timing controls are hospital by year, month, and day of week. Patient-case mix controls are patient race, sex, condition codes, and binned patient ages. Standard errors are two-way clustered at the hospital and year level. Statistical significance at the 10%, 5% and 1% level are denoted by *, **, and *** respectively in the table.

Table 10: Regressions on Two-Way Fixed Effects

	Doctor FE		Hospital FE	
	(1)	(2)	(3)	(4)
IMG	.0009		$-.003$	
	(.0003)		(.0003)	
Immigrant IMG		.0015		-.003
		(.0005)		(.0004)
US Citizen IMG		-.0001		-.003
		(.0005)		(.0004)

Notes: The table reports the results of regressions of doctor IMG characteristics on fixed effects estimated from a two-way fixed effects across the set of doctors and hospitals connected by movers. The regressions on hospital fixed effects are estimated assuming equal weighting of their hospital employers for doctors observed at more than one hospital.

Table 11: Summary Statistics of Residency Sample

Statistic	**Value**
# of Doctors	29,890
Share IMG	10.03%
Share US Citizen IMG	3.75%
Share Immigrant IMG	6.28%
Share HPSA Workplace	4.14%
Share HPSA Residency	.92%
Share Residency-Workplace State Concordance	44.8%
Avg. Years from Residency End	9.16

Notes: The table reports summary statistics for the sample of ER doctors for which I observe data on residency training programs. The residency program of interest is the most recent program attended. The workplace of interest is the first hospital in which the doctor is observed in the 2010-2019 claims data. Residency-workplace state concordance is defined as if the residency program is located in the same state as the first workplace. The last row reports the average number of years between residency graduation and the year of first observation in the workplace data.

Table 12: Physician Mobility OLS Regressions

	State Concordance			
	(1)	(2)	(3)	(4)
IMG	$-.08^{***}$		$-.073^{***}$	
	(.009)		(.009)	
US Citizen IMG		$-.041^{**}$		$-.047^{***}$
		(.015)		(.015)
Immigrant IMG		$-.103^{***}$		$-.089^{***}$
		(.011)		(.012)
Year Diff Control	No	No	Yes	Yes

Notes: Table reports regressions of (last) residency to (first) workplace state concordance status on IMG characteristic in the residency ER doctor sample. IMG doctors appear to be less likely to remain in the same state, implying greater mobility, with immigrant IMGs more mobile than US citizen IMGs. The third and fourth columns include the number of years passed between residency and workplace observation as a control variable. Statistical significance at the 10%, 5% and 1% level are denoted by *, **, and *** respectively in the table.

Table 13: HPSA Location OLS Regressions

	HPSA Residency		HPSA Work			
	(1)	(2)	(3)	(4)	(5)	(6)
IMG	.011***		.04***		.027***	
	(.002)		(.004)		(.005)	
US Citizen IMG		.006*		.017**		.005
		(.004)		(.007)		(.06)
Immigrant IMG		.014***		.057***		.043***
		(.003)		(.006)		(.06)
Residency FE	-	-	No	No	Yes	Yes

Notes: Columns (1) and (2) report regression results of IMG doctor characteristics on an indicator for residency located in a health professional shortage area (HPSA). Columns (3) and (4) report regression coefficients on IMG doctor characteristics on an indicator for whether the first observed workplace is located in an HPSA. Columns (5) and (6) report the same coefficients as previously but including fixed effects for each residency program. Statistical significance at the 10%, 5% and 1% level are denoted by *, **, and *** respectively in the table.

Table 14: HPSA Source-Destination OLS Regressions

	From Non-HPSA Res.		From HPSA Res.	
	(1)	(2)	(3)	(4)
IMG	.032***		.011**	
	(.005)		(.05)	
US Citizen IMG		.012*		−.016
		(.007)		(.06)
Immigrant IMG		.043***		.159**
		(.006)		(.06)
N	29,616	29,616	274	274

Notes: The table splits the residency ER doctor sample into doctors who attended residency located outside of a health professional shortage area (HPSA) and those located within an HPSA. The outcome variable is an indicator of whether the first workplace observed for the doctor is in an HPSA. Statistical significance at the 10%, 5% and 1% level are denoted by *, **, and *** respectively in the table.

Table 15: Maximum Score Matching Estimator Results

Characteristic	**Coefficient**
Distance	-9.08
Non-Immigrant IMG $\times$ Distance	0.0005
Immigrant IMG $\times$ Distance	-0.462
Non-Immigrant IMG $\times$ HPSA	0.9693
Immigrant IMG $\times$ HPSA	8.2275

Notes: The table reports the estimated coefficients for a selected set of interaction variables between ER doctor mover and ER hospital characteristics as estimated by the maximum score matching estimator, described in equation 10. The distance variable is defined as the distance between the prior workplace and the location of the hospital to which they move, measured in miles.

Appendix A Medical School Sample

A.1 Web Scraping Physician Profiles

To supplement the National Provider File with more complete data on medical school, I rely on the publicly available physician information commonly found on online physician look-up tools. Services such as Doximity, WebMD, and USNews physician profiles exist to allow prospective patients to find and evaluate doctors. Typically, doctors can claim their profile, but the website may also automatically generate a profile for a doctor and fill in their information using commercially available data. This allows these sites to cover a large portion of the set of doctors working in the US. For example, Doximity claims to have profiles covering 80% of the doctor workforce. As the coverage of any one website is not complete, I check both WebMD and USNews profiles (these two in particular chosen for ease of web-scraping) for a given physician. My detailed procedure for gathering physician information is as follows:

- For a doctor in the NPF with no medical school name, search the profile website using the doctor's first and last name .
- Within the HTML source of the first page of search results, search for a profile indexed with the NPI of the doctor. If one exists, save the URL of the doctor profile page.
- Scrape the education and training data from the profile page.
- If no profile page is found, try searching by first, middle and last name and as well just middle and last name.

I implement the above procedure first using the USNews website. For the set of remaining doctors for who I find no profile or no medical school information, I repeat the search using WebMD. This procedure, combined with the education information in the NPF, returns a medical school name for 97% of doctors. While this procedure misses a small number of doctors, it cannot induce incorrect medical school data, as all profiles are matched to doctors using the NPI.

A.2 Medical School Name Matching

School Name Matching Procedure: The matching procedure proceeds as follows: given a medical school name that appears in the physician data, first check if it matches any school exactly in the World Directory of Medical Schools (WDOMS) database. For those without an exact match, query OpenAI's GPT4o-mini model through their API with this name as well as the WDOMS list of names, and ask it to output the closest matching name on the WDOMS list. I manually supplement this mapping generated by the LLM with the names of defunct U.S. medical schools.

Name Matching Validation: I manually validate the fuzzy match by examining a random set of non-exact school matches generated by my matching procedure. I sample 100 such matches, and find 91% of fuzzy matches are completely correct in the validation set and 96% are almost certainly at least matched to the correct country. This is a conservative estimate of the measurement error in my matched physician data analysis. A large portion of the medical school name data can be exactly matched, and even slightly non-matching but standardized raw names are much less likely to be duplicated and thus are less likely to be sampled. As a further check, I also take a random sample of 100 doctors who appear in my analysis set and find that all medical schools appear to be correctly matched if not missing. The fuzzy matching procedure does not appear to induce significant measurement error in my findings.

In the randomly selected validation sample of 100 medical school name mappings generated with the fuzzy matching procedure, I validate the mapping by manually inspecting the relationship between the raw name to the matched WDOMS school name. I find that 91 are clearly matched correctly, 5 refer to schools not in the 2024 WDOMS database but are clearly matched to the correct country, 1 is likely misclassified and 3 raw names clearly do not refer to a medical school and are not matched to any country.

Below I report all mismatched names as well as 11 correct non-exact matches.

Figure A1: Match Verification Results

(a) Correctly Matched Examples

Raw Name	**Matched Name**	**Matched Country**
s s g hospital (medical education)	Medical College Baroda	India
faculte de medecine pierre et marie curie	UFR de Médecine Broussais Hôtel Dieu, Université Pierre et Marie Curie	France
universidad peruana cayetano herredia	Universidad Peruana Cayetano Heredia Facultad de Medicina Alberto Hurtado	Peru
university of north texas health science center	University of North Texas Health Science Center Texas	United States of America
louisiana state university, shreveport, la	Louisiana State University School of Medicine in Shreveport	United States of America
state university of haiti school of med and pharmacy	Université dEtat dHaïti Faculté de Médecine et de Pharmacie	Haiti
k s hegde medical academy	K.S. Hegde Medical Academy	India
kj somaiya medical college and research centre maharashtra university of health sciences	K.J. Somaiya Medical College	India
des moines univers	Des Moines University College of Osteopathic Medicine	United States of America
st petersburg medical and technical institute	Saint Petersburg Medical and Technical Institute	Russian Federation
ramathibodi hospital faculty of medicine, mahidol university, faculty of medicine,bangkok, thailand	Ramathibodi Hospital Faculty of Medicine	Thailand

(b) Incorrectly Matched or Missing

Raw Name	**Matched Name**	**Matched Country**
boston univ goldman school of dental medicine	Boston University Chobanian & Avedisian School of Medicine	United States of America
anatomic and clinical pathology; pathology		
veer narmad south gujarat university	Government Medical College Surat	India
col of osteo med of the pacific at lebanon	University of the Incarnate Word School of Osteopathic Medicine	United States of America
pathology		
institute of medicine (medical education)	Institute of Medicine, Tribhuvan University	Nepal
froedtert hospital		
yunnan college of traditional chinese medicine	Kunming University of Science and Technology Medical School	China
umdnj-new jersey medical school	Rutgers New Jersey Medical School	United States of America

Notes: Table (a) reports a sample of correctly matched school names. Table (b) reports the incorrectly matched names in the validation set of 100 randomly sampled matches.

A.3 International Medical Schools

Medical schools in the Caribbean service a significant portion of US citizens. Such schools exist in the following countries.[29]

Table A1: Medical Schools Considered Caribbean

Caribbean Country	**School Name**
Barbados	Ross University School of Medicine
	American University of Integrative Sciences School of Medicine
	Washington University of Barbados School of Medicine
	Queens University College of Medicine
Grenada	St. Georges University School of Medicine
Sint Maarten	American University of the Caribbean School of Medicine
Antigua and Barbuda	American University of Antigua College of Medicine
	Atlantic University School of Medicine
	University of Health Sciences Antigua School of Medicine
Saint Kitts and Nevis	Grace University School of Medicine (Nevis)
	International University of the Health Sciences (IUHS)
	Medical University of the Americas (Nevis)
	Saint Theresas Medical University
	University of Medicine and Health Sciences, St. Kitts
	Windsor University School of Medicine
Cayman Islands	St. Matthews University School of Medicine (Grand Cayman)
Saint Lucia	American International Medical University School of Medicine
	International American University College of Medicine
	Spartan Health Sciences University School of Medicine
	College of Medicine and Health Sciences, St. Lucia
	Commonwealth School of Medicine
Saint Vincent and the Grenadines	All Saints University School of Medicine
	Saint James School of Medicine St. Vincent and the Grenadines
	Trinity School of Medicine
Aruba	Aureus University School of Medicine
	Xavier University School of Medicine, Aruba
Belize	Avicina Medical Academy
	Central America Health Sciences University Belize Medical College
	Columbus Central University School of Medicine
	Grace University School of Medicine (Belize)
	Hope University School of Medicine
	Medical University of the Americas (Belize)
	St. Lukes University School of Medicine
	St. Matthews University School of Medicine (Belize)
Curaçao	Avalon University School of Medicine
	Caribbean Medical University School of Medicine
	St. Martinus University Faculty of Medicine
Jamaica	All American Institute of Medical Sciences
	University of the West Indies Faculty of Medical Sciences, Jamaica
Montserrat	University of Science, Arts & Technology (USAT) Faculty of Medicine
Saba	Saba University School of Medicine
Trinidad and Tobago	University of the West Indies Faculty of Medicine St. Augustine, Trinidad
Dominica	St. Joseph University School of Medicine and Allied Health Sciences

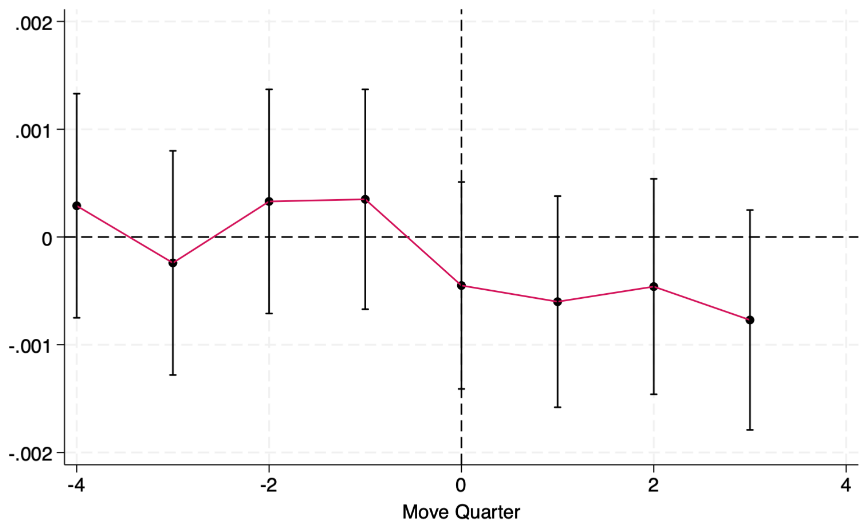
Notes: Table reports the medical schools found in the data set of doctors which are considered Caribbean.

[29] https://caam-hp.org/programs/

Appendix B Two-Way Fixed Effects Identification

B.1 Quality Around Move

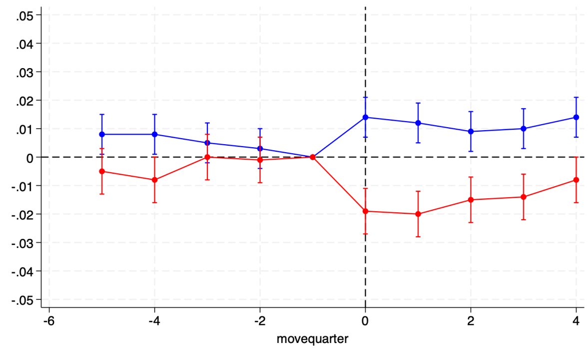
Figure A2: Adjusted Avg. Outcome Measure Around Move



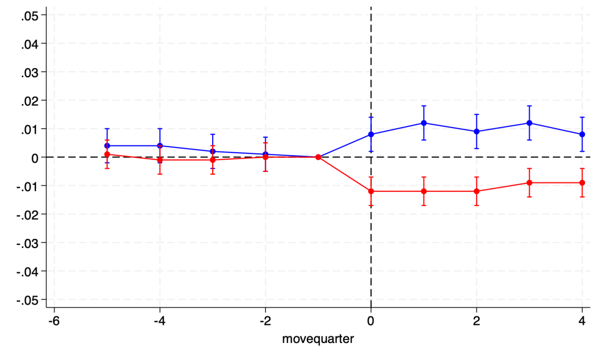
Notes: Figure plots relative quarter fixed effects υ_q as estimated in the regression equation $y_{it} = \beta X_{it} + T_t + \omega_j + \Sigma_{q=-4}^{4} \upsilon_q + e_{it}$ in the stacked sample of the cases involving doctor movers five quarters before and after their move. This regression is estimated with all patient-case mix controls and year, month and day-of-week fixed effects as well as doctor fixed effects.

B.2 Quality Change Symmetry Around Move

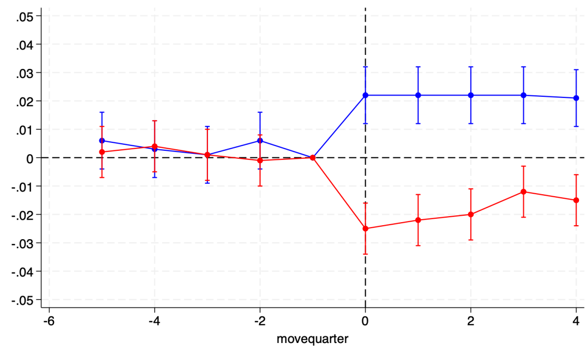
Figure A3: Symmetry of Moves between Hospital Quality Quartiles on Patient Outcomes



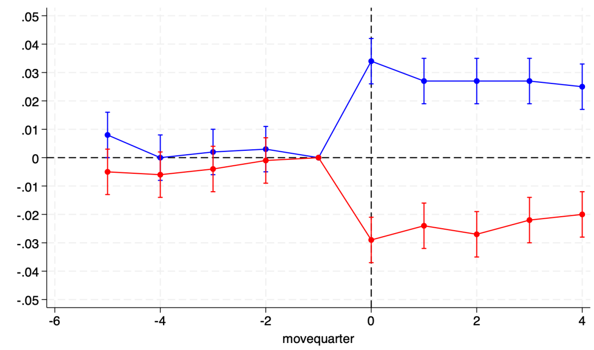
(a) Outcomes Around Moves Between 1-2 Quality Quartile Hospitals



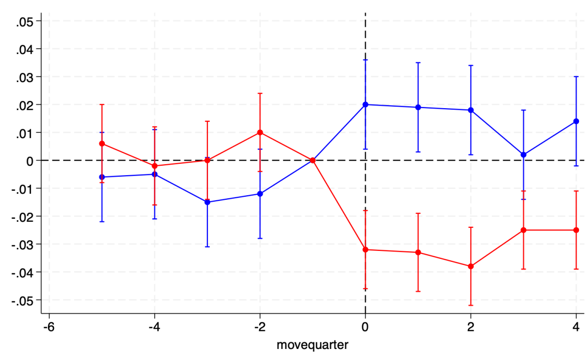
(b) Outcomes Around Moves Between 2-3 Quality Quartile Hospitals



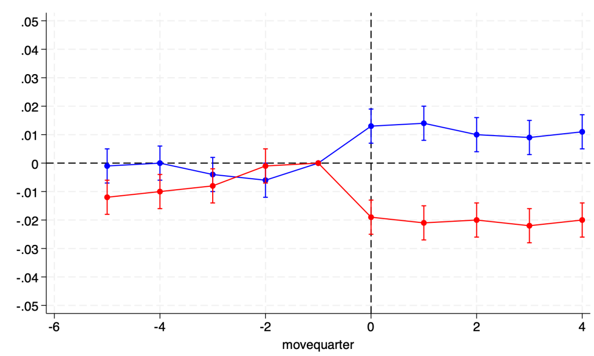
(c) Outcomes Around Moves Between 1-3 Quality Quartile Hospitals



(d) Outcomes Around Moves Between 2-4 Quality Quartile Hospitals



(e) Outcomes Around Moves Between 1-4 Quality Quartile Hospitals



(f) Outcomes Around Moves Between 3-4 Quality Quartile Hospitals

Notes: These figures depict changes in patient outcomes in the quarters surrounding a doctor move. Hospitals are grouped into quartiles based on their fixed effect as estimated in the main TWFE specification. Relative quarter fixed effects are estimated in each subsample of movers between hospitals in different quartile bins.

Appendix C Residency Rank and Location

Table A2: Residency Rank HPSA Workplace Distribution

	Overall	**Domestic**	**IMG**	**Caribbean**	**Immigrant**
All	4.6%	4.2%	8.9%	6.3%	10.6%
Tercile 1	4.3%	3.9%	10.6%	7.8%	11.4%
Tercile 2	4.1%	4.0%	4.8%	1.5%	7.5%
Tercile 3	6.1%	5.2%	12.3%	10.6%	13.4%

Notes: This table reports the share of doctors in each group who have a first workplace located in a health professional shortage area. The bottom 3 rows further split doctors by a proxy for the ranking of the residency program they attend. Tercile 1 is the highest-ranked tercile of residencies.